WORKER PROFILING AND REEMPLOYMENT SERVICES EVALUATION OF STATE WORKER PROFILING MODELS FINAL REPORT

MARCH 2007

Prepared for:

U.S. Department of Labor
Employment and Training Administration
Office of Workforce Security

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This project has been funded, either wholly or in part, with Federal funds from the Department of Labor, Employment and Training Administration under Contract Number AF-12985-000-03-30, Task Order 19. The contents of this publication do not necessarily reflect the views or policies of the Department of Labor, nor does mention of trade names, commercial products, or organizations imply endorsement of same by the U.S. Government.

ACKNOWLEDGEMENTS

The contributors to this report were many. From the Office of Workforce Security, Ron Wilus and Michael Miller provided overall direction and perspective that helped to bound and focus the study. We are especially grateful to Scott Gibbons for his invaluable assistance and guidance throughout the project. He was also most helpful in providing feedback on the various approaches that were considered, helping to acquire needed data, and managing the OWS review process. The reviewers included Wayne Gordon, Jonathan Simonetta, Stephen Wandner and Diane Wood.

We are grateful to the State Workforce Agencies for their promptness in completing the surveys and providing data needed to conduct the study. Without the information and data they provided, the analyses and resulting product could not have been achieved.

Amy Coffey served as the managing editor and was assisted by Bernie Ankowiak and Carol Johnson.

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EXECUTIVE SUMMARY

The Worker Profiling and Reemployment Services (WPRS) system, mandated by Public Law 103-152 of the Unemployment Compensation Amendments of 1993, is designed to identify and rank or score unemployment insurance (UI) claimants by their potential for exhausting their benefits for referral to appropriate reemployment services. The goals of this report are to 1) describe ways that state workforce agencies (SWAs) have implemented the worker profiling and reemployment services system (WPRS), 2) describe the methodology used to evaluate SWA worker profiling model accuracy, 3) determine the effectiveness of SWA models in profiling unemployment insurance (UI) claimants most likely to exhaust their benefits, and 4) prepare a summary of "best practices" (models) for SWAs to use in improving their WPRS systems.

With Department of Labor administrative support, we collected survey data for 53 SWAs (50 states, the District of Columbia, Puerto Rico and the Virgin Islands) regarding their WPRS operations. The diversity of their operations is described in tabular form in Appendix B. Individual reports for each SWA and territory are in Appendix C.

The survey responses demonstrated the variety of approaches SWAs use in the WPRS systems. The following describes some highlights.

Summary of WPRS System Differences

- Seven SWAs use the Characteristic Screen Model.
- Forty-six SWAs use a Statistical Model. Of these, 38 use logistic regression (logit) as the functional form, five use linear multiple regression, one uses neural network, one uses Tobit and one uses discriminant analysis.
- One SWA does not use any variables. Instead, it provides an electronic file based on the characteristics of all claimants who are eligible for WPRS services to the One-Stop Centers, and they determine the number and type of claimants to be called in for service.
- Seventeen SWAs have never updated their models since they were put into use.
- The major reason for updates has been to convert the occupational classification system from DOT to SOC or O*Net and industry classification system from SICs to NAICS.
- Twenty-nine SWAs have never revised their models since they were put into use.

- Of those SWAs that have revised their models, five were completed and put into use in 2005.
- Forty-two SWAs run the model weekly. The remaining 11 run the model daily.
- Forty-nine SWAs run the model against the claimant first payment file. The remaining four run it against the initial claim file.
- The list of eligible candidates is produced when the model is run for 47 SWAs and when a service provider requests referrals for SWAs. In two SWAs, the list is produced weekly even though the model is run daily.
- Thirty SWAs use occupation as a variable in their model. Twelve SWAs use DOT codes as their occupational classification system; 11 SWAs use the O*NET system (some directly and some based on feedback from the One-Stop; the remaining SWAs use the SOC classification system).
- Thirty-nine SWAs use industry as a variable. The most common method to verify employment and industry classification is a cross-match against the UI wage record files. Even if the industry classification is not used in the model, it is collected for other purposes. Forty-eight SWAs use the cross-match method, and the remaining five base the industry classification on the initial claim interview.
- Ineligibility for selection/referral to WPRS varies considerably. The most common reasons are:
    - Obtain employment through a union hiring hall
    - Interstate claimant
    - Temporary layoff
    - Will be recalled to previous employment
    - First payment occurred five weeks or more from the date of filing the initial claim

Eligible candidates:

- In 50 SWAs, lists of candidates are either mailed or sent electronically to the reemployment services provider. In most SWAs, the lists go directly to workshop/orientation staff, while in a few they go to local management personnel. In three SWAs, the lists are sent to administrative staff for review before being sent to the local service provider.
- The two most important determinants of the number of candidates to be served are staff availability and space. Most of the decisions on the number to be served are made locally. However, in six SWAs the number of claimants to be selected and referred is determined by central office personnel and/or a negotiation between central and local office personnel.
- In all SWAs (with the exception of the one SWA that does not calculate a score) that use the statistical model, candidates are sorted by their probability of exhaustion. In those SWAs that use characteristic screens, all candidates who are eligible for WPRS services are listed.

Variables:

- Fifty SWAs use benefit exhaustion as the dependent variable in the WPRS model equation. Other dependent variables used are:
    - Specific benefit duration – one SWA
    - Proportion of total benefits paid – one SWA
    - Exhaustion of benefits and long-term unemployed

Independent variables used in statistical models vary widely. The majority of SWAs still use the variables recommended by ETA when WPRS became law. These are:

- Industry (39 SWAs)
- Occupation (30 SWAs)
- Education (39 SWAs)
- Job tenure (40 SWAs)
- Local unemployment rate (24 SWAs)

We note that the above variables are entered into the models directly. Other SWAs may collect these variables and not use them in their models, or use these variables to create other variables that are in the models, such as industry unemployment rate.

Regarding our analysis of SWA profiling models, we had sufficient data to fully analyze nine SWA profiling models, which are included in Appendix D. For all SWAs, we attempted to replicate the existing SWA profiling score, develop a measure for UI benefit exhaustion for each individual, develop a control for endogeneity[1] (if possible), demonstrate the original model's effectiveness using a decile table and a comparison metric, develop an "updated" model and demonstrate its effectiveness, develop a "revised" model and demonstrate its effectiveness, develop a Tobit model and demonstrate its effectiveness, and analyze the effectiveness of specific variables for discriminating between exhaustees and non-exhaustees for individuals with the highest profiling scores, or Type I errors. Type I errors are individuals with high profiling scores and therefore predicted to exhaust benefits but who actually do not exhaust them.

Our analysis includes two innovations that we think significantly improve the analysis of WPRS models. First is the development of a metric that demonstrates the effectiveness of various profiling scores. Second is the control for endogeneity. Because profiling and referral affect

[1] Endogeneity refers to the problem that the profiling scores determine the individuals who get referred to reemployment services, and that these services may affect the probability of exhaustion. Therefore, observed exhaustion of profiled individuals would be a biased outcome measure. As described below, we developed a method for measuring and controlling for endogeneity.

observed benefit exhaustion, it is necessary to control for the effect of reemployment services when developing new profiling models.

Our metric is a statistic that demonstrates the effectiveness of a profiling score. Normally, the metric ranges from 0 to 1. If a profiling score is as effective as a random number generator, then the metric will be insignificantly different from 0. If a metric is a perfect predictor of UI benefit exhaustion, then it will take a value of 1. A metric of 0.100, means that, for individuals with high scores, the profiling score selects exhaustees 10 percent better than a random number. For the metric, we also calculate a standard error. For SWAs, the standard error allows comparison of multiple profiling models for statistically significant improvements. Details on how we calculated the metric are included below.

Profiling data from SWAs were analyzed using the respective models of the SWAs. We used those data submissions from SWAs which were complete and ran their models (without any changes) to rank individuals by their profiling scores. This ranking was then used to select individuals likely to exhaust benefits. For example, Arkansas had a calculated average exhaustion rate of 49.9 percent or 26,273 claimants who exhausted their benefits. After ranking individuals by profiling score, we selected the top 26,273 claimants with the highest profiling scores. This ranked group would have an exhaustion percentage that was either better or worse than the actual exhaustion rate experienced by Arkansas. We then revised the SWA's model, including changing some variables, and ran it to compare results.

Using data for Arkansas to gauge the predictive improvement of the SWA's profiling over its average exhaustion rate, we developed a metric that subtracts from 1.0 the ratio of the probability of claimants not expected to exhaust over the share (% divided by 100) of claimants not exhausting benefits. The metric will be referred to as the *profiling score effectiveness* metric, because it shows the extent that the SWA's profiling model beat its average exhaustion rate. Algebraically, the metric improvement for the data that Arkansas submitted is as follows:

$$\begin{aligned}
\text{Metric} &= 1 - (100 - \text{Pr}[\mathit{Exh}]) / \{100 - \mathit{Exhaustion}\} \\
&= 1 - [\text{Pr}\{\mathit{non\text{-}exhaustion}\} / (\text{Percent not exhausted})] \\
&= 1 - (100 - 54.64) / (100 - 49.9) \\
&= 1 - (45.36 / 50.1) \\
&= 1 - 0.905 \\
&= 0.095 \\
&= 9.5\%.
\end{aligned}$$

The 9.5 percent is the percentage of additional exhaustees selected by the profiling score over a score that is a random number. This percentage is the metric score.

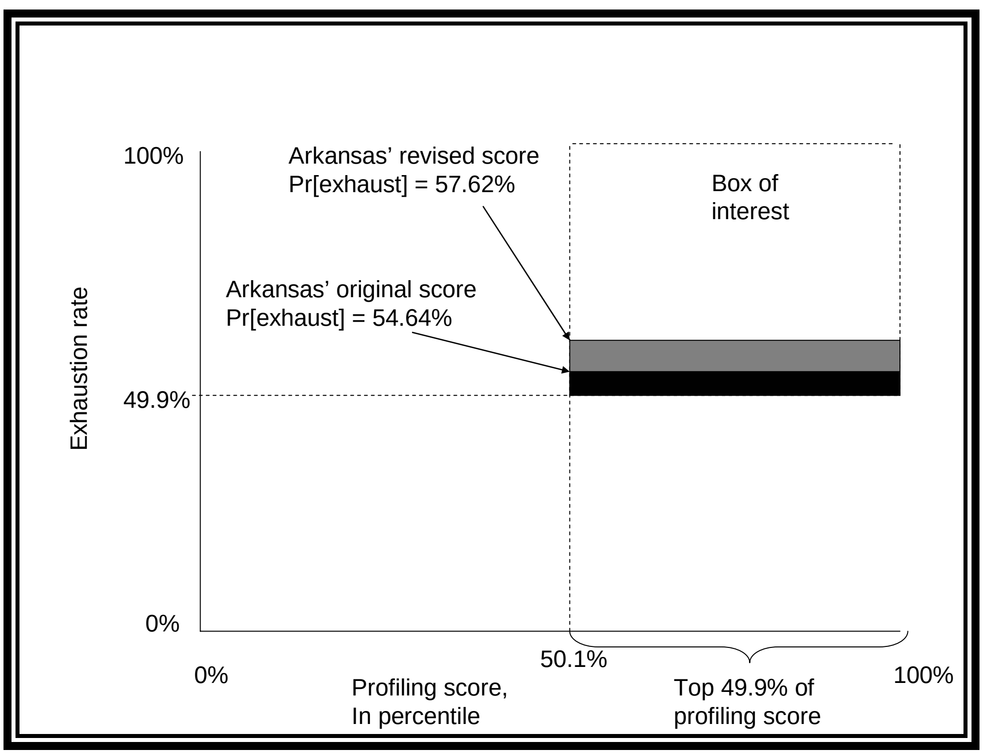
We revised the profiling model for Arkansas. This new score was better than the original score. For the top 49.9 percent of this new profiling score, or 26,273 claimants, the exhaustion rate was 57.62 percent; in the above formula, this number would be the new Pr[*Exh*]. For this revised score, the metric was 15.4 percent. The 15.4 percent is the percentage of additional exhaustees selected by the profiling score over a score that is a random number.

In all cases where the metric could be computed for a state, the SWA's profiling model predicted exhaustion in excess of the state average. Were the two values equal, the profiling model would not be better, on average, than the random selection of individuals for likely exhaustion. Arkansas' profiling model predicted that 54.62 percent of the claimants would exhaust, more than the 49.9 percent experienced by the state that included claimants with some low profiling scores.

If the profiling score were perfect, then the exhaustion rate of those selected would be 100 percent. If the profiling score were a random number, or not at all related to exhaustion, then we would expect the exhaustion rate of those selected to be the same as for the sample as a whole, or 49.9 percent.

To summarize, for Arkansas, the exhaustion rate for the top 49.9 percent of the sample (26,273 individuals) was 54.64 percent, which suggests that the profiling score is better than a random selection (54.64 percent is greater than 49.9 percent). Hence, the model beats the average by about 4.7 percentage points. Our revised metric score beats the average by about 7.7 percentage points. This information is displayed in Figure 1 below.

Figure 1
Illustration of Profiling Score Effectiveness Metric



The metric ranges from 0.0, for a score that is no better than a random number, to 1.0 for a score that predicts exhaustion perfectly. Graphically, the metric is illustrated by the figure above.

The figure is a rough illustration that contrasts the profiling score on the X axis, with individuals ranked from lowest to highest score. On the Y axis is the exhaustion rate of individuals. With higher profiling scores, we expect the exhaustion rate to increase.

The Box of Interest is the upper right rectangle defined by individuals with percentile profiling scores above (1.0 minus the state exhaustion rate) and an exhaustion rate above 49.9 percent. This area represents the set of non-exhaustees expected for a random profiling score.

If the profiling score were a random number, then the metric would be 0. The 49.9 percent of the sample with the highest profiling score, or 26,273 individuals, would have an exhaustion rate of 49.9 percent. This rate is the same as the state overall. For the sample with the highest profiling score, 26,273 individuals, 49.9 percent of them would exhaust, or 13,110 individuals. Non-exhaustees would be 50.1 percent of the 26,273, or 13,163 individuals. This group of 13,163 individuals represents the box of interest. The extent that a profiling score selects these 13,163 as exhaustees determines the value of the metric. For a score that selects all 13,163 as exhaustees, the metric will have a value of 1.0.

For Arkansas, the original score has a value of 54.64 percent, which is better than the state exhaustion rate of 49.9 percent. The area under this line, as a percentage of the area of the entire Box of Interest, is 9.5 percent. This area is shown in Figure 1 in black.

The revised score has a metric of 0.154, which implies that the area under this line, shown in the Figure above the line for the original score is 15.4 percent of the area in the entire Box of

Interest. The area corresponding to this revised score is shown in the figure as the sum of the black and gray areas.

From our experience working with these profiling models, we recommend the following:

- Use a logistic regression model
- Include at least the following independent variables:
    - Maximum benefit amount
    - Wage replacement rate
    - Education level
    - Delay in filing for UI benefits
    - Benefit exhaustion rate for the applicant's industry
    - Unemployment rate
    - County/metro area of residence
    - Industry and occupation codes
- Include continuous variables
- Include second-order variables
- Include interaction variables for models with more than one continuous variable

We note that exhaustion of UI benefits is the result of a very complex process that involves the interaction of individual characteristics and environmental characteristics. None of the models included enough information to explain a large percentage of exhaustion. However, our development of a metric allows SWAs to compare the effectiveness of different versions of their models.

The following table contains our metrics for assessing the effectiveness of profiling model scores in 28 SWAs. Each row of the table contains the SWA name, a description of the type of profiling score used, an indicator of whether the score has been corrected for endogeneity, the exhaustion rate for the sample of individuals provided by the SWA, the number of individuals with the highest profiling score (if the score were a perfect measure for exhaustion, then only these number of individuals would exhaust benefits), the rate of UI benefit exhaustion for the individuals with high profiling scores, the metric, the variance of the metric, and the standard error of the metric. For nine SWAs, Arkansas, District of Columbia, Georgia, Hawaii, Idaho, New Jersey, Pennsylvania, Texas and West Virginia, we were provided all data to replicate the original profiling score and were able to calculate an improved profiling score using the data provided. We include these other scores on our table for comparison purposes.

Metric for Assessing the Effectiveness of SWA Profiling Scores

SWA	Profiling score	Control for endogeneity?	Exhaustion rate for the state	Number of individuals with the highest profiling score	Exhaustion rate for individuals with high profiling scores	Metric	Variance of the Metric	Standard Error of the metric
Arizona	original score	Y	37.9	21,502	42.8	0.079	1.153	0.007
Arkansas	original score	N	49.9	26,273	54.6	0.095	1.804	0.008
Arkansas	revised score	N	49.9	26,273	57.6	0.154	1.686	0.008
Delaware	estimated score*	N**	39.0	4,207	42.4	0.055	1.227	0.017
District of Columbia	original score	N**	56.0	5,385	60.3	0.097	2.277	0.021
District of Columbia	revised score	N**	56.0	5,385	63.8	0.176	2.057	0.020
Georgia	original score	Y	35.7	75,994	44.0	0.129	1.017	0.004
Georgia	revised score	Y	35.7	75,994	47.3	0.181	0.976	0.004
Hawaii	original score	Y	39.7	3,526	43.9	0.069	1.248	0.019
Hawaii	revised score	Y	39.7	3,526	44.8	0.085	1.232	0.019
Idaho	estimated score*	Y	45.9	15,605	56.1	0.189	1.400	0.009
Idaho	revised score	Y	45.9	15,605	59.3	0.247	1.306	0.009
Iowa	original score	Y	15.4	2,456	16.2	0.010	0.368	0.012
Louisiana	original score	Y	42.6	22,825	51.9	0.161	1.282	0.007

Maine	original score	Y	37.3	7,346	42.6	0.084	1.121	0.012
Maryland	original score	N**	50.4	18,974	54.1	0.075	1.877	0.010
Michigan	original score	Y	52.7	60,128	55.2	0.052	2.110	0.006
Minnesota	original score	Y	33.6	37,395	43.5	0.150	0.922	0.005
Mississippi	original score	N	45.5	8,208	47.3	0.033	1.620	0.014
Missouri	original score	Y	50.6	18,727	58.3	0.156	1.726	0.010
Montana	original score	Y	53.4	1,678	58.0	0.100	2.051	0.035
Nebraska	original score	N***	95.2	44,098	95.5	0.054	36.698	0.029
New Jersey	original score	Y	62.4	67,030	66.0	0.096	2.947	0.007
New Jersey	revised score	Y	62.4	67,030	67.6	0.137	2.789	0.006
New York	original score	Y	40.4	205,729	55.5	0.253	1.073	0.002
Pennsylvania	original score	Y	46.1	103,172	51.2	0.095	1.564	0.004
Pennsylvania	revised score	Y	46.1	103,172	52.5	0.118	1.527	0.004
South Dakota	original score	N**	18.5	1,107	25.6	0.087	0.475	0.021
Tennessee	original score	Y	49.7	26,299	53.5	0.075	1.830	0.008
Texas	original score	Y	48.0	190,270	56.6	0.165	1.555	0.003
Texas	revised score	Y	48.0	190,270	56.9	0.170	1.545	0.003
Vermont	original score	N**	28.3	359	37.9	0.133	0.756	0.046
Virginia	original score	Y	23.3	21,186	27.7	0.057	0.611	0.005
West Virginia	original score	Y	41.0	12,209	50.7	0.164	1.205	0.010
West Virginia	updated score	Y	41.0	12,209	55.4	0.243	1.109	0.010
Wisconsin	original score	N	44.2	8,991	46.2	0.036	1.533	0.013
Wyoming	original score	N**	43.9	47	46.8	0.051	1.497	0.178

* SWA used a characteristic screen. We calculated a profiling score that used the same variables as the screen.

** SWA provided data indicating individuals who were referred, but the effect was insignificant.

*** Nebraska had possible data problems, with 95% of the sample having more benefits paid than mba(maximum benefit allowance)

INTRODUCTION

In 1993, Congress passed Public Law (P.L.) 103-152, an amendment to Section 303 of the Social Security Act, which required state employment security agencies to establish and utilize a system for profiling new Unemployment Insurance (UI) claimants. This legislation charged states with developing a profiling system that:

- "identifies which claimants will be likely to exhaust regular compensation and will need job search assistance services to make a successful transition to new employment;"
- "refers claimants identified pursuant to subparagraph (A) [first paragraph above] to reemployment services, such as job search assistance services, available under State or Federal law;"
- "collects follow-up information relating to the services received by such claimants and the employment outcomes for such claimants subsequent to receiving such services and utilizing such information in making identifications pursuant to subparagraph (A) [first paragraph above];" and
- "meets such other requirements as the Secretary of Labor determines appropriate."

This legislation also provided that as "a condition of eligibility for regular compensation for any week, any claimant who has been referred to reemployment services pursuant to the profiling system…participate in such services or in similar services unless the State agency charged with the administration of the State law determines – (A) such claimant has completed such services; or (B) there is a justifiable cause for such claimant's failure to participate in such services."

In effect, P.L. 103-152, <u>required</u> state workforce agencies (SWAs) to develop a profiling system which met the above criteria and to place additional conditions of eligibility on claimants who had been referred to reemployment services pursuant to the implemented profiling system as a condition for receiving administrative grants.

Guidance in Implementing Worker Profiling Models

Department of Labor ("DOL") Field Memorandum No. 35-94 was published as a guide to state administrators on the implementation of a system of profiling Unemployment Insurance claimants and the provision of reemployment services to those claimants. DOL states that the primary objective of the Worker Profiling and Reemployment Services (WPRS) system is to efficiently identify and match dislocated UI claimants with needed services by coordinating and balancing the flow of referrals with available reemployment services, with matching being done at an early stage in the claimant's unemployment period in order to foster a rapid return to productive employment in a manner that is cost effective.

The basic components of profiling are outlined in the memorandum as: (1) **Identification** - the proper identification of claimants most likely to exhaust using either a statistical model or a non-statistical claimant characteristic screen; (2) **Selection and Referral –** the process of selecting and referring those UI claimants identified as dislocated workers to appropriate reemployment service providers by no later than the end of the fifth week from each identified claimant's UI initial claim date; (3) **Reemployment Services –** the provision of appropriate reemployment services to referred claimants, accomplished most effectively through a coordination of effort between the UI system and service providers; and (4) **Feedback** – the establishment of an information system between the UI system and service providers that will provide information on the services provided to referred claimants and/or the claimant's failure to report or to complete such services in order to make determination on continuing UI eligibility as well as for evaluation of the effectiveness of profiling and reemployment service systems.

In an examination of dislocation factors, DOL found the worker and economic characteristics or "data elements" discussed below to be significantly associated with long-term employment. The memorandum recommends that states incorporate as many of these data elements as they can into their WPRS systems. The recommended data elements or factors are:

- **Recall Status –** identifies claimants who are permanently separated from their jobs versus those with a definite date(s) of recall to work or who expect to be called back to work but do not have a definite recall date(s). Claimants with recall date(s) are considered much less likely to exhaust their UI benefits during their present spell of unemployment. The memo recommends that this data element be used as part of an initial or "first level" screen in order to include only permanently separated claimants in the WPRS system and exclude those claimants with job attachment.

- **Union Hiring Hall Agreement –** suggests that union-sponsored job search resources are available that obviate the need for reemployment services traditionally needed by other workers. This data element is also recommended to be used as part of a "first level" screen to exclude claimants who use union hiring halls because they do not need assistance given through the referral to a reemployment service provider.
- **Education (level) –** is closely associated with dislocation and that generally claimants with less education are more likely to exhaust benefits than claimants with higher levels of education.
- **Job Tenure –** is the measure of the length of time that a worker was employed in a specific job. Tenure on the previous job is positively related to reemployment difficulty because it measures knowledge and skills that are specific to the worker's previous job. DOL cites studies that show the longer a worker is attached to a specific job, the more difficulty the person has in finding an equivalent job elsewhere.
- **Previous Industry –** affects a claimant's search for employment. This is due to the fact that claimants who worked in industries that are declining relative to other industries in a state experience greater difficulty in obtaining new employment than claimants who worked in industries that are experiencing growth. DOL notes that obtaining data concerning a claimant's former industry would be done by most states at the initial claims process and that these data would then be matched with labor market information regarding growing and declining industries within the state or sub-state areas.
- **Previous Occupation –** workers who are in low demand occupations can expect to experience greater dislocation and greater reemployment difficulty than workers who are in high-demand occupations. Occupational data will enable states to more effectively identify those UI claimants in need of reemployment services and recommend that occupation could be collected at the time of initial claim filing or via work registration. Occupation could then be matched with labor market information regarding expanding and contracting occupations in the state in order to determine which occupations are high-demand and low-demand.
- **Total Unemployment Rate –** in sub-state areas with high unemployment, this variable suggests unemployed workers will have greater difficulty becoming reemployed than those workers in areas with low unemployment, all other conditions being equal. DOL

recommends that states which are able to utilize unemployment data for sub-state regions or areas use this information to enhance the accuracy of their profiling model.

The field memorandum also recognizes that, in most states, data about individual claimant characteristics must be collected during the initial claims process, while in other states this information may be available through other sources. Data elements that are most likely to be collected through the initial claims process include the claimant's recall status, union hiring hall agreements, education level, years of tenure on the pre-UI job, and the industry and occupation codes for their pre-UI jobs.

Evaluation Objectives and Design

This report provides the Department of Labor with an examination of the states' models while controlling for selection and referral using data provided by the states. To the extent that reemployment services affected subsequent exhaustion, the observed exhaustion rate would be an invalid dependent variable for evaluating state models. The primary objective of this study was to improve state worker profiling models by 1) establishing an approach for evaluation of the accuracy of worker profiling models, 2) applying this approach to current state models to determine how effective they were at predicting UI benefit exhaustion, and 3) based on the results, developing guidance on best practices in operating and maintaining worker profiling models.

The specific goals of this report are to:

- Describe the worker profiling and reemployment services system states have implemented.
- Describe the methodology used to evaluate state worker profiling model accuracy.
- Determine the effectiveness of state models in profiling UI claimants most likely to exhaust their benefits.
- Prepare a summary of "best practices" (models) for states to use in improving their WPRS systems.

Research Methods for this Report

The primary source of data for this report is a survey that was sent to state administrators in January 2006 that requested information and data on the operational and structural aspects of their worker profiling models. **Appendix A** contains the survey instrument. The operational section of the survey included a description of the state WPRS system operations, such as: how often the model is run, how much control the area offices have over the number who are referred for reemployment services, how often the model is updated, and who maintains and monitors model performance. Structural aspects describe how the model predicts the likelihood of claimants exhausting their benefits; including the data elements used, and how they are categorized or transformed, how the state defines exhaustion, the functional form of the model, and the model coefficients. Some states determined that the most efficient and effective way to provide the highly technical structural information requested was to simply attach technical reports or computer print-outs containing the pertinent information.

Secondary sources for the report include scholarly, legislative, governmental and professional reports on the WPRS system, as well as previous evaluations of the system (see bibliography and literature review). It is important to note that even though P.L. 103-152 was enacted in 1993, limited research has been conducted to determine how effective states are at targeting those most likely to exhaust benefits.

LITERATURE REVIEW

I. WPRS: Program Initiation and Research Support

Enacted on March 4, 1993, P.L. 103-6 required the Secretary of Labor to establish a worker profiling system within the Unemployment Insurance (UI) program nationwide. State participation in this new program was voluntary at first. However, P.L. 103-152, enacted on November 24, 1993, required the States to profile all new claimants for regular UI benefits (U. S. Department of Labor, Employment and Training Administration 1994). The new law required States to operate a system that "(A) identifies which claimants will be likely to exhaust regular compensation and will need job search assistance services to make a successful transition to new employment; (B) refers claimants identified pursuant to subparagraph (A) to reemployment services, such as job search assistance services, available under any State or Federal law; (C) collects follow-up information relating to the services received by such claimants and the employment outcomes for such claimants subsequent to receiving such services and utilizes such information in making identifications pursuant to subparagraph (A); and (D) meets such other requirements as the Secretary of Labor determines are appropriate" (P.L. 103-152, Sec. 4. Worker Profiling). Participation in the reemployment services program was required of everyone claiming state UI benefits unless the claimant had recently completed a similar program or had 'justifiable cause' for not doing so.

The combination of worker profiling and reemployment services had its foundation in demonstration projects that took place in the 1980s. Using characteristic screens to identify those most likely to exhaust, the New Jersey Unemployment Insurance Reemployment Demonstration Project (NJUIRDP) enrolled 8,675 claimants. Workers were assigned to one of three treatment groups: 1) Job Search Assistance (JSA) only; 2) JSA plus training/relocation assistance; 3) JSA plus a cash bonus for early reemployment. An evaluation of the project showed that all three treatment groups had increased employment and earnings and reduced collection of benefits (Corson and Haimson 1996). These results were persuasive to policymakers: "Based in part on the design and the initial findings from the NJUIRDP, the Unemployment Compensation Amendments of 1993 mandated that states identify workers likely to exhaust UI and refer them to reemployment services" (Corson and Haimson 1996, p.55).

Other UI reemployment experiments used random assignment of claimants to treatment groups. Meyer (1995) looked at bonus experiments in Illinois, New Jersey, Pennsylvania and Washington State, and he looked at five job search experiments (Charleston, New Jersey, Washington, Nevada and Wisconsin), including some where the state increased enforcement of the job search. In the bonus states, the results were positive: "First, the bonus experiments show that economic incentives do affect the speed with which people leave the unemployment insurance rolls….This is shown by the declines in weeks of UI receipt found for all the bonus treatments, several of which are statistically significant" (Meyer 1995, p.124). Structured job search appeared effective as well: "The job search experiments test several alternative reforms which appear promising. The five experiments try several different combinations of services to improve job search and increase enforcement of work search rules. Nearly all these combinations reduce UI receipt and (when available) increase earnings" (Meyer 1995, p.128).

The Department of Labor defined the new Worker Profiling and Reemployment Services (WPRS) system as "an early intervention approach for providing dislocated workers with reemployment services to help speed their return to productive employment. It consists of two components: a profiling mechanism and a set of reemployment services" (U. S. Department of Labor, Employment and Training Administration 1994, p.3). The profiling mechanism had one purpose: to determine which claimants are likely to collect all of the benefits to which they are entitled. The scope of the new profiling system was extensive: "Profiling will select those UI claimants who are likely to be dislocated workers out of the broad population of UI claimants and refer them to re-employment services early in their unemployment spell. Over the next several years, the result will be to select about two million dislocated workers from eight to nine million UI initial claimants" (U. S. Department of Labor, Employment and Training Administration 1994, p.3).

The Department of Labor requirements were clear: Each state had to establish a profiling system that identifies new claimants who were unlikely to return to their previous occupation or industry and refers those workers to reemployment services that could reduce the duration of their unemployment (U. S. Department of Labor, Employment and Training Administration, 1994). While the other components of WPRS posed challenges for the states (e.g., UI staff had to negotiate with local employment services program managers to ensure the delivery of job search services that claimants needed), the method for selecting claimants who were likely to exhaust was of prime importance. Although many states had traditionally identified permanently separated claimants and considered many to be dislocated workers, there was no established system nationwide for targeting these individuals or prioritizing reemployment services.

The model provided to states by the Department of Labor was designed to accomplish several objectives. It had to be sensitive to state economic conditions and understandable to UI staff in the states. Unemployment Insurance policymakers had to be able to set thresholds for referral of claimants in need of services. The result had to be selection of a target group of likely exhaustees that could actually be provided services under existing staffing constraints (Worden 1993). A two-step method was created. First, in order to avoid interfering with workers' connections to existing employers, claimants with a recall date were excluded. Workers whose job search focused solely on union hiring halls were excluded as well, since they were unlikely to profit from the job search services being offered. Second, five variables (education, occupation, industry, job tenure, and the state unemployment rate) were used to identify and rank by probability of exhaustion the group to be referred for services. An evaluation of the model indicated that it would effectively select a target population that needed services: "Historic data indicate that the model would target a group of claimants equal to 30 percent of the total UI population, while including 53 to 60 percent of all UI recipients with serious reemployment difficulties" (Worden 1993, p.126).

Although the Department outlined two approaches to developing a profiling method (i.e., statistical models and characteristics screening), it recommended that states use the statistical model approach because the model predicted a probability of benefit exhaustion for each claimant. However, the Department cautioned states that chose to use the model that adoption of the national model was only the first step: "This profiling model is not meant to be standardized for all States or to be constant over time. Rather, it is subject to modification by individual States to meet their particular needs. The coefficients used in this profiling model should optimally be re-estimated based on State (and possibly sub-state) historical data for each variable, in order to derive State-specific coefficients for the model. Additional variables can be added to the model, in order to pick up factors specific to the state. The definitions of the variables can be altered, if necessary, to reflect particular circumstances that are unique to the State (U. S. Department of Labor, Employment and Training Administration, 1994, p.11).

II. WPRS: The First Four Years

A comprehensive review and evaluation of the first few years of WPRS implementation found that states were, for the most part, following the directions provided by the Department of Labor (Hawkins, Kreutzer, Dickinson, Decker, and Corson 1996). Focusing on data from the five states that were initially funded to develop a program, as well as a survey of state program managers, the research team found all states excluded workers with recall dates and attachments to union hiring halls. Each state was able to develop and implement a method for identifying the target group of likely exhaustees, although some states required expertise provided by area universities and others. Most states used statistical models and adopted the same approach as the original Department of Labor model: "Four of the five states that used statistical models specified a binary indicator of UI benefit exhaustion as the dependent variable. These four states all estimated the models of benefit exhaustion using logit regression analysis, which was also used by DOL to estimate the prototype" (Hawkins et al 1996, p.III-6).

The State of Kentucky took a different approach. Based on a model developed by the Center for Economic and Business Research, Kentucky specified the dependent variable as the proportion of benefits collected. "Researchers at the Center adopted this dependent variable because they felt it provided greater information than the simpler binary exhaustion indicator. After experimenting with several estimation methods, the researchers at the Center decided to estimate the model using Tobit regression methods because they felt it provided the most accurate predictions" (Hawkins et al 1996, p.III-6).

Generally, in building their models, States used the explanatory variables recommended by the Department of Labor. Again, Kentucky was an exception: "the (Kentucky) model contained a large number of explanatory variables, including those related to a claimant's previous wage, UI benefit parameters, reservation wage, pensions, assistance receipt, prior UI receipt, industry growth, occupation growth, job tenure, work experience, reason for separation, county unemployment rate, and county employment growth" (Hawkins et al 1996, p.III-7 & III-8).

The models were considered to be effective: "The models clearly identified claimants who were most likely to exhaust their benefits" (Hawkins et al 1996, p.III-10). However, looking to the future, the research team expressed concern that states might soon begin re-estimating their models using samples that included WPRS participants.

The 1997 *Report to Congress* on the effectiveness of WPRS supported the evaluation findings contained in the interim report. The research team concluded that claimants likely to exhaust were being identified and referred for services early in their benefit year. Claimants who did not need services were being excluded. Most states were using statistical models to identify and rank WPRS participants. These participants were receiving more services than claimants who were not referred (Dickinson, Decker, and Kreutzer 1997). There was also preliminary evidence that WPRS participants had favorable outcomes: "Estimates based on the early implementation states provide reasonably strong evidence that WPRS, as it was implemented in these states, significantly reduced UI receipt: For two of the three states that appeared to have the most accurate data (Kentucky and New Jersey), the WPRS reduced benefit receipt by slightly more than half a week per claimant, which translates into a UI savings of about $100 per claimant" (Dickinson et al 1997, p.IV-4). Nevertheless, the research team recommended that the Department of Labor and the states monitor WPRS more closely to make certain that the claimants most likely to exhaust are being selected and referred for reemployment services.

At a conference in 1999, the same research team presented several conclusions based on their investigations of state profiling methods: 1) states that were using characteristics screens were not accurately identifying those claimants most likely to exhaust because they did not differentiate among those who passed the screens; 2) the states that were using national coefficients provided by the Department of Labor were not as successful as those that had developed state-specific models; and 3) states need to continually update their models to reflect recent changes in the economy, e.g., growth or decline of occupations and industries (Dickinson, Decker, and Kreutzer 2002).

III. WPRS: Following the *Report to Congress*

In 1998, the Department of Labor closely reviewed the specifications used in the profiling models of thirteen states. The results (Kelso 1999) indicated that the states not only had to develop alternative specifications, but also had to introduce new data elements and variables in order to achieve the purpose of profiling, i.e., identify the individuals most likely to exhaust benefits. For the most part, however, states were using benefit exhaustion for the dependent variable and focused on the amount each claimant was paid during the benefit year. This approach follows the national model, which envisioned a binary outcome: "Thus, the dependent variable in the DOL model was coded as '1' for exhaustees and '0' for non-exhaustees. The output of the model is a predicted probability between zero and one that each claimant will exhaust benefits. Both the national and Maryland[2] versions of the DOL model used logistic regression, the preferred statistical technique that accounts for the complexities introduced by a binary dependent variable…. A binary dependent variable is a special constrained case which usually cannot be modeled using simple ordinary least squares (OLS) regression analysis…" (Kelso 1999, p. 20).

Some states modified the DOL model, which coded as exhaustees only those who had collected 100 percent of their benefits. These states have used a lesser standard to determine exhaustion (e.g., the claimant collected 90 percent of entitlement), set a minimum amount of weeks to prevent identifying claimants whose benefit entitlement consisted of only a few weeks, or simply coded all workers receiving federal extended benefits as exhaustees.

Other states decided to explore alternatives to a binary dependent variable (e.g., the number of weeks claimed). The ratio of benefits drawn to potential benefit entitlement was also tested, using ordinary least squares (OLS) regression. However, this alternative was not considered by the reviewer to be more effective: "Experimentation with this dependent variable concluded that using it in a WPRS model incurred significantly more estimation difficulties and gained little with respect to predictive capability. Ultimately, this method was abandoned in favor of logistic

[2] The State of Maryland was the test site for the DOL profiling model.

regression using a binary dependent variable.…In general, since logistic regression is more straightforward and well-supported in economic literature, and since it focuses on the characteristics of claimants who exhaust benefits, it is the preferred method for targeting claimants for WPRS" (Kelso 1999, p. 21).

States were also exploring the use of a wide variety of independent variables. Some states were using continuous variables (can take on a range of values) instead of categorical indicators (can take on a binary or restricted set of values) for the variables that had been determined to be good predictors, e.g., education and job tenure. Industry of the claimant's last job was found to be a valuable predictor and states were able to include industry change rates. The impact of the claimant's occupation on exhaustion rates was less clear. Lack of consistency in assigning occupational codes to claimants and the use of different occupational coding schemes in determining rates of growth or decline created problems. More work was needed: "Few states at this point have been able to incorporate meaningful occupational effects into their WPRS systems. Since occupation would seem to have a great deal of intuitive value in forecasting long-term unemployment, the challenge for the future is in developing reliable methods for coding claimants' occupations and collecting data that accurately measure the relative labor-market demand for them" (Kelso 1999, p. 26).

States experimented with several other data elements: weekly benefit amount; wage replacement rate; base year wage; potential duration; the time delay in filing for UI benefits following a separation; the ratio of high quarter wage to base year wage; number of base period employers; and benefits drawn on a seasonal basis.

The evaluation of the 13 state models concluded with a reminder that further evaluation, redesign, and updating of state models is critical to achieving the objectives of WPRS and that new challenges will emerge: "The estimation of profiling equations will need to evolve over time to avoid the omitted variable bias that could be otherwise introduced by the impact of re-employment services on exhaustion outcomes. This is likely to require controls for both the receipt of reemployment services and for the types of services completed" (Kelso 1999, p.33).

During 1998, workforce development professionals from both state and federal government reviewed the first four years of WPRS and made several recommendations to improve the system. The first recommendation dealt with the use of models: "Within State resource constraints, States should update and revise their profiling models regularly, as well as add new variables and revise model specifications, as appropriate. DOL should provide technical assistance to the States in model development and collect and disseminate best practices from the States" (Wandner and Messenger, eds. 1999, p.16). More specifically, the WPRS Workgroup encouraged states to update the weights assigned to different variables in their models, investigate the potential value of research done by other states, change model specifications every few years and include a variable related to the claimant's main occupation. DOL was encouraged to assist states in testing new variables and making changes in model specifications.

Olsen, Kelso, Decker, and Klepinger (2002) investigated the effectiveness of profiling models in predicting exhaustion of benefits. Using data from the Florida Job Search Assistance Demonstration of 1995-1996 and the New Jersey UI Reemployment Demonstration Project, they compared the effects of both the initial screen for "recall" and the predicted probability of exhaustion for both treatment and control groups. The models did identify claimants who were likely to exhaust and both steps were important. "However, the targeting power of the model is modest….Exhaustion seems to be very difficult to predict accurately with available demographic and labor market data" (Olsen et al 2002, p.53).

The authors also investigated whether the implementation of the WPRS program itself will seriously contaminate new estimates of the profiling models. Concerned that states would use data that include claimants who received WPRS services to predict the behavior of new claimants, they used data from the Florida Job Search Assistance Demonstration to construct "contaminated" and "uncontaminated" profiling models and investigate whether the models were equally accurate in identifying likely exhaustees. They concluded that there is little difference in the groups identified by each model, thereby suggesting that contamination from mandatory services under WPRS is not a serious issue as states re-estimate their models: "This conclusion is consistent with previous research that measures fairly modest effects of WPRS on UI receipt, because the contaminating effect of WPRS on exhaustion should only be large if WPRS generates large reductions in UI receipt" (Olsen et al 2002, p.52).

IV. Recent Evaluations and Modeling Improvements

Black, Smith, Berger, and Noel (2003) set out to determine the effects of being profiled on claimant behavior. Using data from Kentucky and an experimental design that randomly assigned claimants with the same profiling score into treatment and control groups, the research team found that the profiling program was very cost-effective: mean weeks of unemployment benefits were reduced by 2.2 weeks, the amount collected was reduced by $143, and the mean gain in earnings from employment was about $1,000. The impacts of WPRS were substantial: "The WPRS impacts reported here also tend to be larger than those reported from experimental evaluations of job search assistance programs for UI claimants summarized by Meyer (1995)" (Black et al 2003, p.1320).

Analysis of these data led to two other major findings: 1) most of the impact is due to claimants' voluntarily leaving the unemployment rolls soon after being profiled and referred to reemployment services, and 2) there was no significant relationship between the estimated impact of treatment and the profiling score. The findings reinforce the value of further research on the effectiveness of profiling models: "the underlying assumption of the WPRS program is that those with the longest expected UI spell duration would benefit the most from the requirement that they participate in reemployment services in order to continue to receive their UI benefits. It is also assumed that treating these claimants will result in the largest budgetary savings for the state UI systems. Our results provide little justification for either assumption, as we do not find a monotone relationship between the profiling score and the impact of treatment" (Black et al 2003, p.1325).

Black, Smith, Plesca, and Shannon (2003) investigated alternative profiling models using UI administrative data from Kentucky for fiscal years 1989-1995 and offered several recommendations to states that could both simplify their existing models and improve their predictive power. Since these years included very different economic conditions, the research team expressed confidence that other states could rely on both their methodology and their conclusions. Analysis of different approaches to estimating profiling models led to "six substantive guidelines for the specification of UI Profiling models," including: 1) a preference for ordinary least squares estimation of linear models; 2) selection of a *continuous* measure as the dependent variable; 3) elimination of variables describing local employment conditions; 4) introduction of several additional variables that will increase the predictive power of the model without increasing its complexity; 5) omission of regional economic variables; and 6) acknowledgment that the business cycle does affect the predictive power of the model (Black, Smith, Plesca, and Shannon 2003, pp.35-36).

Eberts and O'Leary (2003) redesigned the profiling model that the state of Michigan used since 1995 to meet the federal requirement for a WPRS system. After considering the recommendations contained in the study by Black, Smith, Plesca, and Shannon (2003) and exploring an alternate specification that predicts the "fraction of benefits drawn during the benefit year," Eberts and O'Leary recommended that the model be re-estimated *retaining* exhaustion of benefits as the dependent variable: "This model performed slightly better and it is easier to interpret" (Eberts and O'Leary 2003, p. 16). However, Eberts and O'Leary recommended to the Michigan UI policymakers that the claimants profiled using the new model be divided into 20 percentile groups, following Kentucky's approach, and that Michigan UI refer groups with the highest scores to reemployment services first. Recognizing that wage record data are now available to Michigan UI staff, the state was also encouraged to update the model periodically with new variables.

V. Conclusion

In April, 2003, Christopher J. O'Leary, Senior Economist at the W.E. Upjohn Institute for Employment Research, summarized for the U.S. Congress the impact of the WPRS system that resulted from the passage of P.L. 103-152 in 1993. He pointed out to Congress that WPRS was a unique approach to actually allocating services to people in need and that independent evaluations of WPRS had documented the ability of profiling models to identify those most likely to exhaust. Noting that about 85 percent of the states now use statistical models, O'Leary testified that states need to improve their ability to accurately identify likely exhaustees: "At the heart of WPRS is a statistical model that predicts the probability that a UI beneficiary will exhaust his or her benefits… In order to ensure that the predictions are as accurate as possible, states must be diligent in updating their statistical models on a regular basis" (O'Leary 2003). He also recognized the need for some states to rely on universities and other professional groups to redesign and test changes to their models.

Subsequently, O'Leary summarized the impact that program evaluations have had on the UI system: "Research has guided the development of at least three aspects of the UI system: programs for dislocated workers, targeted job search assistance and institutions for the coordination of services. These in turn have led to the establishment of the WPRS system, one-stop career centers, and State Eligibility Review Programs as part of the work test that is administered by UI and one-stop career center staff" (O'Leary 2006, p.31).

WPRS MODEL EVALUATION STUDY

As noted earlier, even though WPRS became law in 1993 and was implemented by the states shortly thereafter, research on the effectiveness of the model to accomplish its goals has been limited. Twenty-nine state workforce agencies (SWAs) have never revised the model, and of those, 17 have never updated it. Major changes have taken place in the way initial UI claims are taken. In-person filing occurs in only a few states. Many SWAs have moved to allowing individuals to file using the telephone, and more recently, states are taking initial claims by the Internet. The delivery of reemployment services has been decentralized, with local Workforce Investment Boards (WIBs) determining the individuals to target for services, and in many cases, who should provide the services. These factors contributed to a decision by DOL to undertake a thorough examination of the effectiveness of WPRS models used by the SWAs.

This study has two major components: data collection and evaluation of the data and information collected.

- Qualitative information and data regarding WPRS activities were collected by survey from agencies (generally UI) responsible for profiling UI claimants and referring them to reemployment services. The survey asked SWAs to supply narrative responses and 12 months of data in order for the contractor to analyze the effectiveness of their profiling models. The survey consisted of two sections:
    - An operational section that included an outline of the logistics of the model, including model monitoring, frequency of the runs, controls on the flow of candidates, business practices, etc.
    - A structural section to gain insight into the model composition, the process used to capture and validate data, and other associated practices. The information

provided by the SWAs was utilized to replicate the screening of characteristics and claims data of individual claimants.

- Twelve months of profiling data was used to replicate the WPRS models used by the SWAs. The data included:
  - Administrative data records used for profiling a claimant such as the initial claim, continued claims, claimant characteristics and monetary determination(s).
  - Data for any other explanatory independent (right-hand side) variables included in the prediction equation such as local unemployment rate.
  - Predicted values of the dependent (left-hand side) variable of the exhaustion equation associated with profiling a claimant.

Our research was guided by three questions. First, how do the WPRS models and processes operate and how accurate are the models currently in use? Second, what strategies or tactics could be used to improve existing models? Third, based on our analyses, findings, and conclusions, what are some potential best practices and models that state policymakers should consider for improving their current WPRS systems?

To begin answering these questions, the Worker Profiling and Reemployment Services survey in Appendix A was submitted for SWAs to complete. As noted above, the survey was divided into two sections: Operational and Structural. Operational elements cover the attributes that are found in the operating environment such as who is responsible for operating the WPRS system, when the model is run, how the model is updated (run with new data to generate new statistical parameters), how claims and other data are used, etc. Structural elements included the type (characteristic screen or statistical) of model, the functional form (eg. logit, probit, tobit, linear, or characteristic screen), and variables used to predict exhaustion. Together, the two sections were designed to gain insight into the following:

- How frequently a SWA's model is updated

- How often the SWA's model has been revised
- Whether or not there were model revisions planned
- How the SWA goes about determining and implementing revisions
- How initial claims are filed and what characteristics are captured at that time
- How frequently the model is run
- When a list of candidates is produced
- What file the model is run against (first pay records, other)
- Who determines occupation codes
- Who determines industry codes
- Who is not eligible for referral to WPRS services
- How many candidates are referred to reemployment services on a periodic ongoing basis such as weekly
- What type of WPRS model and functional form is used for profiling claimants
- What the model's dependent and independent variables and associated coefficients consist of
- How the SWA defines exhaustion of UI benefits

With support from the U.S. Department of Labor, we collected survey responses from the 50 SWAs and the District of Columbia, Puerto Rico, and Virgin Islands. We also received datasets from Arizona, Arkansas, Connecticut, Delaware, the District of Columbia, Florida, Georgia, Hawaii, Idaho, Iowa, Louisiana, Maine, Maryland, Michigan, Minnesota, Mississippi, Missouri, Montana, Nebraska, New Jersey, New York, North Dakota, Pennsylvania, South Carolina, South Dakota, Tennessee, Texas, Vermont, Virginia, West Virginia, Wisconsin, and Wyoming. These datasets, combined with the surveys, allowed us to analyze the models used by the SWAs to identify claimants that were likely to exhaust their UI benefits and who will likely be referred to reemployment service providers.

We would have liked to use the data provided to also study the difference in SWA model effectiveness during pre- and post-recessionary time periods. However, after examining the models and datasets, we determined that this comparison would be invalid. First, SWAs had markedly different models and data collection procedures. So using just 2003 data and comparing the models of SWAs that were pre-recession with models of SWAs that were post-recession would be invalid. We would not be able to separate the differences due to model type and data quality from differences in general economic conditions. Second, within SWAs, we considered comparing 1999 data with 2003 data, but several SWAs had revised their models between 1999 and 2003. Therefore, we could not separate differences in model performance due to differences in the model and differences in general economic conditions. Third, comparison of 1999 and 2003 data within states also was due to differences in data quality for the two periods. We could not separate differences in model performance due to data quality from differences due to general economic conditions. Fourth, we did not develop a way to measure whether states were in pre- or post- recessionary economies in 1999 and in 2003. It is not likely that state business cycles would aligh with national ones. Therefore, we concluded that these problems were intractable, and decided not to conduct an analysis on the differences in model effectiveness for pre- and post- recessionary economies.

What was found from the WPRS SWA Submitted Surveys and Data

Outlined in our spreadsheet matrix in Appendix B are the individual SWA responses to the WPRS survey that were transmitted to the SWAs in UIPL No. 9-06 on January 6, 2006. The SWAs include the District of Columbia, Puerto Rico and the Virgin Islands. Fifty-three SWAs submitted responses to the survey. Highlights of the survey responses are described below:

- Seven SWAs utilize a Characteristic Screening Model.
- Forty-six SWAs utilize a Statistical Model. Of these, 38 use logistic regression (logit) as the functional form (one of these does not use the variables - rather they electronically transmit a file based on characteristics), five use linear multiple regression, one uses neural network, one uses Tobit and one uses discriminant analysis.
- Seventeen SWAs have never updated their models since they were put into use.
- The principal reason for updates has been to convert the occupational (from DOT to SOC and/or O*Net) and industry (from SICs to NAICS) classification systems.
- Twenty-nine SWAs have never revised their models since they were put into use. Of those SWAs who have revised their models, five were completed and put into use in 2005.
- A trend in initial claims filing has been to encourage workers to file using the Internet. Forty SWAs reported that initial claims are filed online. In one SWA, 95 percent of the initial claims are filed using this method. When claims are filed using this method, individuals select their occupational code from a “drop down” menu.
- Forty SWAs take claims over the telephone. Nationwide, the highest volume of initial claims are filed via the phone.
- Four SWAs continue to take 100 percent of their initial claims in-person.
- Forty-two SWAs run the model weekly. The remaining 11 run the model daily.
- Forty-nine SWAs run the model against the claimant first payment file. The remaining four run it against the initial claim file.
- The list of eligible candidates is produced when the model is run for 47 SWAs; when a service provider requests referrals for four SWAs; weekly for two SWAs (even though the model is run daily).
- Twelve SWAs use DOT codes as their occupational classification system; 11 SWAs use the O*NET system (some directly and some based on feedback from the one-stop); and the remaining SWAs use the SOC classification system.
- The most common method of verifying employment is a cross-match against the UI wage record files. Forty-eight SWAs use this method, and the remaining five base the industry classification on the initial claim interview.

- Ineligibility for selection and referral to WPRS varies considerably. The most common reasons for claimants to be ineligible for referral to WPRS services are:
  - Obtain employment through a union hiring hall
  - Interstate claimants
  - In temporary layoff status
  - Will be recalled to previous employment
  - Received first payments five or more weeks from the date of filing the intitial claim

Eligible candidates:

- In 50 SWAs, lists of candidates are either mailed or sent electronically to the reemployment services provider. In most SWAs, the lists go directly to workshop/orientation staff, while in a few they go to local management personnel. In three SWAs, the lists are sent to central office staff to review the list and send it to the local service provider.
- The two most important determinants of the number of candidates to be served are staff availability and space. Most of the decisions on the number to be served are made locally. However, in six SWAs the number of claimants to be selected and referred is determined by central office personnel directly or after consultation and negotiation with local staff.
- In all SWAs that use a statistical model, candidates are ranked by their probability of exhaustion with those most likely to exhaust having the highest scores. Maryland was an exception, ranking in reverse order.

Seven SWAs (Delaware, Idaho, Massachusetts, New York, Ohio, Puerto Rico, and the Virgin Islands) used characteristic screens to separate claimants into those who would be eligible for referral to WPRS services and those who would not.

The majority of the SWAs used logistic regression to estimate the probability of exhaustion for UI benefit recipients. These SWAs often used threshold scores that determine who is likely to exhaust UI benefits. Individuals with predicted probability scores at or above a “cut off” point are identified as potential benefit exhaustees. These individuals are then pooled and ranked in descending order by predicted probability score for referral to reemployment services.

Dependent variables used in profiling models:

- Fifty SWAs use benefit exhaustion as the dependent variable in the WPRS model equation. Other dependent variables used are:
  - Specific benefit duration – one SWA
  - Proportion of total benefits paid – one SWA
  - Exhaustion of benefits and long-term unemployed

Independent variables used in WPRS models to predict likely exhaustees vary widely. The majority of SWAs still utilize the variables recommended by ETA when WPRS became law. They are:

- Industry (39 SWAs)
- Occupation (30 SWAs)
- Education (39 SWAs)
- Job tenure (40 SWAs)
- Local unemployment rate (24 SWAs)

Additional variables beyond those used in the original prototype model:

- Wage replacement rate (15 SWAs)
- Time from employment separation to the date the claim is filed, known as delay in filing (15 SWAs)
- Number of employers in the base period (8 SWAs)
- Potential duration (7 SWAs)

Evaluation of Characteristic Screen and Statistical Models

The characteristic screen approach to estimating the predicted probability of benefit exhaustion is simple. Individuals are profiled based on their characteristics – such as industry of employment, county of residence, occupational title, and/or number of years tenure at their most recent employer. Individuals who fit the model's characteristics are considered likely to exhaust and potentially referred to reemployment services. All other individuals are not referred. The characteristic screen model only divides individuals into two classes – those who are likely to exhaust and those who are not. In contrast, the statistical model usually calculates for each individual a probability of exhaustion that can take many values.

From the SWA surveys and data, we found there were seven SWAs that used characteristic screens. The characteristic screen has both strengths and weaknesses. It can be tailored to various subsets of applicants and can be revised quickly as economic conditions change. That is, individuals within an industry, such as manufacturing, are selected very differently from individuals from the retail trade industry. However, characteristic screens may also leave out many individuals who are likely to exhaust and/or select individuals who are not likely to exhaust. For example, individuals from the mining industry might not be selected on the basis of any variable except duration and county of residence, depending on the structure of the characteristic screen. It is possible that SWAs will exclude individuals who are potential benefit exhaustees due to one characteristic. The characteristic screens do not allow for multiple characteristics to be considered simultaneously, and do not weight characteristics. The result of the characteristic screen is binary, while the statistical models generate probabilities that allow reemployment services to prioritize individuals according to their likelihood of exhausting benefits.

EXTENDED DATA ANALYSIS

We conducted an extended data analysis on the data from nine SWAs: Arkansas, the District of Columbia, Georgia, Hawaii, Idaho, New Jersey, Pennsylvania, Texas, and West Virginia. We attempted to conduct the extended analysis for each SWA, but data problems limited the number to nine. We only conducted the extended analysis for SWAs where we could replicate the state profiling score, which implied that we had all the variables and coefficients used in the model. In addition, we needed data on the state exhaustion rate to analyze the profiling score effectiveness. One SWA, Wyoming, gave us all the necessary data and we were able to replicate the profiling score. However, Wyoming's sample size was only 107, which was not sufficiently large to conduct a reliable extended analysis. For each state, we describe the variables, coefficients, or exhaustion rate problem in Appendix C.

For each SWA, we attempted to perform the following eight-step analysis.

1. Understand and replicate the profiling model
2. Test for endogeneity in the model
3. Demonstrate the effectiveness of the original profiling score, corrected for endogeneity
4. Update the model using current data
5. Revise the model by refining the variables and adding second order and interaction terms
6. Apply a TOBIT model
7. Use metrics to evaluate model effectiveness
8. Analyze the variables that appear to best reduce Type I errors or improve the performance of the model for individuals with high profiling scores

A detailed presentation of our analyses for each SWA is in Appendix D. In the sections below, we describe the statistical procedures used in each step. At the end of this section, we offer conclusions regarding which SWAs have the best models in terms of predicting benefit exhaustion. For purposes of this section, the term "endogeneity" refers to situations in which the independent variables used for predicting the probability of benefit exhaustion are also influenced by the referral to reemployment services, and therefore, influenced the derivation of the probability of benefit exhaustion.

Step 1 - Understand and Replicate the Profiling Model

Replication of the SWA-provided probability of exhaustion scores was paramount to our analysis of the profiling models currently used by SWAs. By successfully replicating their profiling scores, we were able to develop a baseline from which we could gauge improvements in our model revisions. Using those profiling scores in conjunction with the model specifications and provided datasets, we are able to provide each SWA with an overall analysis of how well its current model performs, and we can provide ways in which their current model can be adjusted to increase predictive performance.

While every effort was made to analyze all data submitted, we were unable to replicate the predicted probability scores and/or profiling model for a number of datasets for a number of SWAs. However, for those SWAs that provided profiling scores and data that allowed us to replicate the profiling scores, we found results that should be useful and applicable to other SWAs seeking to improve their profiling models.

We analyzed the data for each individual in the dataset. First, we categorized or transformed the data as needed to replicate the structure used in the profiling model. For example, there could be a variable for "delay in filing" measured in days, but the profiling model categorized this continuous variable into five possible SWAs: 1) lag of 0 to 1 day, 2) lag of 2 to 5 days, 3) lag of

6 to 10 days, 4) lag of 11 to 20 days, and 5) lag of 21 or more days. To replicate the model, all of these possible categories would need to be computed from the SWA-supplied data.

Second, for each individual, we replicated the profiling score by multiplying the variables by the SWA-supplied coefficients and doing any other needed transformations. One common transformation was the logistic transformation. If the sum of the variables times the coefficients were S, the logistic transformation would be $e^{S}/(e^{S}+1)$. This transformation has the desirable property of always taking a value between 0.0 and 1.

Third, we compared our computed probability of exhaustion with the SWA-supplied profiling score. We analyzed any discrepancies in order to check for errors in our calculations or data problems. This exercise helped us understand how a SWA calculated its profiling score.

The analysis of SWA datasets that used characteristic screens involved an extra step. For these SWAs, we first estimated a proxy profiling score (continuous variable) that used the same information as the characteristic screen. We conducted a logit analysis using exhaustion as the dependent variable and the variables used by the SWA in its screen as independent variables. Then we saved the model's predicted probability as a proxy profiling score.

Step 2 - Test for Endogeneity in the Model

An essential part of our analysis was to determine how successful profiling models were at classifying potential benefit exhaustees and at determining which variables are important in explaining the differences between exhaustees and non-exhaustees. Based on datasets provided by the SWA, we found that the majority included a binary variable indicating whether or not individuals had been referred to reemployment services.

Each SWA has its own process for determining the number of claimants to refer to services, how they would be notified to report to a service provider, and what services they could receive. As mentioned earlier, no data were collected on what reemployment services each SWA provided or made available to referred individuals. For the purposes of our analysis, we were primarily interested in determining whether or not the referral to reemployment services had an effect on benefit exhaustion.

If referral to reemployment services did have an effect on benefit exhaustion, then we have a problem of endogeneity that will require a correction. By endogeneity, we mean that the independent variables used for predicting the probability of benefit exhaustion are also influenced by the referral to reemployment services and affected benefit exhaustion.

The problem of endogeneity can be described using two points in time. At time 0, individuals who apply for UI benefits are profiled. Their individual characteristics are used in a statistical model to predict the probability that they will exhaust benefits. The model then generates a score that is used by the UI system to refer individuals for reemployment services.

At time 1, or over the next year, some individuals will exhaust their UI benefits. Our task is to assess the effectiveness of a SWA's profiling model for predicting benefit exhaustion.

If we simply use the variables in the statistical model, or in aggregation as the profiling score, as independent variables in a logistic regression model with observed exhaustion as a dependent variable, we have a possible endogeneity problem. Observed exhaustion is likely to be affected by the services that individuals receive through the referral system. So there is a functional relationship between the independent variables and observed exhaustion, which violates the assumption of non-stochastic X[3] in the statistical model.

For example, suppose the profiling score is a perfect predictor of the likelihood of exhaustion. All individuals over a percentile score of 0.5 would exhaust UI benefits over their benefit year. Also suppose that reemployment services are very effective, and that 75 percent of individuals who receive these services get jobs before their UI benefits expire. Also, assume that individuals with the top 20 percent of profiling scores receive reemployment services.

Given the above example, we will observe a profiling score with certain specific characteristics. For individuals with percentile scores of 0.0 to 0.5, nobody will exhaust. For individuals with percentile scores of 0.5 to 0.8, all will exhaust. But for individuals with percentile scores of 0.8 to 1, only 25 percent will exhaust because they were referred to reemployment services. When we analyze the model, we will find that the model would not predict exhaustion very well, even though in actuality it is perfect. Our other analyses would also be affected, because the variables we use in our revised and updated models to predict exhaustion would not explain true exhaustion; it would only explain the biased observed exhaustion.

Endogeneity will not be a problem if there is no effect of referral on subsequent exhaustion. Thus, the test for endogeneity will first determine if there is an effect of referral to employment services on exhaustion. And, second, the model will estimate a correction for endogeneity.

[3] The non-stochastic X assumption refers to the assumption that the model is using independent variables ("X" variables) to explain variation in a dependent variable ("Y" variable). If the X variables have values that are in part determined by the dependent variable or by factors that also affect the dependent variable, then the assumption of independence between the X variables and the disturbance term will be violated. The model will not generate unbiased and valid estimates of the coefficients.

In technical terms, the endogeneity problem can be described as follows. Endogeneity implies that the cross product of e, the disturbance term, and B(hat)X, will not be zero. This violates a fundamental assumption for unbiasedness for regression models of least squares, logit, logistic, and TOBIT forms. The standard algorithm for estimating parameters breaks down. The solution we propose is to first diagnose if there is an endogeneity problem.

To illustrate, the standard ordinary least squares regression equation takes the form:

$$Y = \beta X + \varepsilon$$

Y is the dependent variable, β is an array of coefficients, X is a matrix of independent variables that begins with a column of "1"s, so that the first β is the coefficient for the constant term, and ε is the disturbance term. Statistical analysis generates estimates for each β, called B(hat), and an associated standard error, which is necessary to determine the parameter's significance. In the estimated model, there is an error term which is an estimate of ε, called e. So the result of the analysis is a set of B(hat)s and associated standard errors.

Y = B(hat)X + e

In order to solve the original equation, statisticians normally make a number of assumptions, including that on average, e = 0, and that the product of B(hat)X and e sums to zero across all individuals. For the non-stochastic X problem, this assumption does not hold.

The solution we propose is to first diagnose if there is an endogeneity problem, or that referral affects the probability of exhaustion, and then to make an adjustment to the model that corrects for the "referral effect."

To diagnose the problem, we borrow from the literature on DIF, or differential item functioning, which is used to assess whether test items generate different response patterns for different groups of people (Camilli & Shepard, 1994). For example, it has been shown that certain SAT (Scholastic Assessment Tests) questions are answered more correctly by young men than young women, especially if the question refers to sports or outdoors concepts.

With respect to our problem, we test whether the response pattern of UI benefit exhaustion for referred individuals differs from that of non-referred individuals. The variables used for this are the probability of exhaustion (Pr[exh]), the profiling score (score), and a binary variable for referral (refer). Consider Figure 2.

Figure 2
Item Characteristic Curve

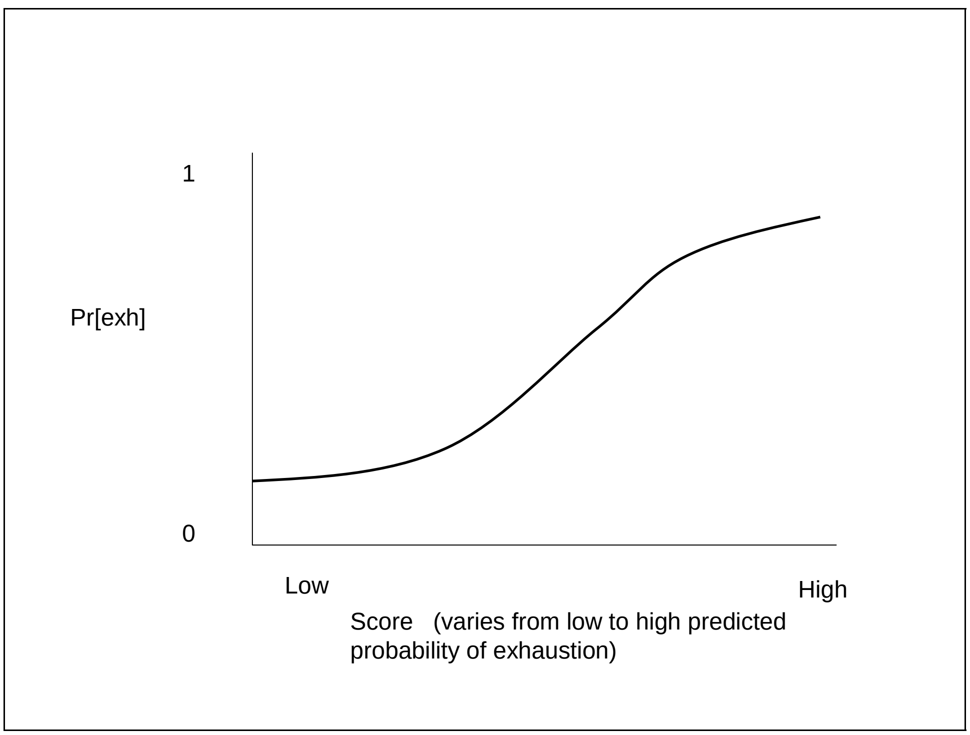


Figure 2 shows the typical shape of the relationship between profiling score and Pr[exh]. Higher scores correspond to higher Pr[exh], and lower scores to lower Pr[exh]. The "S" shape of the curve is typical for logistic relationships. If the curve for the referred and non-referred individuals is similar, then we can say that referral has no effect on the probability of exhaustion. However, if there is an effect, it can be of two types. Consider Figure 3.

Figure 3
Uniform, or Signed, DIF

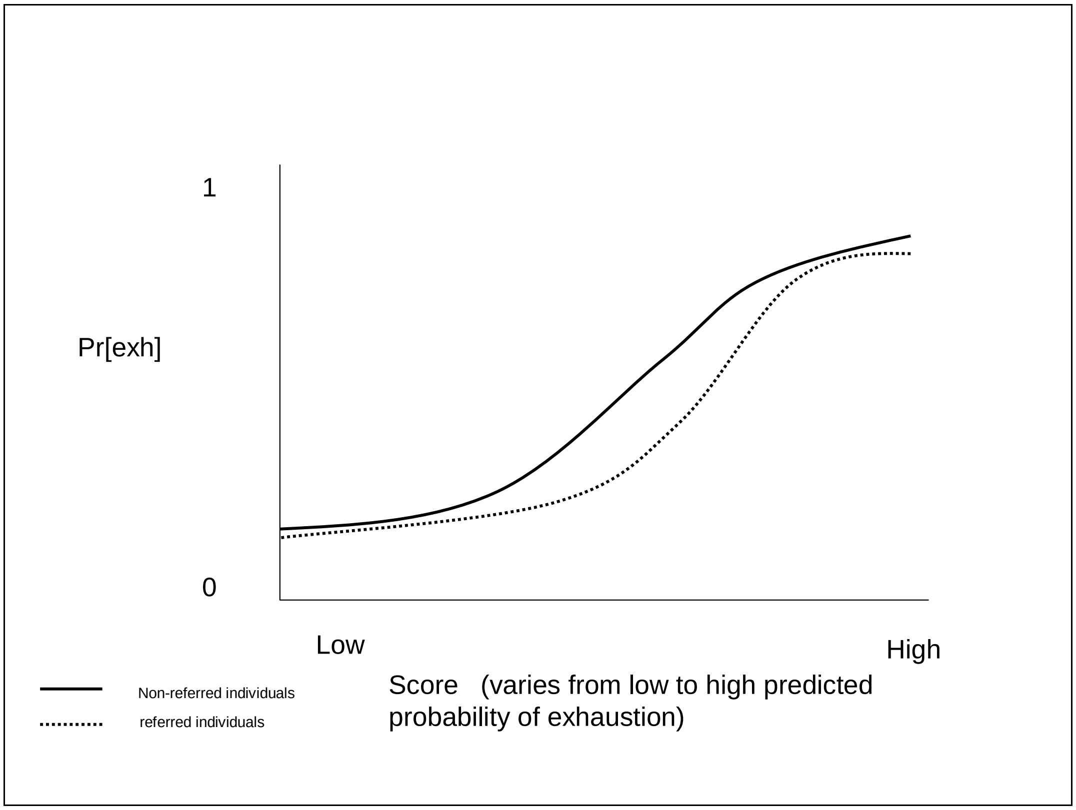
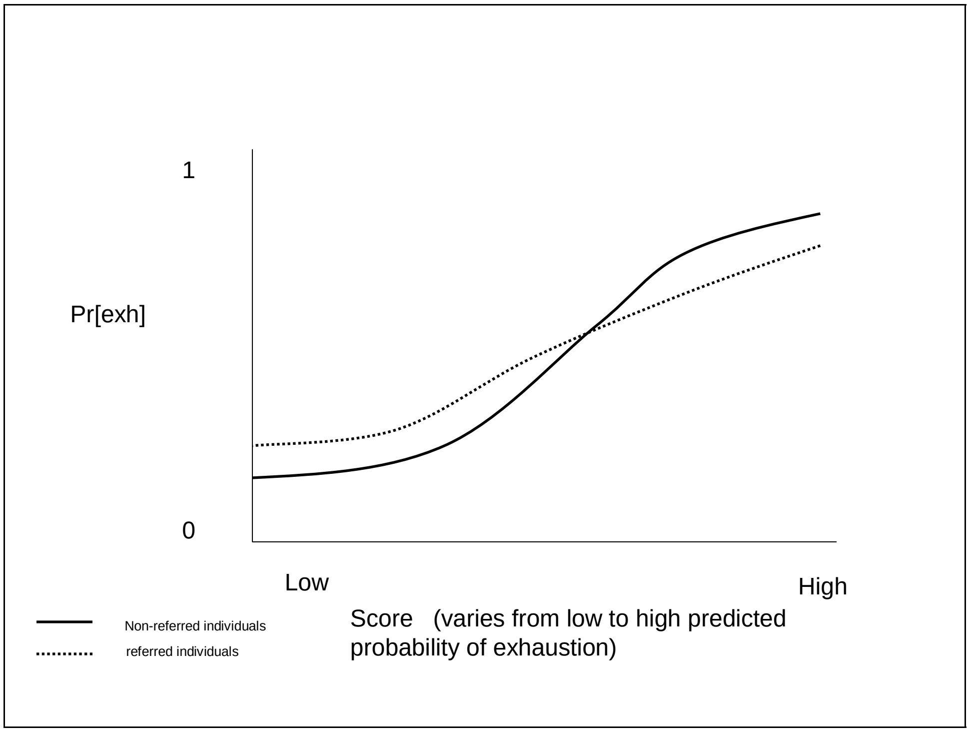


Figure 3 shows different line curves for the referred and non-referred individuals. In this case, for any value of score, the referred individuals have lower Pr[exh] than the non-referred. In other words, referring means that on the average there is a benefit to referral that helps individuals prevent exhaustion. This type of bias is called uniform or signed bias. There is also unsigned or non-uniform bias as shown in Figure 4.

Figure 4
Non-uniform or Unsigned DIF



Here, at some levels of score, the referred individuals have a positive difference and at other levels of score there is a negative difference. The net area between the curves may approach zero because the positive and negative differences cancel each other, but there is still a bias.

In our extended SWA analyses, we first tested for a difference in exhaustion between referred and non-referred individuals using logistic regression (Camilli & Congdon, 1999; Swaminathan & Rogers, 1990). Our procedure was to use the binary variable for referral to reemployment services, coded as 0 for those not referred and 1 for referred individuals. Introducing this variable in a logit model that uses exhaustion as a dependent variable and the SWA profiling score as an independent variable allows us to test for uniform or signed bias due to endogeneity. Introducing a cross term, the product of the referral variable and the profiling score, will test for unsigned bias due to endogeneity.

The tests mirror the graphs shown above. According to the relevant literature, the tests are conducted in the form of nested models. Introduction of each variable – the referral variable and the cross term – requires estimation of a new logit model. We use a chi-squared test of (-2 times the difference in model log likelihood) statistic to determine whether endogeneity is a significant influence.

We then propose a remedy. It was to calculate and introduce a variable in the logistic regression model that corrects for the referral effect. The new variable will have a fixed coefficient of 1, and it is intended to bring the curve for referred individuals in line with the curve for non-referred individuals. In the STATA statistical package, this variable is called an offset variable.

The exact calculation of the offset variable is described in the extended analyses. A typical logistic regression that diagnoses endogeneity takes the following form:

Exhaustion = α + β_1(profiling score) + β_2(refer to services binary variable) + β_3(cross term of refer X score) + ε

Provided that β_2 and β_3 are significant, the correction for endogeneity is β_2 X (refer to services binary variable) + β_3 X (cross term of refer X score). This variable will normally be a different value for most individuals in the sample. The offset variable must be included in the model without an estimated coefficient, or else the endogeneity problem will not be addressed. If a software package that does not allow for offset variables, then a new algorithm should be constructed using an appropriate statistical package.

Step 3 - Demonstrate the Effectiveness of the Original Profiling Score Corrected for Endogeneity

The next step was to recalculate the profiling score with a correction for endogeneity. The example that follows shows our procedure. Some of the statistics presented will be described in more detail later. The result of this procedure is a score that has correction for the bias due to endogeneity and represents a more valid basis for determining the effectiveness of the profiling model.

We will use data from Pennsylvania to illustrate the approach and to demonstrate how we correct the original profiling score. First, we calculated the logistic regression model where only score (along with a constant) is used to predict benefit exhaustion Pr[exh]. This example is slightly complicated because there were two special classes of individuals, referred individuals and exempt individuals. The analysis corrects for both signed and unsigned bias due to endogeneity for both classes.

Logistic Regression Model with Score Only

Logistic regression	Number of observations	=	223906
	LR chi2(1)	=	1317.60
	Prob > chi2	=	0.0000
Log likelihood = -153875.72	Pseudo R2	=	0.0043

exhaust	Coefficient	Std.	Err.	Z	P>z [95%	Conf.
score	2.592343	.0717106	36.15	0.000	2.451793	2.732894
_cons	-1.133801	.0274493	-41.31	0.000	-1.187601	-1.080001

Next, we add the variables for referral and exempt to see if the addition of these variables increases explanatory power. The test is a chi-squared test of the difference in the (-2 X log likelihood) statistic for the nested models.

Logistic Regression Model with Score, Referral, and Exempt

Logistic regression	Number of observations	=	223906
	LR chi2(3)	=	3314.48
	Prob > chi2	=	0.0000
Log likelihood = -152877.28	Pseudo R2	=	0.0107

exhaust	Coefficient	Standard error	z	P>z	[95% Conf.	Interval]
score	2.835601	.0806119	35.18	0.000	2.677605	2.993598
referred individuals	.1078473	.0117285	9.20	0.000	.0848599	.1308348
exempt	-.7580491	.0192067	-39.47	0.000	-.7956935	-.7204046
_cons	-1.201052	.0296161	-40.55	0.000	-1.259098	-1.143005

The addition of the variables for referred and exempt individuals improves the log likelihood from -153,875.72 to -152,877.28. This represents a significant difference, showing signed or uniform bias from endogeneity. Now, we add two interaction terms (referral-not-exempt X score, and exempt X score) to test for non-uniform or unsigned DIF.

Logistic Regression Model with Score, Referral-not-exempt, Exempt and Their Interactions

Logistic regression	Number of observations	=	223906
	LR chi2(5)	=	3357.87
	Prob > chi2	=	0.0000
Log likelihood = -152855.59	Pseudo R2	=	0.0109

exhaust	Coefficient	Standard error	z	P>z	[95% Conf.	Interval]
score	3.126434	.0948357	32.97	0.000	2.940559	3.312308
referred individuals	.4218879	.0828933	5.09	0.000	.25942	.5843558

exempt individuals	.0027421	.1330698	0.02	0.984	-.2580698	.263554
refer X score	-.784345	.2004544	-3.91	0.000	-1.177228	-.3914616
exempt X score	-1.857989	.3193107	-5.82	0.000	-2.483827	-1.232152
_cons	-1.306397	.0347128	-37.63	0.000	-1.374433	-1.238361

Again, the addition of the interaction terms changed the log likelihood from -152,877.28 to -152,855.59. This represents a significant difference, showing unsigned or non-uniform bias from endogeneity. The coefficients suggest that the difference between the referred and non-referred individuals is similar to that shown in Figure 4 above. For the referred and exempt individuals, when score is 0 their logit is .4218879 X refer + .0027421 X exempt, which for both types of individuals is a positive number. Therefore when score is 0, the referred and exempted individuals will have estimated probabilities of exhaustion greater than other individuals. When score is 1, referred individuals have logits of (.4218879-.784345) X refer, which is a negative number below that of non-referred individuals. Similarly, for exempt individuals when score is 1, their logits are (.0027421-1.857989) X exempt, which is negative. So, similar to the pattern shown in Figure 4, referred and exempt individuals (as the dotted line) will be above the curve for low scores, and below the curve for high scores.

Our proposed remedy is to include a variable in the model with a fixed coefficient that controls for the referral and exempt effect. This variable, called an offset variable, or ***offset***, will account for the deviation from the "score minus Pr[exhaust]" curve for individuals who are referred or exempted. The value of this variable is derived from the coefficients of the above regression as:

.4218879*refnex+.0027421*exempt-.784345*xexrfnesco-1.857989*xexsco

This value represents the difference between the Pr[exh] for referred and non-referred, and exempt and non-exempt individuals. Adding this variable to the logistic regression as a fixed coefficient variable should adjust referred and exempted individuals to the Pr[exh] that they would have had if they were not referred or exempted.

By adjusting the original scores with this control for endogeneity, we can estimate the true exhaustion rate for the original score. We calculate the model as follows. The logistic regression has exhaustion as a dependent variable, with score as the independent variable and the offset, named endogeneity control, to control for endogeneity. We saved the predicted values of this model as a profiling score corrected for endogeneity.

Logistic regression	Number of observations	=	223906
	Wald chi2(1)	=	1871.93
Log likelihood = -152855.59	Prob > chi2	=	0.0000

exhaust	Coefficient	Standard error	z	P>z	[95% Conf.	Interval]
score	3.126434	.0722611	43.27	0.000	2.984804	3.268063
_cons	-1.306397	.0276347	-47.27	0.000	-1.36056	-1.252234
endogeneity control	(offset)					

To create tables that show the association between profiling score and subsequent benefit exhaustion, we first ordered the resulting profiling scores in ascending order and then divided them into deciles. We then looked at the mean exhaustion rate for each decile. Ideally, what we would expect is for the lower deciles to have lower exhaustion rates and the higher deciles to have higher exhaustion rates. This decile table is one way we can demonstrate the effectiveness of each model.

Decile	Mean	Standard Error (Mean)
1	.3263136	.0030338
2	.3936042	.0033309
3	.4170953	.0033266
4	.4557091	.0033146
5	.4790516	.0033477
6	.489566	.00331
7	.508395	.0033587
8	.4939282	.0033718
9	.5168695	.0033428
10	.5405574	.0033307
Total	.4614749	.0010535

At the end of Appendix C, we include decile tables for all 28 SWAs that provided data on exhaustion rate and profiling score.

Step 4 - Update the Model Using Current Data

This step involved calculation of a statistical model for benefit exhaustion using the data provided. Our aim was to develop the best model possible, and our approach allows us to compare updated, revised, and Tobit models because they all use the same data. We note that the original profiling score was generated without knowing who would exhaust benefits. The original scores were developed using parameters estimated at some time in the past, while the updated, revised, and Tobit models use the current data, including the data for who actually exhausted benefits. Therefore, the original profiling score is not really comparable to the scores from the other models and should be used only as a baseline for comparison.

Following standard research procedures, our analyses included a number of statistics and model diagnostic procedures. These allow us to argue that the model has some power for predicting exhaustion and it conforms relatively well to the assumptions of a valid statistical analysis. Using the example below[4], we describe our procedures.

In our analysis of the SWA provided data, we used the statistical software package STATA to perform our logistic regression analysis. In the made-up example that follows, we created a dataset containing the following variables:

- Maximum Benefit Amount (MBA)
- Level of Education
- Wage Replacement Rate (WRR)
- NAICS Industry Code

For this example, much like with our analysis in Appendix D, we applied a logistical regression to estimate the probability of UI benefit exhaustion. Using the data in our example, we used a logistic regression to estimate the probability of UI benefit exhaustion:

Logistic regression	Number of observations	=	52913
	Wald chi2(26)	=	713.03
Log likelihood = -36385.239	Prob > chi2	=	0.0000

Exhaust	Coefficient	Standard Error	Z-Score	P>z	[95% Conf.	Interval]
MBA	0.00000986	0.00000828	1.19	0.235	-6.40e-06	.0000261
Education	-.0427225	.0046309	-9.23	0.000	-.051799	-.0336461
WRR	.7504832	.082631	9.08	0.000	.5885294	.912437
NAICS 0	-.3378624	.1024779	-3.30	0.001	-.5387155	-.1370093
NAICS 1	-.1215718	.1670119	-0.73	0.467	-.4489091	.2057655
NAICS 2	-.1938156	.0436113	-4.44	0.000	-.2792922	-.108339
NAICS 3	.1391356	.0343293	4.05	0.000	.0718515	.2064197
NAICS 4	-.0863585	.0329422	-2.62	0.009	-.1509241	-.0217929
NAICS 5	-.0528057	.0317214	-1.66	0.096	-.1149785	.0093671
NAICS 7	-.2384586	.0428455	-5.57	0.000	-.3224343	-.1544829
NAICS 8	.0991142	.0551996	1.80	0.073	-.0090751	.2073034
NAICS 9	.1364398	.0523579	2.61	0.009	.0338202	.2390593

[4] We use a mix of data to illustrate our methods. Our objective is to provide simplicity of understanding and authenticity. Both contribute to a clear and useful illustration of our methods.

Constant	.2107467	.1084804	1.94	0.052	-.0018709	.4233643

These results show the variable coefficients, the standard errors of the variable coefficients, the Z-score used to determine variable significance, the P-value for our Z-score, and the upper and lower limits of the 95 percent confidence interval.

The variable coefficient from our regression represents the value to be applied to a variable which, in our model, is used to predict the probability of benefit exhaustion. The value of this coefficient falls between the lower limit and the upper limit of the confidence interval. For example, for the maximum benefit amount we are 95 percent confident that its marginal impact on benfit exhaustion, given the other variables in the regression, is between -0.0000064 and 0.0000261. This confidence interval is created by adding and subtracting approximately two times the standard error of the coefficient.

From our results, we see that the Z-score for the MBA coefficient is 1.19, and it is calculated by dividing the variable coefficient by its standard error as detailed below:

$$\text{Z-score} = \frac{\text{Variable Coefficient}}{\text{Variable Standard Error}}$$

$$\text{Z-score} = \frac{0.00000986}{0.00000828} \approx 1.19$$

This Z-score is used to determine whether or not our coefficients are significantly different from zero. This Z-score value is used to determine what the area under the standard normal curve is that corresponds to this value. If our Z-score corresponds to an area of 95 percent or less we cannot be confident that the true value for our coefficient is different than zero. For our analysis, we are concerned only with P-values of 0.05 or smaller, which correspond to our being 95 percent confident that the true value of the coefficient is different from zero. Our Z-score of 1.19

means that we are only about 76.5 percent sure that the variable is above 0. Therefore, we conclude that MBA is not a significant factor in explaining exhaustion in our ficticious sample.

From the above STATA output we applied the corresponding coefficients to the corresponding values for each variable. In doing so, we determined what the value of X based on the coefficients and corresponding variables through the following equation:

$$
\begin{aligned}
X = {} & \text{MBA}*(0.00000986) + \text{Education}*(-0.0427225) + \text{WRR}*(0.7504832) \\
& + \text{NAICS 0}*(-0.3378624) + \text{NAICS 1}*(-0.1215718) + \text{NAICS 2}*(-0.1938156) \\
& + \text{NAICS 3}*(0.1391356) + \text{NAICS 4}*(-0.0863585) + \text{NAICS 5}*(-0.0528057) \\
& + \text{NAICS 7}*(-0.2384586) + \text{NAICS 8}*(0.0991142) + \text{NAICS 9}*(0.1364398) \\
& + \text{Constant}
\end{aligned}
$$

In the logistic transformation, the “X” calculated above will be implanted into the following transformation:

$$e^{X}/(e^{X}+1)$$

e is a special number in statistics. It has a value of about 2.7.

The transformation yields a value between 0 and 1. The model will estimate all the parameters such that the squared difference between the above transformed expression and the dependent variable (ex., exhaustion - $e^{X}/(e^{X}+1)$) is minimized.

We use classification tables to indicate how many benefit recipients were correctly classified as likely to exhaust (defined as having a predicted probability score of 0.50 or higher). Sensitivity is defined as the probability of a benefit recipient being properly classified as a benefit exhaustee. From the example set and profiling model we created, we found that from our sample of 150,000 benefit recipients, 42,000 recipients were given profiling scores of 0.50 or higher and exhausted benefits. Sensitivity here measures the probability that a benefit exhaustee is correctly classified as an exhaustee. The equation used to determine sensitivity is defined as follows:

$$\Pr(+ D) = \frac{\text{Number of Correctly Identified Benefit Exhaustees}}{\text{Total Number Benefit Exhaustees}}$$

$$\Pr(+ D) = \frac{42{,}000}{70{,}000} = 0.6$$

	--------	True	--------	
Classified	D		~D	Total
+	42000		10000	52000
-	28000		70000	98000
Total	70000		80000	150000

Classified + if predicted	Pr(D)	>=	.50
True D defined as exhaust	!= 0		

Sensitivity		Pr(+ D)	60%	
Specificity		Pr(-~D)	87.5%	
Positive predictive value		Pr(D +)	80.76%	
Negative predictive value		Pr(~D -)	71.43%	
False + rate for true ~D		Pr(+~D)	12.5%	
False - rate for true D		Pr(- D)	40%	
False + rate for classified	+	Pr(~D +)	19.23%	
False - rate for classified	-	Pr(D -)	28.57%	
Correctly classified				74.66%

Specificity is defined as the probability of a benefit recipient being properly classified as a non-benefit exhaustee. Here specificity is a metric that measures the probability that a non-exhaustee is correctly classified as non-exhaustee. From our profiling model, 70,000 recipients were identified as non-benefit exhaustees out of 80,000 benefit recipients that did not exhaust benefits. The equation used to determine specificity is defined as follows:

$$\Pr(\text{ -}{\sim}\text{D}) = \frac{\text{Number of Correctly Identified Non - Benefit Exhaustees}}{\text{Total Number of Non - Benefit Exhaustees}}$$

$$\Pr(\text{ -}{\sim}\text{D}) = \frac{70{,}000}{80{,}000} = 0.875$$

Positive predictive value (PPV) is a ratio of the number of correctly classified benefit exhaustees to the total number of benefit recipients identified as benefit exhaustees. From our profiling model, 42,000 recipients were correctly identified as benefit exhaustees out of 52,000 benefit recipients that were identified as benefit exhaustees. The equation used to determine the positive predictive value is defined as follows:

$$\text{PPV} = \frac{\text{Number of True Non - Benefit Exhaustees}}{\text{Total Benefit Recipients Identified as Non - Benefit Exhaustees}}$$

$$\text{PPV} = \frac{42{,}000}{52{,}000} \approx 0.8076$$

Negative predictive value (NPV) is a ratio of the number of correctly classified non-exhaustees to the total number of benefit recipients identified as non-exhaustees. From our profiling model, 70,000 recipients were correctly identified as non-exhaustees out of 98,000 benefit recipients that were identified as non-benefit exhaustees. The equation used to determine the negative predictive value is defined as follows:

$$\text{NPV} = \frac{\text{Number of True Non - Benefit Exhaustees}}{\text{Total Benefit Recipients Identified as Non - Benefit Exhaustees}}$$

$$\text{NPV} = \frac{70{,}000}{98{,}000} \approx 0.7143$$

The additional metrics included in the classification table are measurements of false positives and negatives. For examples, “False + rate for true ~D” measures how many benefit recipients were identified as benefit exhaustees that were not actually exhaustees. The equation used to determine the false positive rate for true negative values is defined as follows:

“False + rate for true ~D” = $\frac{\text{\# of Individuals Identified Incorrectly as Benefit Exhaustees}}{\text{Total Number of Individuals Incorrectly Classified}}$

“False + rate for true ~D” = $\frac{10{,}000}{80{,}000} = 0.125$

“False - rate for true D” measures how many benefit recipients were identified as not exhausting benefits that did exhaust benefits. The equation used to determine the false negative rate for true positive values is defined as follows:

“False - rate for true D” =

$$\frac{\text{\# of Individuals Identified Incorrectly as Non - Benefit Exhaustees}}{\text{Total Number of Benefit Exhaustees}}$$

“False - rate for true D” = $\frac{28{,}000}{70{,}000} = 0.4$

“False + rate for classified” measures how many benefit recipients were identified incorrectly as exhausting benefits that did not. The equation used to determine the false positive rate for benefit exhaustees is defined as follows:

“False + rate for classified” = $\frac{\text{\# of Individuals Identified Incorrectly as Benefit Exhaustees}}{\text{Total Number of Individuals Classified as Benefit Exhaustees}}$

“False + rate for classified” = $\frac{10{,}000}{52{,}000} \approx 0.1923$

“False - rate for classified” measures how many benefit recipients were identified incorrectly as not exhausting benefits that in fact did. The equation used to determine the false negative rate for benefit exhaustees is defined as follows:

$$\text{“False - rate for classified”} = \frac{\text{\# of Individuals Identified Incorrectly as Non - Benefit Exhaustees}}{\text{Total Number of Individuals Classified as Non - Benefit Exhaustees}}$$

$$\text{“False - rate for classified”} = \frac{28{,}000}{98{,}000} \approx 0.2857$$

In addition to classification tables, we examined all logistic models for multicollinearity through the examination of variance inflation factors and nonspherical disturbances through the analysis of residuals and variable distributions. The models we include in this report all conform to statistical assumptions.

From the above analysis, we see that in determining the effectiveness of a profiling model, we must pay close attention to how the model classifies potential benefit exhaustees. In our example above, we see that this particular model, using a profiling “cut off” score of 0.5, correctly classifies approximately 75 percent of benefit exhaustees. Ideally, we would want to see high values for sensitivity and specificity similar to the values in our analysis above.

With reference to our constructed dataset above, we estimate a new profiling score using the updated model for an individual with a maximum benefit amount of $3,000, 12 years of education, a wage replacement rate of 0.523871, and most recent employment in NAICS industry 9, we apply the following variables values in the above equation:

Maximum Benefit Amount = 3,000	NAICS 0 = 0*	NAICS 4 = 0*
Education = 12	NAICS 1 = 0*	NAICS 5 = 0*
Wage Replacement Rate = 0.523871	NAICS 2 = 0*	NAICS 7 = 0*
Constant = 0.2107467	NAICS 3 = 0*	NAICS 8 = 0*
		NAICS 9 = 1*

- Note: NAICS industry code variables are binary. In our example the claimant was last employed in an industry corresponding to the one-digit NAICS code 9

$$X = (3{,}000)*(0.00000986) + (12)*(-0.0427225) + (0.523871)*(0.7504832)$$

+ (0)*(-0.3378624) + (0)*(-0.1215718) + (0)*(-0.1938156)
+ (0)*(0.1391356) + (0)*(-0.0863585) + (0)*(-0.0528057)
+ (0)*(-0.2384586) + (0)*(0.0991142) + (1)*(0.1364398)
+ 0.2107467

X = 0.02958 – 0.51267 + 0.393156384 + 0 + 0 + 0 + 0 + 0 + 0 +0 + 0
+ 0.1364398 + 0.2107467

X = 0.257252884

Next, we use this value, X, in the following logistic regression transformation to determine the predicted probability of benefit exhaustion.

$$\Pr[\text{exh}] = \frac{e^X}{e^X + 1}$$

$$\Pr[\text{exh}] = \frac{e^{0.257252884}}{e^{0.257252884} + 1}$$

$$\Pr[\text{exh}] = \frac{1.293372159}{2.293372159}$$

$$\Pr[\text{exh}] \approx 0.56396$$

From the STATA provided coefficients, we find that our predicted probability of benefit exhaustion for this individual is approximately 56 percent. It is important to note that by using a logistic regression, the predicted probability of benefit exhaustion can range from only 0 percent (very low probability of exhaustion) to 100 percent (very high probability of exhaustion). These predicted probability of benefit exhaustion scores are used by some SWAs to determine who is referred to reemployment services. For most SWAs, there is a "cut off" score that is used to determine which eligible benefit recipients are referred to reemployment services.

After computing scores for all claimants, we can construct a decile gradient like the one below. In this decile gradient, we see that for seven of our deciles the mean exhaustion rate hovers around 0.25 or 25 percent. Ideally, we would expect to see a lower mean benefit exhaustion rate for the first decile and increasingly higher exhaustion rates for each decile there after. In updating and revising the current profiling models used by SWAs, we hope to steepen the decile gradient range, starting with lower exhaustion rates and having consistently higher exhaustion rates for each decile. By improving the decile gradient range we are proving the proper classification of benefit exhaustees.

Decile	Mean	Standard Error (Mean)
1	.25	.0047
2	.27	.0045
3	.26	.0046
4	.26	.0045
5	.23	.0045
6	.25	.0046
7	.26	.0047
8	.31	.0045
9	.34	.0047
10	.36	.0049
Total	.28	.0046

Step 5 - Revise the Model by Refining the Variables and Adding Second Order and Interaction Terms

The revised model is the same as the updated model except that variables are added to account for nonlinear and second order interaction effects. For nonlinear effects, we generally make more variables for all continuous variables. We calculate second order variables by subtracting the mean value and squaring the variable. This allows us to limit the potential for multicollinearity common with second-order terms. We also include variables for interaction terms. To calculate these, we first subtracted the mean value from each variable and then multiplied them.

We included all continuous variables and all interaction terms if possible. We did conduct some diagnostics of the variable sets where possible. If a variable had characteristics such as only taking a few values, or was skewed, or was otherwise not suitable for use in the model, we discarded it. In addition, we conducted tests for multicollinearity and removed variables that significantly contributed to this problem. Details of our methods are included in the expanded analyses in Appendix D.

To illustrate our approach to revised models, we include the model for Pennsylvania. The updated model included continuous variables for a) 10-year historical exhaustion rate of primary base year employer's industry, and b) 12-month moving average for the labor market area. The model below includes these variables, named "indexh" and "tur." In addition, there are second order variables for each named "xi2" and "xt2," and an interaction term "xit." Included below are the classification table and decile table for this analysis.

Logistic regression	Number of observations	=	223906
	Wald chi2(15)	=	4102.60
Log likelihood = -151684.36	Prob > chi2	=	0.0000

exhaust	Coefficient	Standard error	z	P>z	[95% Conf.	Interval]
tenind	-.1868556	.0088761	-21.05	0.000	-.2042524	-.1694588
eduind1	-.0968022	.0135224	-7.16	0.000	-.1233056	-.0702987
eduind2	.0675245	.0125174	5.39	0.000	.0429909	.0920581
decind	-.0815156	.0383682	-2.12	0.034	-.156716	-.0063152
lowrr	-.0599267	.0163153	-3.67	0.000	-.0919041	-.0279493
hibrr	-.0258075	.078488	-0.33	0.742	-.1796411	.1280261
indexh	5.015172	.1268003	39.55	0.000	4.766648	5.263696
tur	-.0423947	.0069549	-6.10	0.000	-.0560259	-.0287634
xit	-.2096412	.0774124	-2.71	0.007	-.3613667	-.0579157
xid	-3.772136	.5402018	-6.98	0.000	-4.830912	-2.71336
xtd	.0116573	.0223247	0.52	0.602	-.0320982	.0554129
xiten	-1.996344	.1574447	-12.68	0.000	-2.30493	-1.687758
xtten	.0253426	.0089136	2.84	0.004	.0078723	.042813
xi2	-15.11698	1.167127	-12.95	0.000	-17.4045	-12.82945

xt2	-.0209703	.0017147	-12.23	0.000	-.024331	-.0176096
_cons	-1.873164	.0681795	-27.47	0.000	-2.006793	-1.739535
endogeneity control	(offset)					

Classification Table

	--------	True	--------	
Classified	D		~D	Total
+	73578		71064	144642
-	29749		49515	79264
Total	103327		120579	223906

Classified + if predicted Pr(D) >= .46
True D defined as exhaust != 0

Sensitivity		Pr(+ D)	71.21%	
Specificity		Pr(-~D)	41.06%	
Positive predictive value		Pr(D +)	50.87%	
Negative predictive value		Pr(~D -)	62.47%	
False + rate for true ~D		Pr(+~D)	58.94%	
False - rate for true D		Pr(- D)	28.79%	
False + rate for classified	+	Pr(~D +)	49.13%	
False - rate for classified	-	Pr(D -)	37.53%	
Correctly classified				54.98%

The decile table for the revised model is as follows.

Decile	Mean	Standard Error (Mean)
1	.2835068	.003012
2	.3783363	.0032347
3	.4261983	.0032915
4	.4586336	.003244
5	.4701638	.0034389
6	.4902339	.003346
7	.4876519	.0033224
8	.5153135	.0031217

9	.5333196	.0035789
10	.577338	.0033472
Total	.4614749	.0010535

Step 6 - Apply a Tobit Model

The Tobit model is similar to the logistic regression models except that it uses information about non-exhaustees, assuming that non-exhaustees who are closer to exhaustion are more similar to exhaustees than those who are further from exhaustion. As discussed by Tobin (1958), Amemiya (1973), Maddala (1983) and Davidson and MacKinnon (1993), we applied a regression model containing a censored dependent variable to describe the relationship between our dependent variable and our independent variables.

For our analysis, we defined this dependent variable as the percentage of Unemployment Insurance (UI) benefits that individuals eligible for WPRS services had remaining. The equation used to calculate our dependent variable is defined below:

$$\text{Percentage of Remaining Benefits} = 100 \times \frac{\text{Maximum Benefit Amount - Benefits Paid}}{\text{Maximum Benefit Amount}}$$

For example, if an individual received a maximum benefit allowance of $7,950 and received $1,430 in UI benefit payments, we would arrive at the following score:

$$\text{Percentage of Remaining Benefits} = 100 \times \frac{\$7{,}950 - \$1{,}430}{\$7{,}950} \approx 82.01258$$

Individuals that exhausted their UI benefits or received benefits in excess of their maximum benefit allowance were assigned a value of 0 for this variable. In assigning these benefit exhaustees a score of 0 for the dependent variable, we are, in essence, censoring and placing a lower limit for this variable. If we were to use a standard ordinary least squares regression with the censored data, our results would be inconsistent. Therefore, due to the censoring of our dependent variable, we use a Tobit model to estimate the following:

$$y = \begin{cases} y^* & \text{if } y^* > 0 \\ 0 & \text{if } y^* \leq 0 \end{cases}$$

y* is our latent, unobservable variable defined as:

$$y^* = \beta x + \underline{u},\ u \sim N(0, \sigma^2)$$

where β' represents the vector of coefficients, x is the vector of independent variables, and *u* is the normally distributed error term that represents the random influences our independent variables have on the dependent variable.

If y*, our latent, unobserved dependent variable, is greater than zero, then the observable variable y is equal to y*. Otherwise, y is 0.

After calculating the dependent variable for each of the claimants in our sample, we then used the statistical software package STATA to calculate the predicted percentage of remaining benefits for benefit recipients. For our analysis, we used the coefficient estimates from our Tobit regression model (detailed in the below STATA output) to calculate the predicted percentage of remaining benefits.

% of remaining UI Benefits	Coefficient	Standard Error	Z-Score	P>Z-score	[95% Conf.	Interval]
Job Tenure	.2384517	.0258301	9.23	0.000	.1878248	.2890785
Education	-1.668245	.0406602	-41.03	0.000	-1.747938	-1.58855
MBA	.00101	.0000691	14.63	0.000	.0008746	.0011454
NAICS0	-13.09871	.7170144	-18.27	0.000	-14.50405	-11.6934
NAICS1	-4.662368	2.704195	-1.72	0.085	-9.962565	.6378284
NAICS2	2.707084	.5935808	4.56	0.000	1.543672	3.870497
NAICS3	11.07219	.4986012	22.21	0.000	10.09493	12.04944

NAICS4	1.801049	.524212	3.44	0.001	.7735985	2.828499
NAICS6	.0147146	.6974458	0.02	0.983	-1.352272	1.381702
NAICS7	1.731505	.706849	2.45	0.014	.346088	3.116922
NAICS8	-5.59905	1.066334	-5.25	0.000	-7.689054	-3.50904
NAICS9	.5823798	1.368488	0.43	0.670	-2.099844	3.264604
Constant	58.69107	.6801786	86.29	0.000	57.35793	60.02422
/sigma	46.45215	.1334193			46.19065	46.71365

In calculating the predicted percentage of remaining UI benefits, we applied the variable coefficients to our variables and estimated the equation below:

$$y = \beta' x_t + u_t$$

β' is a vector of coefficients to be applied to our independent variables

For a non-benefit exhaustee with job tenure of seven years, who is a high school graduate, with a maximum benefit allowance of $6,000, and employed in the one-digit NAICS code 4 industry we use the above STATA output and model equation to estimate his/her predicted percentage of remaining UI benefits. Our results are as follows:

y = Job Tenure*(0.2384517) + Education*(-1.668245) + MBA*(0.00101) +
NAICS0*(-13.09871) + NAICS1*(-4.662368) + NAICS2*(2.707084) +
NAICS3*(11.07219) + NAICS4*(1.801049) + NAICS6*(0.0147146) +
NAICS7*(1.731505) + NAICS8*(-5.59905) + NAICS9*(0.5823798) + Constant

y = (7)*(0.2384517) + (12)*(-1.668245) + (6000)*(0.00101) +
(0)*(-13.09871) + (0)*(-4.662368) + (0)*(2.707084) +
(0)*(11.07219) + (1)*(1.801049) + (0)*(0.0147146) +
(0)*(1.731505) + (0)*(-5.59905) + (0)*(0.5823798) + 58.69107

Predicted Percentage of remaining UI Benefits = 48.2023409 or 48.2%

That is, our Tobit model predicted that this particular benefit recipient will have approximately 48.2 percent of his benefits remaining. In order to compare our Tobit model to the original, the updated, and the revised models, we used these predicted values to create a decile table. We first multiplied these predicted values by a negative one and then ordered them from smallest to largest.

For our example above, this claimant would now have a score of -48.2023409, whereas a claimant with a score of -38.2145 would now have a score of 38.2145. We then ordered these scores from smallest to largest, divided them into deciles, and then calculated the exhaustion rate for each. Ideally, what we would like to see from this decile is low benefit exhaustion rates at the lower deciles and higher exhaustion rates at the higher deciles. The decile gradient from our example above is shown below:

Decile	Mean	Standard Error (Mean)
1	.0600801	.0025067
2	.2025738	.0042335
3	.225954	.0044179
4	.2118616	.0043107
5	.2473298	.0045513
6	.2599046	.0046205
7	.2743195	.0047127
8	.2524196	.004582
9	.2741738	.0047059
10	.3231334	.0049335
Total	.2331631	.0014105

From this table, we see that those individuals with predicted scores falling in the first decile had a mean exhaustion rate of approximately 0.06, or 6 percent. This means that the majority of persons we profiled that received scores falling in the first decile range did not exhaust benefits. On the other hand, those individuals with scores falling in the tenth decile had a mean exhaustion rate of approximately 0.323, or 32.3 percent. With the overall exhaustion rate for this example being approximately 0.233 or 23.3 percent; this difference is significant.

Step 7 - Use Metrics to Determine Which Model Performed Significantly Better both Within and Across SWAs

To compare models across SWAs, we developed a metric to gauge classification improvements between our models and the original model. This metric involved two variables, *"Exhaustion"* and "Pr[*Exh*]."

Profiling data from SWAs were analyzed using the respective models of the SWAs. We used those data submissions from SWAs which were complete and ran their models (without any changes) to rank individuals by their profiling scores. This ranking was then used to select individuals likely to exhaust benefits. For example, Arkansas had a calculated average exhaustion rate of 49.9 percent or 26,273 claimants who exhausted their benefits. After ranking individuals by profiling score, we selected the top 26,273 claimants with the highest profiling scores. This ranked group would have an exhaustion percentage that was either better or worse than the actual exhaustion rate experienced by Arkansas. We then revised the SWA's model, including changing some variables, and ran it to compare results.

Using data for Arkansas, to gauge the predictive improvement of the SWA's profiling over its average exhaustion rate, we developed a metric that subtracts from 1.0 the ratio of the probability of claimants not expected to exhaust over the share (% divided by 100) of claimants not exhausting benefits. The metric will be referred to as the *profiling score effectiveness* metric, because it shows the extent that the SWA's profiling model beat its average exhaustion rate. Algebraically, the metric improvement for the data that Arkansas submitted is as follows:

$$\text{Metric} = 1 - (100 - \Pr[\textit{Exh}]) / \{100 - \textit{Exhaustion}\}$$

$$= 1 - [\Pr\{\textit{non-exhaustion}\} / (\text{Percent not exhausted})]$$

$$= 1 - (100 - 54.64) / (100 - 49.9)$$

$$= 1 – (45.36 / 50.1)$$

$$= 1 – 0.905$$

$$= 0.095$$

$$= 9.5\%.$$

The 9.5 percent is the percentage of additional exhaustees selected by the profiling score over a score that is a random number. This percentage is the metric score.

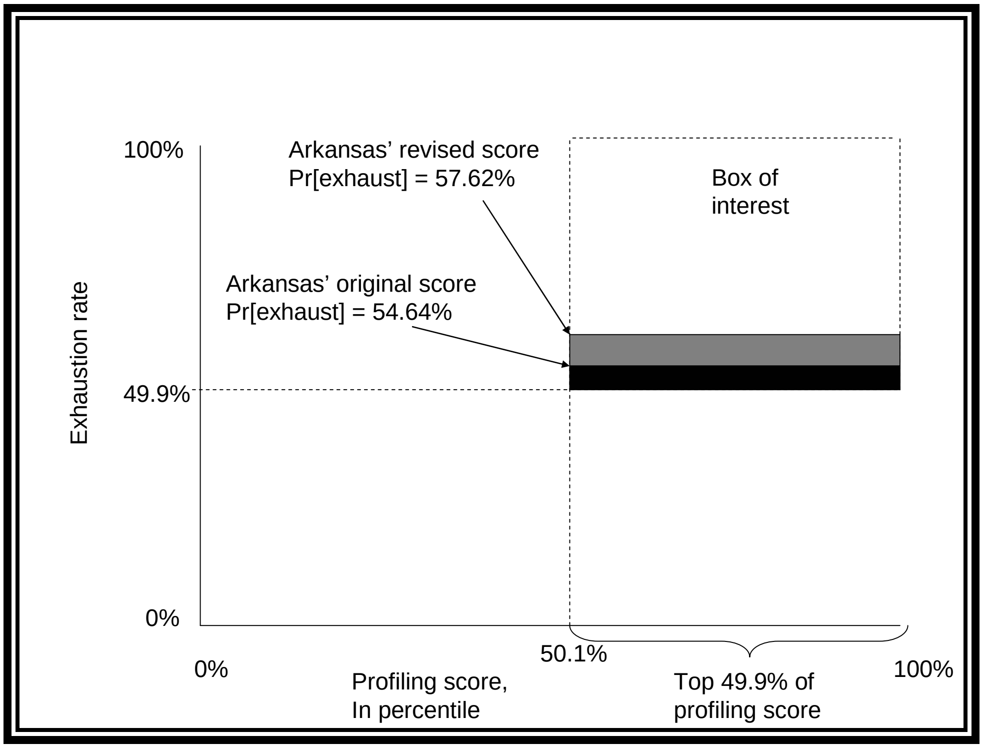
We revised the profiling model for Arkansas. This new score was better than the original score. For the top 49.9 percent of this new profiling score, or 26,273 claimants, the exhaustion rate was 57.62 percent; in the above formula, this number would be the new Pr[*Exh*]. For this revised score, the metric was 15.4 percent. The 15.4 percent is the percentage of additional exhaustees selected by the profiling score over a score that is a random number.

In all cases where the metric could be computed for a state, the SWA's profiling model predicted exhaustion in excess of the state average. Were the two values equal, the profiling model would not be better, on average, than the random selection of individuals for likely exhaustion. Arkansas' profiling model predicted that 54.62 percent of the claimants would exhaust, more than the 49.9 percent experienced by the state that included claimants with some low profiling scores.

If the profiling score were perfect, then the exhaustion rate of those selected would be 100 percent. If the profiling score were a random number, or not at all related to exhaustion, then we would expect the exhaustion rate of those selected to be the same as for the sample as a whole, or 49.9 percent.

To summarize, for Arkansas, the exhaustion rate for the top 49.9 percent of the sample (26,273 individuals) was 54.64 percent, which suggests that the profiling score is better than a random selection (54.64 percent is greater than 49.9 percent). Hence, the model beats the average by about 4.7 percentage points. Our revised metric score beats the average by about 7.7 percentage points. This information is displayed in Figure 5 below.

Figure 5
Illustration of Profiling Score Effectiveness Metric



The metric ranges from 0.0, for a score that is no better than a random number, to 1.0 for a score that predicts exhaustion perfectly. Graphically, the metric can be illustrated by the figure above.

The figure is a rough illustration that contrasts the profiling score on the X axis, with individuals ranked from lowest to highest score. On the Y axis is the exhaustion rate of individuals. With higher profiling scores, we expect the exhaustion rate to increase.

The Box of Interest is the upper right rectangle defined by individuals with percentile profiling scores above (1.0 minus the state exhaustion rate) and an exhaustion rate above 49.9 percent. This area represents the set of non-exhaustees expected for a random profiling score.
If the profiling score were a random number, then the metric would be 0. The 49.9 percent of the sample with the highest profiling score, or 26,273 individuals, would have an exhaustion rate of 49.9 percent. This rate is the same as the state overall. For the sample with the highest profiling score, 26,273 individuals, 49.9 percent of them would exhaust, or 13,110 individuals. Non-exhaustees would be 50.1 percent of the 26,273, or 13,163 individuals. This group of 13,163 individuals represents the box of interest. The extent that a profiling score selects these 13,163 as exhaustees determines the value of the metric. For a score that selects all 13,163 as exhaustees, the metric will have a value of 1.0.

For Arkansas, the original score has a value of 54.64 percent, which is better than the state exhaustion rate of 49.9 percent. The area under this line, as a percentage of the area of the entire Box of Interest, is 9.5 percent. This area is shown in the Figure in black.

The revised score has a metric of 0.154, which implies that the area under this line, shown in Figure 5 above the line for the original score is 15.4 percent of the area in the entire Box of Interest. The area corresponding to this revised score is shown in the figure as the sum of the black and gray areas.

For SWAs with hypothetically perfect models, this metric will have a value of 1, and for SWAs with models that predict no better than random, the metric will take a value of 0. For SWAs to improve this metric, they would have to develop models that better explain benefit exhaustion, which is a desirable outcome. This outcome differs from standard measures of goodness of fit because these focus on explaining non-exhaustion as well as exhaustion. Because this metric focuses on exhaustion, we think that SWAs will be better able to identify individuals who will require reemployment services.

In addition to this metric, we also applied the equation below, derived by Silverman, Strange, and Lipscombe (2004), for calculating the variance (σ_z^2) of a quotient (p. 1069). This equation allowed us to calculate the variance for our metric, Z = X/Y, which is the quotient of two random variables: X (100 - "Pr[*Exh*]") and Y (100 - "*Exhaustion*"). In the equation below, σ_X^2 is the variance of 100 - "Pr[*Exh*]", σ_Y^2 is the variance of 100 - "*Exhaustion*," $E(X)$ is the mean for (100 - "Pr[*Exh*]"), and $E(Y)$ is the mean for (100- "*Exhaustion*"). By dividing the variance of the quotient of the two random variables (here 100 - "*Exhaustion*" and 100 - "Pr[*Exh*]") by the square root of our observations, we were able to determine the standard error of the metric.

$$\text{Variance of Metric: } \sigma_z^2 \approx \frac{\sigma_X^2}{E(Y)^2} + \frac{E(X)^2 \sigma_Y^2}{E(Y)^4}$$

$$[\mathrm{X} = (100 - \mathrm{Pr}[Exh]),\ \mathrm{Y} = (100 - Exhaustion)]$$

$$\text{Standard error of the metric: } \sqrt{\frac{\sigma_Z^2}{N}}$$

The standard error of our metric is important because it defines the value range for it. For instance, if our standard error for this dataset was 0.0041, this would imply that the true value for our metric ranges from a low score of 0.3959 to a high score of 0.4041 with a mean of 0.40. Larger standard errors indicate more variation in our data and less confidence in our estimates.

The standard error is an important aspect of our analysis because it enables us to compare SWAs and determine if specific SWAs have models that are significantly better than others. The standard error enables us to determine significant versus non-significant differences in model performance.

Applying this metric analysis to the 28 SWAs for which we had data for both profiling score and exhaustion results in the following table.

Metric for Assessing the Effectiveness of SWA Profiling Scores

SWA	Profiling score	Control for endogeneity?	Exhaustion rate for the state	Number of individuals with the highest profiling score	Exhaustion rate for individuals with high profiling scores	Metric	Variance of the Metric	Standard Error of the metric
Arizona	original score	Y	37.9	21,502	42.8	0.079	1.153	0.007
Arkansas	original score	N	49.9	26,273	54.6	0.095	1.804	0.008
Arkansas	revised score	N	49.9	26,273	57.6	0.154	1.686	0.008
Delaware	estimated score*	N**	39.0	4,207	42.4	0.055	1.227	0.017
District of Columbia	original score	N**	56.0	5,385	60.3	0.097	2.277	0.021
District of Columbia	revised score	N**	56.0	5,385	63.8	0.176	2.057	0.020
Georgia	original score	Y	35.7	75,994	44.0	0.129	1.017	0.004
Georgia	revised score	Y	35.7	75,994	47.3	0.181	0.976	0.004
Hawaii	original score	Y	39.7	3,526	43.9	0.069	1.248	0.019
Hawaii	revised score	Y	39.7	3,526	44.8	0.085	1.232	0.019
Idaho	estimated score*	Y	45.9	15,605	56.1	0.189	1.400	0.009
Idaho	revised score	Y	45.9	15,605	59.3	0.247	1.306	0.009
Iowa	original score	Y	15.4	2,456	16.2	0.010	0.368	0.012

Louisiana	original score	Y	42.6	22,825	51.9	0.161	1.282	0.007
Maine	original score	Y	37.3	7,346	42.6	0.084	1.121	0.012
Maryland	original score	N**	50.4	18,974	54.1	0.075	1.877	0.010
Michigan	original score	Y	52.7	60,128	55.2	0.052	2.110	0.006
Minnesota	original score	Y	33.6	37,395	43.5	0.150	0.922	0.005
Mississippi	original score	N	45.5	8,208	47.3	0.033	1.620	0.014
Missouri	original score	Y	50.6	18,727	58.3	0.156	1.726	0.010
Montana	original score	Y	53.4	1,678	58.0	0.100	2.051	0.035
Nebraska	original score	N***	95.2	44,098	95.5	0.054	36.698	0.029
New Jersey	original score	Y	62.4	67,030	66.0	0.096	2.947	0.007
New Jersey	revised score	Y	62.4	67,030	67.6	0.137	2.789	0.006
New York	original score	Y	40.4	205,729	55.5	0.253	1.073	0.002
Pennsylvania	original score	Y	46.1	103,172	51.2	0.095	1.564	0.004
Pennsylvania	revised score	Y	46.1	103,172	52.5	0.118	1.527	0.004
South Dakota	original score	N**	18.5	1,107	25.6	0.087	0.475	0.021
Tennessee	original score	Y	49.7	26,299	53.5	0.075	1.830	0.008
Texas	original score	Y	48.0	190,270	56.6	0.165	1.555	0.003
Texas	revised score	Y	48.0	190,270	56.9	0.170	1.545	0.003
Vermont	original score	N**	28.3	359	37.9	0.133	0.756	0.046
Virginia	original score	Y	23.3	21,186	27.7	0.057	0.611	0.005
West Virginia	original score	Y	41.0	12,209	50.7	0.164	1.205	0.010
West Virginia	updated score	Y	41.0	12,209	55.4	0.243	1.109	0.010
Wisconsin	original score	N	44.2	8,991	46.2	0.036	1.533	0.013
Wyoming	original score	N**	43.9	47	46.8	0.051	1.497	0.178

* SWA used a characteristic screen. We calculated a profiling score that used the same variables as the screen.
** SWA provided data indicating individuals who were referred, but the effect was insignificant.
*** Nebraska had possible data problems, with 95% of the sample having more benefits paid than mba(maximum benefit allowance)

We note that exhaustion of UI benefits is the result of a very complex process that involves the interaction of individual characteristics and environmental characteristics. None of the models included enough information to explain a large percentage of exhaustion. The highest value was .253 for NewYork, a model that only explains 25 percent of exhaustion. However, our development of a metric allows SWAs to compare the effectiveness of different versions of their models.

Step 8 - Analyze the Variables that Appear to Best Reduce Type I Errors or Improve the Performance of the Model for Individuals with High Profiling Scores

Thus far, we have discussed the models we used in our analysis of the SWA-provided data. This discussion has included how well, on average, the original models performed, how introducing additional information from the dataset can possibly improve the proper classification of potential benefit exhaustees, and how we gauged improvements between the original model used by the SWA and the models we created for the data provided. There is, however, one important piece missing from this discussion – how we determine which variables are important in explaining the differences between benefit exhaustees and non-exhaustees.

Below is STATA output from an example dataset we created to explain the difference between benefit exhaustees and non-exhaustees using job tenure. We found that for this example dataset, there is a difference in the means of job tenure between benefit exhaustees and non-exhaustees. As detailed below, there were 655 benefit recipients who did not exhaust benefits, and 1,023 that did. Here we found that non-exhaustees had a mean of approximately 5.096 years at their previous employer. For exhaustees the mean for job tenure was approximately 5.957 years, a difference of approximately 0.861 years. We apply the following equation, as detailed in our STATA output, to determine the difference between the two means:

Difference = mean(non-exhaustees) – mean(exhaustees)

Group	Observations	Mean	Standard Error	Standard Deviation	[95% Conf.	Interval]
Non-Exhaustees	655	5.096183	.3163604	8.096601	4.474979	5.717388
Exhaustees	1023	5.957967	.2839745	9.082746	5.400727	6.515206
Combined	1678	5.621573	.2128432	8.718779	5.204107	6.03904
Difference		-.8617836	.4359302		-1.716809	-.0067586

Difference = mean(non-exhaustees) – mean(exhaustees) Z-score = -1.9769
Ho: difference = 0 degrees of freedom = 1676

Ha: difference < 0 Ha: difference != 0 Ha: difference > 0
Pr(T < t) = 0.0241 Pr(T > t) = 0.0482 Pr(T > t) = 0.9759

As detailed in our STATA output, our null hypothesis here is that there is no difference between the two groups of benefit recipients. However, as shown in our STATA output, we reject this null hypothesis and accept that the alternative hypothesis (that the means for the two groups are not same) is true. We determine this by looking at the associated P-values for our null hypotheses. As we can see from our STATA output, the difference between the two means is not zero and has a corresponding P-value of 0.0482. This implies that we are at least 95 percent confident that the difference between the two means is not zero.

We do not include the above table for each variable t-test we performed; however, we include the corresponding P-value, the means for each group, and the Z-score used to determine the significance level (or P- value) for each variable. By testing for differences in means for the two groups, we hope to provide a way for SWAs to determine variables (whether they be categorical or continuous) that are important for explaining the difference between exhaustees and non-exhaustees.

An In-Depth Analysis of the Wage Replacement Rate Variable

Based on the analyses in Appendix D, one of the more powerful variables currently used in WPRS profiling models is the wage replacement rate. However, it is important to note that currently only 15 SWAs use this as a variable. The wage replacement rate measures the proportion of a claimant's wages that are replaced by unemployment insurance (UI) payments. For example, if a claimant received $400 per week prior to filing a UI claim and the claimant receives $240 per week in UI payments, the wage replacement rate is 0.60. For a number of reasons the wage replacement rate is an interesting variable. Chief among them is that it is significant in predicting the probability of exhaustion (Pr[exh]) both as a categorical variable and as a continuous variable.

In our analysis for Arizona, we defined the wage replacement rate for claimants by multiplying the ratio of the weekly benefit amount to base period wages by 52 (the number of weeks in a year) as detailed below.

$$\text{Wage Replacement Rate} = \frac{\text{Weekly Benefit Amount}}{\text{Base Period Wages}} \times 52$$

In doing so we found a range of values for the wage replacement rate: from 0.0019202 to 1.978378 (we ignored all wage replacement rates above 2.0). As detailed in our analysis on the 2003 Arizona data, we first used the wage replacement rate in our updated model as a categorical variable. From our analysis, we found that wage replacement rate was significant, particularly categories 1, 2, 3, 5, and 6 (note: wage replacement rate categories 0 and 7 were removed from our updated model to limit collinearity).

Given the potential explanatory power of the wage replacement rate, we used it as a continuous variable in our revised model. We included a second order wage replacement rate variable and two interaction variables – delay in filing X wage replacement rate and maximum benefit amount X wage replacement rate. From our analysis we found that wage replacement rate as a continuous variable was significant, as were the second order wage replacement variable and the maximum benefit amount X wage replacement rate variable.

Using our revised model and our Type I error analyses in Appendix D (Type I errors are individuals who are predicted to exhaust benefits but do not), the results showed that the wage replacement rate was significant in explaining the difference between Type I errors and correct predictions. In particular, wage replacement categories 1, 3, 4, and 6 are important variables in explaining the difference between Type I errors and correct predictions.

As an additional test for the significance of the wage replacement rate, we calculated the logistic regression model where only wage replacement rate and a constant are used to predict the probability of exhaustion (Pr[exh]) (note: our model includes a reference to an offset variable to control for endogeneity). An analysis regarding how we came to use this variable is including in the following section titled “endogeneity” and also in the extended analysis for Arizona.

Logistic regression	Number of observations	=	56730
	Wald chi2(1)	=	913.45
Log likelihood = -37237.38	Prob > chi2	=	0.0000

exhaust	Coefficient	Standard error	z	P>z	[95% Conf.	Interval]
wrr	.8756011	.028971	30.22	0.000	.818819	.9323832
_cons	-.9980725	.0193361	-51.62	0.000	-1.03597	-.9601745
endogeneity control	(offset)					

As we can see from the associated low P-value, wage replacement rate does have a significant impact on predicting the probability of benefit exhaustion. For a comparison we will look at the predicted probability score that Arizona provided us and the corresponding wage replacement rate for that claimant. Using the coefficients from the above calculations we will first calculate the score using the wage replacement rate, the corresponding coefficient, and the constant.

$$Z = wrr*(0.8756011) – 0.9980725$$
$$Z = (0.6155989)*(0.8756011) – 0.9980725$$
$$Z = -0.45905342600121$$

Next, we use this value, Z, in the following logistic regression transformation to determine the predicted probability of benefit exhaustion.

$$\Pr[\text{exh}] = \frac{e^{Z}}{e^{Z}+1} = 0.38721$$

The probability score provided by Arizona for the claimant with a wage replacement rate of 0.6155989 was 0.13552. From our detailed analysis for the 2003 Arizona data, our predicted probability score for this claimant was 0.3842769. This score was calculated using only the score provided by Arizona along with a constant (we included the offset variable in our model to control for endogeneity). The predicted probability score for this claimant for our updated model was 0.4769786 and 0.4805083 for our revised model.

CONCLUSION:
BEST PRACTICES IN WPRS MODELS
FOR PREDICTING EXHAUSTION OF UI BENEFITS

For this study, we collected information that describes how SWAs operate their models for predicting exhaustion of UI benefits and refer individuals for reemployment services, and we analyzed the models used by SWAs to predict exhaustion. The descriptions of SWA operations are contained in Part 3 above and Appendices B and C, and demonstrate the variety of approaches used by SWAs for profiling. In terms of best practices, our analyses suggest that SWAs can improve their models by including more information, including introducing more variables and including second-order effects.

The profiling models currently operate in terms of their ability to properly classify benefit exhaustees. As a part of our task, we have performed updates and revisions to the provided profiling models and analyzed the results to determine if there are ways to improve the profiling power of the models. We think that there are methods and variables that SWAs can incorporate into their current profiling models to improve performance. A more effective model also will reduce staff effort and help ensure the effective application of valuable reemployment services.

Depending on the SWA and dataset, incorporating continuous variables, such as job tenure and education and second order variables (i.e., variables that are centered and squared) improved the predictions of the profiling models. Furthermore, introducing cross-term variables, i.e., variables that are the product of two centered continuous variables, also led to an improvement.

From our analyses of the profiling models and datasets for nine SWAs (Arkansas, the District of Columbia, Georgia, Hawaii, Idaho, New Jersey, Pennsylvania, Texas, and West Virginia), we found that the following features generally helped to properly classify potential benefit exhaustees:

- Using a logistic regression model
- Including the following independent variables:
  - Maximum Benefit Amount
  - Wage Replacement Rate
  - Potential Duration of Benefits
  - Education Level
  - Delay in Filing for UI Benefits
  - Benefit Exhaustion Rate for Prior Industry
  - County Unemployment Rate
  - County/Metro Area of Residence
  - Industry and Occupation Codes
- Including continuous variables
- Including second-order and cross-term variables if more than one continuous variable is included in the model

Including the wage replacement rate of claimants is significant in explaining the differences between exhaustees and non-exhaustees; moreover, wage replacement rate also has the distinction of being significant as both a categorical variable and as a continuous variable. The same is true of the maximum benefit amount and job tenure, though the significance of each is determined by how their categories are defined.

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APPENDICES

APPENDIX A

SURVEY INSTRUMENT

Worker Profiling Reemployment Services (WPRS) Survey

(Operational Section)

Please enter the name of your State:

1. Please provide the name, title, e-mail address, and phone number of the individual(s) completing this survey including which survey questions they completed:

2. Please provide the name, title, e-mail address, and phone numbers of the individuals within UI, ES (Workforce Development), LMI, and IT who provide daily control and oversight of the WPRS process and model (if different from above).

3. How frequently is the model updated (run to generate new statistical parameters)?

   Yearly ___________
   2-3 Years ___________
   More than 3 Years ___________
   Other ___________

3a. Date of Last Update: _________________________

4. Has the model been revised (i.e., **other than update**, has the model been revised in any way, such as a change in the variables used, the variable definitions, or functional form) since implementation?

   Yes _______
   No _______

4a. If Yes, please provide date of last revision and brief description of revisions made:

4b. Do you have policy guidance to revise your model and if so, how often? Is there a decision maker within your agency who determines that the model will be revised?

5. By which method(s) is your initial claim process performed? (check all that apply and estimate percentages)

   In-Person ________
   By Telephone ________
   By Mail ________
   Internet ________
   Other:(specify) ____
   ____

6. Are all of the claimant "characteristics" data needed for profiling purposes captured at the time of the initial claim?

   Yes ________
   No ________

6a. If you answered "No" above, please describe how, and when, the data are captured or generated:

6b. Are there any checks on the accuracy of claimant provided information?

Yes ________ (If Yes, Please describe below)
No ________

7. How frequently is the WPRS model run?

Daily ____________
Weekly ____________
Other (please describe) ____
____

7a. Is the listing of profiling candidates produced at the same time the model is run?

Yes ________
No ________

If "No," please describe when the listing is produced:
____
____

8. Is the model run against the first pay records?

Yes ________
No ________

8a. If you answered "No" to question 8, please describe against what UI or other data the model is run.
____
____
____

9. Who determines and assigns the claimant's occupational code?

Initial Claims Taker ___________
Workforce Dev. Worker ___________
Other (please describe) ____
____

9a. Which occupational coding system is used (DOT, SOC or, if any other classification system is used, please identify)?

9b. How is the occupational code derived for the claimant? (please describe, if not a standard classification system)

10. How is the claimant's primary employer (for assigning NAICS/SIC code) determined?

Review of work history with claimant __________

Review of wage records ________
Other (please describe) ____

____

11. Who is exempt from profiling in your State?

12. To whom is the list of profiling candidates sent, and using what medium? (describe)

13. Who determines the number of profiled candidates to be served and how is the number determined?

14. How do the probability scores, or rankings, influence selection of candidates from the pool?

15. Under what conditions can the local area skip down ranks in selecting candidates for services?

16. Are there feedback loops in place between local area operations and the WPRS model builders?

Yes ________
No ________

17. The original parameters for WPRS suggested individuals who had received more than 5 weeks of benefits prior to selection be excluded from the pool (e.g. if payment delays have deferred first payments for more than five weeks). Is this parameter in place in your system?

Yes ________
No ________ If No, please provide the number you use

18. Has the accuracy of data needed for the Characteristic Screens been measured or tested to compare it to the predictive equation approach or has the existence of missing or inaccurate data been investigated?

Yes ________ (If Yes, please describe results below)
No ________

19. Has your agency conducted any studies to evaluate the accuracy of the profiling model in predicting who will exhaust benefits?

Yes ________ (If Yes, please describe below)
No ________

(Structural Section)

SOME STATES MAY FIND IT ADVANTAGEOUS TO SIMPLY ATTACH TECHNICAL REPORTS OR COMPUTER PRINT-OUTS TO REPLY TO THE HIGHLY TECHNICAL STRUCTURAL QUESTIONS (especially 24, 25, 26, & 31). PLEASE BE SURE TO ATTACH THE REPORTS AND EXPLAIN WHERE IN THE REPORT OR PRINTOUT THE PERTINENT MATERIAL MAY BE FOUND.

Please note all questions that follow apply to the model that was primarily in use during the period ____________ to ___________.

20. Which type of WPRS Model does your state currently use? Enter “Yes” in appropriate block.

Characteristic Screen __________

Statistical Model __________

20a. What is your model's functional form? (example: logit, probit, tobit, linear, characteristic screen, other).

21. Which individuals are included in the data when the model was first estimated, or when it was updated or revised?

All initial claim filers _______
Only benefit recipients ________
Union member _______
Others not profiled (describe) ____
____

21a. What is the sample size in the model's latest update and what was the original sample size when the model was first estimated?

22. What is your model's dependent (left-hand side) variable?

Exhaustion ________Duration of Benefits________
Both ________
Other (describe) ____
____

23. For the purpose of updating your model, how do you define exhaustion of benefits? (check all options which apply)

Maximum benefits paid __________
Received 26 weekly payments ________
Benefit payments denied but under appeal ________
Other(describe)
____
____

24. What are your model's independent (right-hand side) variables and how are they defined? Please include and explain how to calculate the variables and explain what data are used to create the variable. (examples: maximum duration = maximum benefit amount divided by weekly benefit amount; example 2: industry = the first digit of the NAICS hierarchical code). If you use a characteristic screen, what characteristics do you use?

____
____

25. What determined the selection of the independent (right-hand side) variables used in the predictive equation? Were any other variables examined?

____
____

25a. What are the numerical values of the estimated coefficients for the independent (right-hand side) variables and if this information is readily available, what was the standard error for each? (This information should be found on the original statistical output for the original estimation technique.)

____
____

26. What techniques are followed to prepare a claims data record for profiling using the equation? (e.g., are there checks for missing values, are union member claims profiled, are there data quality checks, etc.)

____
____

27. How are claimants with incomplete records, or records with missing variables, processed? (check all that apply)

_____ a. variable kept blank and a binary variable used to track the missing variable
_____ b. another version of the profiling model used
_____ c. value of missing data estimated by some other procedure
_____ d. missing value replaced by average value for the individuals in the run or some other average value
_____ e. Other method? (please describe)

28. Were the exclusion rules (see question 11) applied to the data records used during the estimation of the predictive equation? That is, were records excluded from the estimation database, and what percentage of claimants is excluded from profiling?

____
____

29. Were the data quality procedures that were used for the data in the estimation of the predictive equation different from those used now for profiling? If so, how? In your view, does the elimination of claim records as a result of data quality procedures have an effect (either negative or positive) on the performance of the equation?

____
____

30. Are the predicted values of the dependent (left-hand side) variables retained in electronic storage archives?

Yes _______
No _______

31. What are the ranges of permissible (or expected) values of the data for the independent (right-hand side) variables (minimum and maximum)? Please describe below.

APPENDIX B

COMPARISON TABLE OF SWA WPRS MODELS

	Structural/Operational					Methods of Initial Filing (percentage, if available)				Model Run Information					Model Use Information		
SWA	**Model Type**	**Functional Form**	**Frequency of Update**	**Date of Last Update**	**Model Revision**	**In Person**	**Telephone**	**Mail**	**Internet**	**Frequency of Model Run**	**Model Run Against?**	**When Candidate List Produced?**	**Occupational Coding System**	**Primary Employer Assignment**	**To Whom Candidate List Sent**	**# to be Served Determined By**	**Discretion in Select. Participants**
Alabama [1]	statistical	logit	2-3 yrs	none	2000		X			weekly	first pay records	time of run	SOC	wage records	career centers using the Alabama Job Link Sys.	career centers based on their capacity	No
Alaska	statistical	logit	yearly	01/06	01/05		92%		8%	weekly	first pay records	time of run	DOT/SOC	work history/wage records	employment services provider	employment services unit	No
Arizona	statistical	INA	2-3yrs	07/03	07/03	X	X		X	daily	first pay records	when requested by orientation provider	INA	last employer	orientation provider	program manager	No
Arkansas	statistical	linear (multiple regression)	>3 yrs	never	none	X		X		weekly	first pay records	time of run	DOT	wage records	Job Search Workshop Coordinators	workshop coordinators based on capacity	No, unless an higher ranked candidate cannot be contacted
California	statistical	logit	>3 yrs	12/01	none		60%	5%	35%	weekly	first pay records	time of run	DOT/SOC	work history/wage records	Employment Service Scheduling System	Field Office Manager or IAW Workshop Leader	No
Colorado	statistical	logit	never	never	never		80%		20%	weekly	first pay records	time of run	SOC	wage records	workforce center	workforce center	Yes
Connecticut	statistical	neural network	never	never	never		91.1%		8.9%	weekly	first pay records	time of run	ONET/SOC	none	State Department of Labor Staff	State Department of Labor Job Center Directors	Yes, if the claimant has returned to work or moved out of state
Delaware	characteristic screen	NA	>3 yrs	never	never	X		X		weekly	at first pay record	time of run	ONET/SOC	work history	Division of Employment and Training	Division of Employment and Training	No
District of Columbia [2]	statistical	logit	2-3 yrs	01/04	10/04	20%			80%	weekly	at first pay records	time of run	ONET	wage records	One Stop Management Staff	One Stop Management Staff	No
Florida	no scoring - regional boards decided those most likely to exhaust	INA	INA	none	01/02		45%	5%	50%	weekly	at first pay records	time of run	ONET	work history	One Stop Management Staff	One Stop Management Staff	Yes
Georgia	statistical	logit	>3yrs	01/98	never	X				daily	at intake process	time of run	DOT	work history/wage records	Employment Services	Career Center Managers	Yes, for non-mandatory participants
Hawaii	statistical	logit	>3yrs	01/95	01/02	10%	90%			weekly	at first pay record	time of run	SOC	work history	UI/WDD/R&S	Workforce Development Division	Yes, only for rescheduling
Idaho	characteristic screen	characteristic	yearly	05/05	05/05	5%	6%		89%	weekly	at first pay record	time of run	SOC	wage records	local consultants	Office management staff	Yes

	Structural/Operational					Methods of Initial Filing (percentage, if available)				Model Run Information					Model Use Information		
SWA	Model Type	Functional Form	Frequency of Update	Date of Last Update	Model Revision	In Person	Telephone	Mail	Internet	Frequency of Model Run	Model Run Against?	When Candidate List Produced?	Occupational Coding System	Primary Employer Assignment	To Whom Candidate List Sent	# to be Served Determined By	Discretion in Select. Participants
																determine yearly target number	
Illinois	statistical	logit	other	1997	none	80%			20%	weekly	first pay records	time of run	DOT	wage records	Local Workforce Investment Area	Local Workforce Investment Area	No
Indiana	statistical	linear regression	never	never	none	X			X	weekly	at first pay record	time of run	DOT	work history	local office staff	local office managers	No
Iowa	statistical	logit	never	never	none	46%	31%		19%	weekly	first pay records	at orientation selection	SOC/DOT	last employer	local profiling coordinators	UI/Workforce Development administration	No
Kansas	statistical	logit	never	never	none		75%		25%	daily	first pay records	time of run	SOC	work history	local workforce development offices	workforce development staff determined by workload	No
Kentucky	statistical	tobit	>3yrs	01/97	none	X	X		X	weekly	first pay records	time of run	OES	wage recodes	local office staff	Director of the Division for Workforce and Employment Svcs.	No
Louisiana	statistical	logit	3-5 yrs	06/03	06/03	5%			95%	weekly	first pay records	time of run	ONET/SOC	work history	Wagner/Peyser and WIA staff via mainframe	local office staff based on capacity	Yes, at will
Maine	statistical	logit	>3yrs	9/04	01/00		X	X	X	weekly	first pay records	time of run	DOT	wage records	Employment Services and then to Career Centers	Career center determined by capacity	No
Maryland	statistical	logit	>3yrs	01/00	none		X		X	weekly	first pay records	time of run	DOT	wage records	WPRS workshop facilitators	WPRS workshop facilitators determined by space available	No
Massachusetts	characteristic screens	characteristic	other	never	05/05			X		weekly	first pay records	following screening of first payments	claimant determines	last employer	ES system for tracking WIA service and outcomes	INA	INA
Michigan	statistical	linear regression	>3yrs	6/03	6/03		X	X	X	weekly	first pay records	time of run	SOC	wage records	Workforce Development Board (WDB) Coordinator	Each WDB determined by resources and staffing	Yes, but only for candidates below the mandatory rank
Minnesota	statistical	logit	2-3yrs	05/05	05/05		55%	5%	40%	daily	first claim data	time of run	DOT/SOC	work history	Resource Area Coordinators	Resource Area Coordinators	Yes
Mississippi	statistical	INA	never	never	none	100%				weekly	first	the day	SOC	work history	workforce	workforce	INA

SWA	Structural/Operational: Model Type	Functional Form	Frequency of Update	Date of Last Update	Model Revision	Methods of Initial Filing (percentage, if available): In Person	Telephone	Mail	Internet	Model Run Information: Frequency of Model Run	Model Run Against?	When Candidate List Produced?	Occupational Coding System	Primary Employer Assignment	Model Use Information: To Whom Candidate List Sent	# to be Served Determined By	Discretion in Select. Participants
											pay records	after the model is run			development worker	development worker	
Missouri	statistical	logit	>3yrs	12/04	12/04		84%		16%	weekly	first pay records	time of run	DOT	work history/wage records	Dept. of Economic Development	local agencies based on service capabilities	No
Montana	statistical	logit	never	never	none		75%	25%		weekly	first pay records	time of run	SOC	work history/wage records	Workforce Services	Workforce Services Division management	No
Nebraska	statistical	logit	>3 yrs	2000	2000		80%		20%	daily	first pay records	time of run	SOC	wage records	Labor Reemployment Services	Office of Workforce Services staff	Yes, if no claimants meet the selection criteria
Nevada	statistical	logit	never	never	none		84%		16%	weekly	first pay records	time of run	INA	wage records	JobConnect Office	State policy sets minimum for JobConnect	No
New Hampshire	statistical	logit	other	4/05	none				X	weekly	first pay records	time of run	ONET	last employer	local office managers	local office manager based on staff workload	No, only veterans programs are allowed to pick their veterans
New Jersey	statistical	logit	2-3 yrs	01/04	01/04	5%	70%		25%	daily	first pay records	time of run	OES/DOT	employer with most base wks in the base yr	Workforce New Jersey (WNJ)	local WNJ manager	No
New Mexico	statistical	logit	other	01/04	none		X		X	weekly	first pay records	time of run	SOC	work history	OWS/One Stop	OWS/One Stop determined by capacity	Yes, if candidates are seasonal workers
New York	characteristic screen	characteristic	2-3yrs	06/05	01/03	1%	58%		41%	weekly	first pay records	time of run	DOT	work history/wage records	All ES/WIA partner staff accessing the One Stop Operating Sys.	local Division of Employment Svcs.	No
North Carolina	statistical	logit	never	never	none	X	X		X	daily	first pay records	time of run	DOT	work history	local office	local office managers	No
North Dakota	statistical	logit	yearly	9/05	01/03		80%		20%	daily	first pay records	time of run	SOC	work history	local One Stop centers	local One Stop Centers	No
Ohio	characteristic screen	characteristic	other	01/00	none		75%		25%	weekly	first pay records	time of run	SOC/ONET	work history	State Merit Staff	district coordinators based on One Stop's capacity	No, unless returned to work or an exemption applies
Oklahoma	statistical	linear regression	never	08/06	none		46%		51%	weekly	first pay	by local offices at	SOC	work history	local offices	Profiling Coordinator in	No

SWA	Structural/Operational					Methods of Initial Filing (percentage, if available)				Model Run Information					Model Use Information		
	Model Type	Functional Form	Frequency of Update	Date of Last Update	Model Revision	In Person	Telephone	Mail	Internet	Frequency of Model Run	Model Run Against?	When Candidate List Produced?	Occupational Coding System	Primary Employer Assignment	To Whom Candidate List Sent	# to be Served Determined By	Discretion in Select. Participants
											records	time of scheduling				each local office	
Oregon	statistical	logit	>3yrs	07/03	none		X	X	X	weekly	first pay records	INA	SOC	work history	Local business and employment services offices	Local business and employment services offices	If number of mandatory candidates does not fill capacity, others can be served
Pennsylvania	statistical	logit	>3yrs	01/05	01/03		69%	1%	30%	weekly	first pay records	time of run	none	wage records	local CareerLink offices	local workforce development offices	No, unless a candidate has been exempt
Puerto Rico	characteristic screen	characteristic	never	never	none	100%				weekly	first pay records	time of run	DOT/ONET	claimant interview	local offices	local office managers based on personnel available	INA
Rhode Island	statistical	linear	>3yrs	01/00	none		65%		35%	daily	first pay records	on a weekly basis	ONET	work history	One Stop offices which profile	local office managers and staff based on capacity	Yes, if seasonal workers or wages are not comparable with existing job openings
South Carolina	statistical	logit	yearly	03/05	none	X	X		X	daily	first pay records	time of run	SOC	work history	local offices	INA	No
South Dakota	statistical	logit	never	never	none		X		X	weekly	first pay records	time of run	SOC	wage records	workforce development worker	local office	No
Tennessee	statistical	logit	2-3 yrs	08/03	none	X	X	X	X	weekly	first pay records	time of run	DOT/SOC	wage records	local office Job Service	coordinated between Job Service and Field operations based on capacity	No
Texas	statistical	logit	other	09/03	07/03		X	X	X	weekly	first pay records	time of run	SOC	work history	Local Workforce Development Boards	each Board based on Capacity	No
Utah	statistical	logit	2-3 yrs	never	none		X		X	weekly	first pay records	time of run	SOC	wage records	workforce development worker	UI director	No
Vermont	statistical	logit	other	03/05	03/05		X			weekly	first pay records	time of run	SOC	wage records	Job Service Offices	Job Service District office	No
Virgin Islands	characteristic screen	characteristic	never	never	none	X				weekly	first pay records	claimants added to a pool of	SOC	work history	Reemployment Services	UI director	Yes, for candidates with unresolved issues

SWA	Structural/Operational: Model Type	Functional Form	Frequency of Update	Date of Last Update	Model Revision	Methods of Initial Filing (percentage, if available): In Person	Telephone	Mail	Internet	Model Run Information: Frequency of Model Run	Model Run Against?	When Candidate List Produced?	Occupational Coding System	Primary Employer Assignment	Model Use Information: To Whom Candidate List Sent	# to be Served Determined By	Discretion in Select. Participants
												potential profiling candidates on a daily basis					
Virginia	statistical	logit	never	never	none	X	X		X	weekly	first pay records	time of run	DOT	claimant provided SIC	local and central offices via mainframe	local office based on capacity	Yes, for candidates that will drop off the list if not selected
Washington	statistical	logit	other	never	07/04	X	X	X	X	weekly	first pay records	time of run	DOT/ONET	INA	WorkSource Offices	WorkSource office	Yes, for similar or same service
West Virginia	statistical	logit	>3 yrs	08/01	08/01	X				weekly	first pay records	time of run	SOC	wage records and work history	INA	Job Service local office staff	No
Wisconsin	statistical	logit	other	1994	none		X		X	weekly	first pay records	time of run	SOC	wage records	none	local office based on capacity	No
Wyoming	statistical	discriminant analysis	2-3 yrs	07/05	05/04	>1%	82%	>1%	18%	weekly	all initial claims	time of run	SOC	wage records and work history	profiling coordinator at the state claims center	profiling coordinator	No

[1] - Individuals who are exempt from work search requirements are not eligible for referral to WPRS services
[2] - Claimants with delayed payments or earnings during the first week of benefits are not eligible for referral to WPRS services
INA - Information Not Available

Appendix B, Part 2

	Model Use Information			Dependent Variable	Independent Variables										
SWA	**To Whom Candidate List Sent**	**# to be Served Determined By**	**Discretion in Select. Participants**	**Dependent Variable (if applicable)**	**Job Tenure**	**Education**	**Occupation Code**	**Industry Code**	**Lag Weeks Since Claim Filed**	**Max Benefit Amount**	**Weekly Benefit Amount**	**Local Unemployment**	**Potential Duration**	**Replacement**	**Number of Employers**
Alabama [1]	career centers using the Alabama Job Link Sys.	career centers based on their capacity	No	benefit exhaustion	X	X	X	X			X				
Alaska	employment services provider	employment services unit	No	benefit exhaustion	X	X		X	X			X	X	X	X
Arizona	orientation provider	program manager	No	INA		X		X		X				X	
Arkansas	Job Search Workshop Coordinators	workshop coordinators based on capacity	No, unless an higher ranked candidate cannot be contacted	Estimated probability of exhaustion score, ranging from zero to one.		X		X		X	X			X	
California	Employment Service Scheduling System	Field Office Manager or IAW Workshop Leader	No	exhaustion of benefits and long-term unemployed	X	X	X	X				X			
Colorado	workforce center	workforce center	Yes	benefit duration											

SWA	Model Use Information			Dependent Variable	Independent Variables										
	To Whom Candidate List Sent	# to be Served Determined By	Discretion in Select. Participants	Dependent Variable (if applicable)	Job Tenure	Education	Occupation Code	Industry Code	Lag Weeks Since Claim Filed	Max Benefit Amount	Weekly Benefit Amount	Local Unemployment	Potential Duration	Replacement	Number of Employers
Connecticut	State Department of Labor Staff	State Department of Labor Job Center Directors	Yes, if the claimant has returned to work or moved out of state	proportion of total eligible benefits paid	X	X	X		X	X		X			
Delaware	Division of Employment and Training	Division of Employment and Training	No	INA	X		X	X							
District of Columbia [2]	One-Stop Management Staff	One-Stop Management Staff	No	exhaustion of benefits	X	X	X	X				X		X	
Florida	One-Stop Management Staff	One-Stop Management Staff	Yes	INA	X	X	X	X				X			
Georgia	Employment Services	Career Center Managers	Yes, for non-mandatory participants	INA											
Hawaii	UI/WDD/R&S	Workforce Development Division	Yes, only for rescheduling	exhaustion of benefits	X	X	X	X			X	X			
Idaho	local consultants	Office management staff determine yearly target number	Yes	exhaustion of benefits	X	X		X					X	X	X
Illinois	Local Workforce Investment Area	Local Workforce Investment	No	exhaustion of benefits	X		X		X						

	Model Use Information			Dependent Variable	Independent Variables										
SWA	**To Whom Candidate List Sent**	**# to be Served Determined By**	**Discretion in Select. Participants**	**Dependent Variable (if applicable)**	**Job Tenure**	**Education**	**Occupation Code**	**Industry Code**	**Lag Weeks Since Claim Filed**	**Max Benefit Amount**	**Weekly Benefit Amount**	**Local Unemployment**	**Potential Duration**	**Replacement**	**Number of Employers**
		Area													
Indiana	local office staff	local office managers	No	exhaustion of benefits	X	X	X			X		X			
Iowa	local profiling coordinators	UI/Workforce Development administration	No	exhaustion of benefits	X	X	X					X			
Kansas	local workforce development offices	workforce development staff determined by workload	No	exhaustion of benefits	X			X				X		X	
Kentucky	local office staff	Director of the Division for Workforce and Employment Svcs.	No	exhaustion of benefits	X			X		X					
Louisiana	Wagner/Peyser and WIA staff via mainframe	local office staff based on capacity	Yes, at will	exhaustion of benefits		X	X	X	X		X	X		X	X
Maine	Employment Services and then to Career Centers	Career center determined by capacity	No	exhaustion of benefits	X	X		X	X					X	X
Maryland	WPRS workshop facilitators	WPRS workshop facilitators determined by space available	No	exhaustion of benefits	X	X	X	X							

SWA	Model Use Information: To Whom Candidate List Sent	Model Use Information: # to be Served Determined By	Model Use Information: Discretion in Select. Participants	Dependent Variable: Dependent Variable (if applicable)	Independent Variables: Job Tenure	Education	Occupation Code	Industry Code	Lag Weeks Since Claim Filed	Max Benefit Amount	Weekly Benefit Amount	Local Unemployment	Potential Duration	Replacement	Number of Employers
Massachusetts	ES system for tracking WIA service and outcomes	INA	INA	INA											
Michigan	Workforce Development Board (WDB) Coordinator	Each WDB determined by resources and staffing	Yes, but only for candidates below the mandatory rank	exhaustion of benefits		X	X	X		X					
Minnesota	Resource Area Coordinators	Resource Area Coordinators	Yes	exhaustion of benefits		X	X	X	X		X	X		X	X
Mississippi	workforce development worker	workforce development worker	INA	exhaustion of benefits	X	X	X	X			X		X		
Missouri	Dept. of Economic Development	local agencies based on service capabilities	No	exhaustion of benefits	X	X		X	X		X			X	X
Montana	Workforce Services	Workforce Services Division management	No	exhaustion of benefits	X	X		X				X			X
Nebraska	Labor Reemployment Services	Office of Workforce Services staff	Yes, if no claimants meet the selection criteria	exhaustion of benefits											

SWA	Model Use Information: To Whom Candidate List Sent	Model Use Information: # to be Served Determined By	Model Use Information: Discretion in Select. Participants	Dependent Variable (if applicable)	Job Tenure	Education	Occupation Code	Industry Code	Lag Weeks Since Claim Filed	Max Benefit Amount	Weekly Benefit Amount	Local Unemployment	Potential Duration	Replacement	Number of Employers
Nevada	JobConnect Office	State policy sets minimum for JobConnect	No	exhaustion of benefits	x	X		X			X	X			
New Hampshire	local office managers	local office manager based on staff workload	No, only veterans programs are allowed to pick their veterans	exhaustion of benefits		X			X					X	
New Jersey	Workforce New Jersey (WNJ)	local WNJ manager	No	exhaustion of benefits	X						X	X			
New Mexico	OWS/One-Stop	OWS/One-Stop determined by capacity	Yes, if candidates are seasonal workers	exhaustion/ duration of benefits		X	X	X							
New York	All ES/WIA partner staff accessing the One-Stop Operating Sys.	local Division of Employment Svcs.	No	exhaustion/ duration of benefits	X	X	X	X							
North Carolina	local office	local office managers	No	exhaustion of benefits	X	X	X	X							
North Dakota	local One-Stop centers	local One-Stop Centers	No	exhaustion of benefits			X	X				X			

	Model Use Information			Dependent Variable	Independent Variables										
SWA	**To Whom Candidate List Sent**	**# to be Served Determined By**	**Discretion in Select. Participants**	**Dependent Variable (if applicable)**	**Job Tenure**	**Education**	**Occupation Code**	**Industry Code**	**Lag Weeks Since Claim Filed**	**Max Benefit Amount**	**Weekly Benefit Amount**	**Local Unemployment**	**Potential Duration**	**Replacement**	**Number of Employers**
Ohio	State Merit Staff	district coordinators based on One-Stop's capacity	No, unless returned to work or an exemption applies	INA											
Oklahoma	local offices	Profiling Coordinator in each local office	No	exhaustion of benefits											
Oregon	Local business and employment services offices	Local business and employment services offices	If number of mandatory candidates does not fill capacity, others can be served	exhaustion of benefits		X	X	X				X		X	
Pennsylvania	local CareerLink offices	local workforce development offices	No, unless a candidate has been exempt	exhaustion of benefits	X	X		X				X		X	
Puerto Rico	local offices	local office managers based on personnel available	INA	duration of benefits											

SWA	Model Use Information			Dependent Variable	Independent Variables										
	To Whom Candidate List Sent	# to be Served Determined By	Discretion in Select. Participants	Dependent Variable (if applicable)	Job Tenure	Education	Occupation Code	Industry Code	Lag Weeks Since Claim Filed	Max Benefit Amount	Weekly Benefit Amount	Local Unemployment	Potential Duration	Replacement	Number of Employers
Rhode Island	One- Stop offices which profile	local office managers and staff based on capacity	Yes, if seasonal workers or wages are not comparable with existing job openings	exhaustion of benefits											
South Carolina	local offices	INA	No	exhaustion of benefits	X	X	X	X	X		X		X		
South Dakota	workforce development worker	local office	No	exhaustion of benefits	X	X	X	X	X	X	X	X			
Tennessee	local office Job Service	coordinated between Job Service and Field operations based on capacity	No	exhaustion of benefits	X	X		X		X	X				
Texas	Local Workforce Development Boards	each Board based on Capacity	No	exhaustion of benefits	X		X	X	X	X	X	X	X		
Utah	workforce development worker	UI director	No	exhaustion of benefits	X	X		X	X					X	
Vermont	Job Service Offices	Job Service District office	No	exhaustion of benefits	X	X	X	X	X		X			X	

	Model Use Information			Dependent Variable	Independent Variables										
SWA	To Whom Candidate List Sent	# to be Served Determined By	Discretion in Select. Participants	Dependent Variable (if applicable)	Job Tenure	Education	Occupation Code	Industry Code	Lag Weeks Since Claim Filed	Max Benefit Amount	Weekly Benefit Amount	Local Unemployment	Potential Duration	Replacement	Number of Employers
Virgin Islands	Reemployment Services	UI director	Yes, for candidates with unresolved issues	exhaustion of benefits and duration of benefits	X	X	X	X							
Virginia	local and central offices via mainframe	local office based on capacity	Yes, for candidates that will drop off the list if not selected	exhaustion of benefits	X	X	X	X				X			
Washington	WorkSource Offices	WorkSource office	Yes, for similar or same service	exhaustion of benefits											
West Virginia	INA	Job Service local office staff	No	exhaustion of benefits	X	X	X	X	X		X				
Wisconsin	none	local office based on capacity	No	exhaustion of benefits	X	X	X	X				X			
Wyoming	profiling coordinator at the state claims center	profiling coordinator	No	exhaustion of benefits	X		X	X		X	X	X			X

[1] - Individuals who are exempt from work search requirements are not eligible for referral to WPRS services

[2] - Claimants with delayed payments or earnings during the first week of benefits are not eligible for referral to WPRS services

INA - Information Not Available

APPENDIX C

REPORTS FOR 53 SWAS AND DECILE TABLES FOR 28 SWAS

ANALYSIS OF ALABAMA PROFILING MODEL

Introduction:

Alabama uses a statistical model, of which the functional form is logistic, to determine a claimant's Worker Profiling and Reemployment Services (WPRS) profiling score. This model is run weekly against the claimant first payment file and the list of eligible candidates, ranked by probability of exhaustion, is produced at that time and sent to career centers via the Alabama Job Link System. The number of candidates to be selected to receive services is based on the size of the career center with claimants to be served being prioritized by their probability of exhaustion. The career centers have no discretion in the selection of candidates and must service each succeeding candidate starting with those claimants with the highest probability of exhaustion.

The model is revised approximately every three years with a substantial revision being undertaken approximately six years ago. During this revision, a continuous variable was incorporated into the model which is reflected in all future model revisions. Prior to revising the current model, its accuracy is evaluated to ascertain what modifications are needed. Those claimants who are required to perform work search are included in the sample for profiling with the most recent sample consisting of 23,561 claimants. The original model had 20,000 claimants in the sample but was reduced to 7,000 due to computer capacity.

Data Collection Process:

Initial claims are filed by telephone only. The occupational code is determined by the initial claims taker using the Standard Occupational Classification (SOC) system, and no verification is performed to ascertain the accuracy of the information provided by the claimant. The primary employer classification is determined by a review of the claimant's wage records. Individuals who are exempt from work search requirements in Alabama are not eligible for referral to WPRS services.

Selection/Referral Process:

Candidates selected to be referred to services are based on running the weekly WPRS model against the first payment file. The list of candidates is produced at that time and is sent to Career Centers using the Alabama Job Link System. The number to be selected for service is based on the size of the Career Center. Claimants are listed by probability of exhaustion and they cannot be skipped. Career Center staff members have no control over the listing.

Profiling Model Structure:

The dependent variable used in the WPRS model is benefit exhaustion, defined as maximum benefits paid, receiving 26 weekly benefit payments, or zero dollars of benefit entitlement remaining. The selected independent variables were based on a study of variable options by the Employment and Training Administration national and regional staff. The result of this study was a list of variables which were determined to have a reasonable probability of statistical significance. Alabama's variables were selected from those recommended, and include the following:

- Tenure
- Weekly Benefit Amount
- Education
- Industry
- Occupation

Note, there are four occupation variables used in Alabama's profiling model – high rate of exhaustion (OCC4), moderately high rate of exhaustion (OCC3), low rate of exhaustion (OCC2), and midrange rate of exhaustion (OCC1). Occupation codes are determined after exhaustion rates for each occupation are calculated and listed in descending order by exhaustion rate. This list is then divided into the four categories with those benefit recipients in occupations with high rates of exhaustion being assigned to OCC4 with a coefficient of 0.5657.

Alabama's model has at least one continuous variable (either Weekly Benefit Amount or Tenure) to prevent a large number of ties. Claimants with missing data are assigned the mid-range value for categorical variables such as OCC1 for missing occupation data. Alabama does not eliminate missing and/or incomplete records since elimination of the records would, in theory, reduce the accuracy of their model.

Profiling Model Performance:

Alabama did not provide a dataset for data analysis and/or model revision; therefore, we were unable to gauge the performance of its current model.

ANALYSIS OF ALASKA PROFILING MODEL

Introduction:

Alaska uses a statistical model, of which the functional form is logistic regression, to determine a claimant's Worker Profiling and Reemployment Services (WPRS) profiling score. The model is run weekly against the claimant first payment file, and a listing of those determined eligible is displayed in the Unemployment Insurance (UI) mainframe system (DB2). The ES recently converted to a new on-line system and negotiations are currently underway with the service provider to determine the referral to reemployment services process. This list ranks candidates in order from highest probability of exhaustion to lowest.

The model is reviewed annually to ascertain if it should be updated and/or revised. It was most recently updated in January 2006, and revised in January 2005. During the January 2005 revision, the variable comparing the date of first payment with day the claim began was added to the model and the variable for the exhaustion rate for the local offices was eliminated. Over 107,000 benefit recipients were used as the sample in the most recent revision.

Data Collection Process:

Initial claims are filed by telephone (92%) and internet (8%). Claimant characteristics necessary to determine an individual's eligibility for WPRS are obtained during the initial filing process. The accuracy of data is checked during random audits conducted as part of the Benefit Accuracy Measurement (BAM) Program. In claims filed telephonically, the claimant's occupational code is assigned by the initial claims taker. In claims filed on the Internet, the occupational code is self-selected by the claimant using a drop-down menu. The UI database uses a crosswalk to the Job Service system to convert the occupational code from Dictionary of Occupational Titles (DOT) system classification to Standard Occupational Classification (SOC) system classification. However, it is important to note that the occupational code is not used in the WPRS model. The industry code is assigned based on the claimant's last employer and is verified through a review of the UI wage record system. The following individuals are not eligible for WPRS services:

- Claimants who received orientation services in the previous year
- Claimants who reside outside of Alaska; or who reside in rural Alaskan areas not serviced by a Job Service office

- Claimants who have separated from their last employment for reasons other than a lack of work
- Claimants who are not required to be fully registered for work with the Alaska Labor Exchange Service

Selection/Referral Process:

The WPRS model is run against the claimant first payment file, and a listing of eligible candidates is produced at that time. The list is arrayed with those individuals most likely to exhaust listed first with the least likely last; it is then displayed in the UI mainframe system (DB2). At the current time, negotiations are ongoing to determine the referral process to be used for selected individuals to receive services. The Employment Service unit of the Agency determines the number of candidates to be served based upon staff and facility capacity. Selection for services begins with those with the greatest likelihood of exhausting benefits and the highest probability score and continues in descending order until the limitations of the service provider have been met.

Profiling Model Structure:

The WPRS profiling model employed by Alaska utilizes a statistical model, of which the functional form is logistic, to estimate benefit exhaustion. The dependent variable used in the model equation is benefit exhaustion, which is defined as the receipt of the maximum benefit amount. Alaska uses a wide array of independent variables, which are as follows:

- Quarter of claim beginning
- Education
- Number of employers in the base period with wage
- Number of dependents times eligible weeks of the claim divided by weekly benefits
- Hiring index based on the industry and geographic region of the state
- Minimum unemployment weighted index based on the geographic region of the state and three years of history
- Weekly benefits divided by the average base period wages
- Reason for separation from employment
- Difference in days between the first pay date and the claim begin date
- History of prior years UI claims
- Duration of claim

- Experience measured by the number of days worked for the previous employer

Profiling Model Performance:

Alaska did not provide a dataset for data analysis and/or model revision; therefore, we were unable to gauge the performance of its current model.

ANALYSIS OF ARIZONA PROFILING MODEL

Introduction:

Arizona uses a statistical model, of which the functional form is logistic, to determine a claimant's Worker Profiling and Reemployment Services (WPRS) profiling score. The model is run daily against the claimant first payment file; however, the list of eligible candidates is not run until an orientation roster request is submitted by an orientation provider. Selection for participation in orientation is automated by a ranking score with those most likely to exhaust Unemployment Insurance (UI) benefits being ranked higher.

Currently, the model is updated every two to three years with the last update occurring in July 2003. At that time, the original model was replaced with a WPRS intranet application developed by Scott Gibbons of the U. S. Department of Labor. The original model had not been updated since its inception in 1994. Currently, there is no policy in place for Arizona that addresses the frequency of model revisions. However, the Research Administration of the Arizona Department of Economic Security and the Employment Administration MIS section will be working together in the future to establish regular reviews of the ability of the model to predict exhaustion.

Data Collection Process:

Initial claims are filed in-person, by telephone and via the Internet. Claimant characteristics necessary to determine an individual's eligibility for WPRS services are captured at the time of the initial claim filing. The claimant's social security number is verified for accuracy. The occupational code is not captured or used in the model. North American Industry Classification System (NAICS) codes are used as the industry classification system and are assigned based on the applicant's last employer. Individuals not eligible for referral to WPRS services include:

- Union members on the out-of-work list
- Claimants who reside more than 25 miles from available services
- Seasonal workers
- Workers who are attached to their last employer

Selection/Referral Process:

Selection for participation in WPRS services is automated using a ranking score. Selection from the pool is made when an orientation provider enters a request for a roster of candidates. Program Managers determine the number of claimants to be scheduled for each of the four service districts based on the availability of staff to provide services. Local areas cannot select candidates. Selection is based upon the number requested and the number available in the pool for the orientation provider.

Profiling Model Structure:

The WPRS profiling model employed by Arizona utilizes a statistical model, of which the functional form is logistic, to estimate benefit exhaustion. The dependent variable used in the equation is benefit exhaustion, defined as the payment of the maximum benefit amount. The independent variables used in the model for Arizona include:

- Job Tenure
- Delay in Filing
- County of Residence
- Education
- NAICS Classification
- Month in Which the Initial Claim is Filed
- Wage Replacement Rate
- Maximum Benefit Amount

Profiling Model Performance:

Arizona provided the model structure and dataset for data analysis but did not provide useable data for education; therefore, we did not conduct an extended analysis for Arizona. We did calculate a decile table for Arizona with a correction for endogeneity. It is shown below.

prorigdec	mean	se(mean)
1	0.350	0.006
2	0.330	0.006
3	0.348	0.006
4	0.346	0.006

5	0.341	0.006
6	0.375	0.006
7	0.373	0.006
8	0.400	0.006
9	0.418	0.007
10	0.508	0.007
Total	0.379	0.002

We also calculated the metric that shows the effectiveness of Arizona's profiling score. It is shown below.

SWA	Profiling score	Control for endogeneity?	Exhaustion rate for the state	Number of individuals with the highest profiling score	Exhaustion rate for individuals with high profiling scores	Metric	Variance of the Metric	Standard Error of the metric
Arizona	original score	Y	37.9	21,502	42.8	0.079	1.153	0.007

The metric has a value of 0.079 and a standard error of 0.007. The metric is useful because it is significantly greater than 0 and provides a basis for comparison with other profiling models.

ANALYSIS OF ARKANSAS PROFILING MODEL

Introduction:

Arkansas uses a statistical model, of which the functional form is linear (multiple regression), to determine a claimant's Worker Profiling and Reemployment Services (WPRS) profiling score. The model is run weekly against the claimant first payment records, and the list of WPRS eligible claimants is sent electronically to the Local Office Job Search Workshop Coordinators. This list ranks candidates in order from highest probability of exhaustion to lowest, and those with higher rankings are to receive services first. The Coordinators determine the number of eligible candidates to be served and cannot skip down the list. The model has not been revised and/or updated since its implementation.

Prior to implementation, a study was conducted on a sample of 10 percent of 1994 fiscal-year benefit recipients. The model predicted 2,180 claimants would exhaust out of a total sample of 5,154. In reality, 50.9 percent (1,110) did actually exhaust their benefits. The model also predicted that 2,974 would not exhaust, and in reality, 2,134 actually did not exhaust. Therefore, the model predicted about 63 percent of the claimants' exhaustion/non-exhaustion experience correctly.

Arkansas is contemplating an update of the model which would allow occupational codes to be obtained from ES O*Net codes and then translated to Standard Occupational Classification (SOC) system codes. This update would also allow employment change factors to be used and would switch to the North American Industry Classification System (NAICS) instead of Standard Industrial Classification (SIC) Codes.

Data Collection Process:

Initial claims are filed in-person, by mail, and through self-service computers in the local offices. In order to determine an individual's eligibility for WPRS, initial claims are processed using a combination of automated records and information obtained from the claimants themselves. Wages, industrial code, benefit rate and benefit duration are obtained from the agency's automated records. The occupational classification is assigned by the initial claims taker. There are no further checks on the accuracy of information provided by the claimant. Individuals not eligible for referral to services through WPRS include:

1 Interstate claimants
2 Shared work claimants
3 Claimants who are work-search exempt because they are still job attached (working part-time for the employer) or expect to be recalled within 10 weeks
4 Claimants who have a union attachment with an expectation of recall
5 Claimants in training

Selection/Referral Process:

Claimants eligible for services through WPRS are selected when they receive their first payment. They are ranked in order by workforce area, and claimants with the highest probabilities of exhausting benefits are ranked first, second, etc. The list is sent electronically each week to the Local Office Workshop Coordinators. Simultaneously, claimants who are selected are sent a notice informing them that they have been profiled. The number of clients who attend Job Search Workshops and the primary service provided to profiled candidates are determined by the availability of Job Search Workshop Coordinators and of workshop seating space in the various communities throughout the state. The Coordinators select from the list on a top-down basis. Individuals are removed from the list after seven weeks.

Profiling Model Structure:

The WPRS profiling model employed by Arkansas uses a statistical model, of which the functional form is linear (multiple regression), to estimate the probability of exhaustion**.** The dependent variable used in the model is the estimated probability of exhaustion score limited to a range between zero and one. Independent variables used in the model are:

- Potential Duration
- Ratio of Claimant's WBA to the State Allowable MBA
- Industry
- Occupation
- Education
- Job Preparation/Appropriateness
- Residence in Specific Workforce Areas

In selecting the variables listed above, a maximum likelihood estimator was used to evaluate each available variable, and from this, a multiple regression equation was derived using the appropriate variables.

Profiling Model Performance:

Our first step was to try to replicate the given score using the data and coefficients provided. From the given data, we identified the variables used in the model, including potential duration of receipt of unemployment benefits, ratio of weekly benefit allowance to maximum benefit allowance, workforce delivery area code, industry code, actual change and percentage change in the industry, occupation code, level of education, and a binary variable for the claim taker's indication of insufficient job preparation. No check for endogeneity was possible because there was no record of referral to reemployment services.

To show the performance of the original profiling score, we ordered individuals into deciles and calculated the exhaustion rate for each decile along with the standard error. This decile table is how we demonstrate the effectiveness of each model. The decile means are calculated by dividing the percentage of recipients that exhaust benefits for a given decile by 100. For example, in the first decile our mean is 0.378, which indicates that approximately 38 percent of benefit recipients in this decile exhausted benefits.

Decile	Mean	Standard Error (Mean)
1	.378	.006683
2	.462	.0068514
3	.466	.0068926
4	.483	.0068891
5	.471	.0068714
6	.49	.0068994
7	.495	.0068945
8	.522	.0068834
9	.576	.0068096
10	.646	.00659
Total	.499	.0021791

Using the provided dataset, we continued our analysis of the Arkansas profiling model by creating three models – an updated, a revised, and a Tobit model. For each of the models, new profiling scores were created, ranked, and divided into deciles. The table below shows the decile gradient for each of our models (detailing the mean for each decile) and includes the decile gradient for the original model for reference. From the table, we see that there was an improvement between the original and updated models and further improvement in the decile gradient between the updated and revised models.

Decile	Original score	Updated score	Revised score	Tobit score
1	.378	.345	.326	.338
2	.462	.421	.413	.415
3	.466	.455	.425	.422
4	.483	.474	.47	.458
5	.471	.486	.476	.483
6	.49	.491	.503	.509
7	.495	.502	.534	.524
8	.522	.535	.551	.543
9	.576	.588	.606	.606
10	.646	.694	.685	.691
Total	.499	.499	.499	.499

While there was improvement between the original and updated and revised models, there was no significant improvement between the revised and the Tobit models. As such, the revised model appears to be the best model using the data available (see Appendix D for information on revised model). Additionally, we tested the performance of each model using the metric described below:

Percent exhausted of the top 49.9% of individuals in the score.

We used 49.9 percent because the exhaustion rate for benefit recipients in the dataset provided by Arkansas was 49.9 percent. This metric will vary from about 49.9 percent, for a score that is a random draw, to 100 percent for a score that is a perfect predictor of exhaustion. The scores for the four models are as follows:

Score	% exhausted of those with the top 49.9% of score	Standard error of the score
Original	54.64	0.30716
Updated	56.24	0.30606
Revised	57.62	0.30486
Tobit	57.51	0.30497

In the below metric, "*Exhaustion*" is the percentage of all benefit recipients in our sample that exhaust benefits. Here we use 49.9 percent for "*Exhaustion*" because the exhaustion rate for all benefit recipients for Arkansas was 49.9 percent. "Pr[*Exh*]" in our metric is determined by the model with the highest percentage of benefit exhaustees with profiling scores falling in the top X percent of the sample, where X percent is determined by the exhaustion rate for all benefit recipients in the sample. For Arkansas, "Pr[*Exh*]" is represented by the revised model with a score of 57.62 percent for benefit recipients that exhaust benefits with scores falling in the top 49.9 percent.

$$\text{Metric: } 1 - \frac{100 - \Pr[Exh]}{100 - Exhaustion}$$

We used the numbers above to calculate a score of 0.095 for the original score and 0.154 for the revised model score.

SWA	Profiling score	Control for endogeneity?	Exhaustion rate for the state	Number of individuals with the highest profiling score	Exhaustion rate for individuals with high profiling scores	Metric	Variance of the Metric	Standard Error of the metric
Arkansas	original score	N	49.9	26,273	54.6	0.095	1.804	0.008
Arkansas	revised score	N	49.9	26,273	57.6	0.154	1.686	0.008

These metrics show that the revised model is significantly better that the original score. The metrics also show a baseline on which other models can improve. A more detailed analysis of Arkansas' model is in the expanded analysis section.

ANALYSIS OF CALIFORNIA PROFILING MODEL

Introduction:

California uses both a characteristic screen and a statistical model, of which the functional form is logistic, to determine a claimant's Worker Profiling and Reemployment Services (WPRS) profiling score. The model is run weekly against the claimant first payment records with a list of WPRS eligible claimants being sent electronically to the Employment Service Scheduling System. This list ranks candidates in order from highest probability of exhaustion to lowest with those with higher rankings scheduled to receive services first.

The Field Office Manager or Initial Assistance Workshop (IAW) Leader determines the number of claimants to be served based on available staffing and office accommodations. The IAW is less than a day and consists of a discussion of why claimants are selected, Unemployment Insurance eligibility, labor market information, and orientation to other reemployment services. Local offices cannot "skip down the rank" in selecting candidates for services. The candidates must be served in order of their probability of exhaustion.

Currently, there is no system in place to determine when the model is to be updated. The model was last updated on December 31, 2001 and has never been revised.

Data Collection Process:

Initial claims are filed by telephone (60 pecent), by mail (5 percent), and via the internet (35 percent). Characteristic data for claimants is captured at the time initial claims are filed; currently there is no check for accuracy of data. If the claim is taken by telephone, the initial claims taker assigns the claimant's occupational code. If the claim is filed by mail, the occupation code is self-reported. For those filing via the Internet, there is currently a drop down menu in place for occupation code selection. The occupational code is determined jointly using the Dictionary of Occupational Titles (DOT) system and the Standard Occupational Classification (SOC) System. The claimant's primary employer is determined by a review of the claimant's wage history and UI Wage records. Individuals not eligible for referral to WPRS services include seasonal workers and active union members.

Selection/Referral Process:

A listing ranks the candidates in order from the highest probability of exhaustion to the lowest, and those with higher rankings are scheduled to receive services first. The Field Office Manager or IAW Workshop Leader determines the number of claimants to be served based on available staffing and office accommodations. Local offices cannot "skip down the rank" in selecting candidates for services. The candidates must be served in order of their probability of exhaustion.

Profiling Model Structure:

The WPRS profiling model employed by California utilizes both a characteristic screen and statistical model, of which the functional form is logistic, to estimate benefit exhaustion and likelihood of long-term unemployment. The characteristic screen is used to determine whether or not a claimant will be recalled to employment or if the claimant is a union member.

The dependent variables used in the model are exhaustion of benefits and long-term unemployment, defined, respectively, as the payment of the maximum benefit amount and 24 weeks or more of benefits paid within 12 months after filing. The independent variables used are:

- Education
- Industry
- Occupation
- Job Tenure
- County and/or Workforce Area

As mentioned, California pre-screens applicants to determine whether or not they will be recalled prior to first benefit payment and whether or not they are a union member. This pre-screen takes place via the characteristic screen.

Profiling Model Performance:

California did not provide a dataset for data analysis and/or model revision; therefore, we were unable to gauge the performance of its current model.

ANALYSIS OF COLORADO PROFILING MODEL

Introduction:

Colorado uses a statistical model, of which the functional form is logistic, to determine a claimant's Worker Profiling and Reemployment Services (WPRS) profiling score. The model is run weekly against the claimant first payment file, and a list of eligible candidates is generated at that time. This list, ordered from highest probability score to lowest, is then sent by file transfer to workforce centers who determine how many profiled candidates will be served. A center may exempt a candidate for various reasons, such as the candidate being a previous client of the center. It has been more than three years since the model was revised, and it has not been updated since implementation. The original sample size, when the model was first estimated, was approximately 40,000.

Data Collection Process:

Initial claims are filed by telephone (80 percent) and Internet (20 percent). All claimant characteristic data necessary to determine WPRS services eligibility are captured during the initial telephone or Internet filing. If a filing is done telephonically, the initial claims taker will determine and assign the claimant's occupational code. If done via internet, the occupational code is self-selected by the claimant. Both filing methods use the Standard Occupational Classification (SOC) system. A review of wage records is used to determine the appropriate industry code. Persons who are job attached, whose first payments are more that five weeks from filing of the initial claim, and those who are hired through union halls are not eligible for referral to WPRS services.

Selection/referral Process:

The model is run weekly against the claimant first payment file, and a list of eligible candidates is generated at that time. The list, ordered from highest probability of exhaustion score to the lowest, is then sent by file transfer to workforce centers who determine how many candidates will be served. A center may exempt a candidate for various rerasons, i.e. the candidate was a previous client of the center.

Profiling Model Structure:

The WPRS profiling model employed by Colorado utilizes a statistical model, of which the functional form is logistic, to estimate benefit exhaustion. The dependent variable used in the model equation is benefit duration defined as maximum benefits paid. Colorado did not provide any information on the independent variables used in their model.

Profiling Model Performance:

Colorado did not provide a dataset for data analysis and/or model revision; therefore, we were unable to gauge the performance of Colorado's current model.

ANALYSIS OF CONNECTICUT PROFILING MODEL

Introduction:

Connecticut uses a statistical neural network model to determine a claimant's eligibility for referral to Worker Profiling and Reemployment Services (WPRS). The model is run weekly against the claimant first payment records, and a listing of WPRS eligible claimants is sent to the Connecticut Department of Labor (DOL) staff via computer network. The model was last revised in July 2004. The latest revision converted the model form to that of a neural networking model.

Data Collection Process:

Initial claims are filed by telephone (91.1 percent) and Internet (8.9 percent). Claimant characteristics are captured at the time the initial claim is filed, and there are no further checks for accuracy. When a claim is taken by telephone, the initial claims taker assigns the claimant's occupational code using the O*NET classification system and when done online, the occupational code is self-selected by the claimant. The NAICS of the claimant's primary employer is assigned from wage records even though industry is not used as a variable in the model. The following claimants are not eligible for referral to WPRS services:

- Union workers who get employment through hiring halls
- Job attached workers

Selection/Referral Process:

The list of profiled candidates is produced at the same time the weekly WPRS model is run, and the list is then sent to Connecticut DOL Staff via computer network. Claimants with the highest probability of exhaustion are selected first for services and the Connecticut DOL Job Center Directors determine how many profiling candidates will be served per office with some input from central office staff.

Profiling Model Structure:

The Connecticut WPRS profiling model utilizes a neural network model to estimate benefit exhaustion. The dependent variable in the model equation is benefit exhaustion. The independent variables are as follows:

- Education

- Tenure
- Occupation
- Effective Date of Claim
- Workforce Area
- Veteran Status
- Weekly Benefit Rate
- Prior Claims
- Prior Exhaustion

Profiling Model Performance:

With their survey, Connecticut provided a dataset and the model structure. However, the data did not indicate whether individuals exhausted benefits. Therefore, we were not able to calculate a metric or conduct an expanded analysis of the model.

ANALYSIS OF DELAWARE PROFILING MODEL

Introduction:

Delaware uses a characteristic screen to determine a claimant's eligibility for Worker Profiling and Reemployment Services (WPRS). The model is run weekly against the claimant first payment records with a list of WPRS eligible claimants being sent to the Division of Employment and Training. All individuals who meet WPRS selection criteria are listed, notified, and required to participate in the WPRS program.

The model has never been updated and/or revised since the inception of WPRS. Delaware evaluated the variables used for WPRS against the actual claims filed to determine the need for possible modification. The SWA examined the characteristics of claimants that actually filed over a period of time and examined what participation would be if the current variables were modified.

Data Collection Process:

Initial claims are filed by mail and in-person. Internet claim filing is currently in development. With the exception of the occupational code, information necessary to make a profiling referral is captured at the time the initial claim is filed. The occupational code will be selected by the claimant from a drop-down box when a claimant completes reemployment registration information online. There is no further check on the accuracy of the claimant's selection. The last employer is also selected from the reemployment application, and that employer's North American Industry Classification System (NAICS) code is captured from the UI employer file. Individuals not eligible for referral to WPRS services include:

- Claimants with a return-to-work date
- Claimants who belong to a union and obtain their work through a union hiring hall
- Claimants who have received more than five weeks of benefit payments

Selection/Referral Process:

All claimants eligible for WPRS are listed and sent to the Division of Employment administrative staff. Subsequently, all claimants are notified and required to participate in WPRS. There are no feedback loops in place.

Profiling Model Structure:

The characteristics screen includes:

- Job Tenure – two years
- Industry Code – three-digit NAICS code
- Occupational Code – three-digit Standard Occupational Classification (SOC) code

All variables must meet yes or no criteria.

Profiling Model Performance:

Delaware uses a characteristic screen to select individuals for referral to WPRS services. The screen used includes job tenure, NAICS industry code, and occupational code. In the sample of 10,790 analyzed, 14.4 percent were referred, and the exhaustion rate was 39.0 percent. We were unable to conduct further analysis of Delaware's model because the occupation variable was not readable in the file received. We could not replicate the SWA's original profiling model.

We do note that the characteristic screen has both strengths and weaknesses. The model has a low cost and can be adjusted to refer individuals to the capacity of the reemployment services providers. However, those referred are not ranked by likelihood of exhaustion, and the system probably fails to refer many individuals very likely to exhaust. For example, individuals with job tenure of less than two years will not be selected, but some of these individuals may have a low attachment to the workforce and be in need of reemployment services. We did estimate a version of Delaware's original profiling score and generated the following decile table.

predscoredec	mean	se(mean)
1	0.350	0.014
2	0.318	0.014
3	0.419	0.015
4	0.383	0.015
5	0.365	0.015
6	0.375	0.015
7	0.394	0.015
8	0.404	0.015
9	0.415	0.015
10	0.475	0.015
Total	0.390	0.005

In addition, we calculated the metric associated with this estimated score. It is shown below.

SWA	Profiling score	Control for endogeneity?	Exhaustion rate for the state	Number of individuals with the highest profiling score	Exhaustion rate for individuals with high profiling scores	Metric	Variance of the Metric	Standard Error of the metric
Delaware	estimated score*	N**	39.0	4,207	42.4	0.055	1.227	0.017

The metric has a value of 0.055 and a standard error of 0.017. The metric is useful because it is significantly greater than 0, and provides a basis for comparison with other profiling models.

ANALYSIS OF THE DISTRICT OF COLUMBIA PROFILING MODEL

Introduction:

The District of Columbia uses a statistical model, of which the functional form is logistic, to determine a claimant's Worker Profiling and Reemployment Services (WPRS) profiling score. The model is run weekly against the claimant first payment records with a list of WPRS eligible claimants being sent electronically via an intranet to the management staff of the One-Stops. This list ranks candidates in order from highest probability of exhaustion to lowest, with those with higher rankings scheduled to receive services first. One-Stop staff then determines the number of eligible claimants to be called in to receive services. The model was updated in January 2004, and is updated every two or three years.

In October 2003, the model was revised by adding the "Filing Delay" and "Number of Employers" variables. The coefficients were calculated using 5,000 benefit recipients. The previous model was estimated using 4,000 recipients. During the 2003 revision, the occupational coding was changed from Dictionary of Occupational Titles (DOT) to O*Net.

Data Collection Process:

Eighty percent of the initial claims are filed over the Internet, and the remaining 20 percent are filed in-person. Characteristic data are captured when the initial claim is filed and the correct North American Industry Classification System (NAICS) code is determined based on a review of wage records. When claims are filed via the Internet, occupation codes are automatically generated based on information provided by the claimant using O*Net criteria. When claims are filed in-person, the initial claims taker assigns the appropriate codes. Currently, there are no checks on the accuracy of the information provided by the claimant. Individuals not eligible for referral to services through WPRS include:

- Interstate claimants
- Transitional claimants
- Claimants involved in a labor dispute
- Claimants on temporary furlough
- Members of a union with a hiring hall
- Prior WPRS participants
- Claimants with earnings during the first week of benefits

- Claimants with delayed payments

Profiling Model Structure:

The WPRS profiling model employed by the District of Columbia utilizes a statistical model, of which the functional form is logistic, to estimate benefit exhaustion. The dependent variable is benefit exhaustion, defined as the payment of the maximum benefit amount. The independent variables include:

- Unemployment Rate
- Job Tenure
- Level of Education
- Occupation Code
- Industry Code
- Base Period Earnings

Note that the variables for job tenure, level of education, and base period earnings are all categorical variables. For job tenure there are six categories:

- 0.00 to 0.25 year
- 0.25 to 0.50 year
- 0.50 to 1.00 year
- 1.00 to 2.00 years
- 2.00 to 5.00 years
- 5.00 and more years

For level of education there are seven categories:

- Low education (maximum of 8 years)
- No high school diploma (over 8 years)
- High school diploma recipient
- Some college
- Bachelor’s degree
- Some graduate education
- Master’s or Ph.D. degree

There is also a binary variable indicating missing education level.

For base period wages (BPW), there were six categories that are delineated in $7,000 increments, starting with BPW1 (BPW is equal to or greater than zero and less than $7,000) and ending with BPW6 (BPW greater than $35,000). BPW2 is defined as BPW greater than $7,000 but less than $14,000.

Profiling Model Performance:

The District of Columbia provided its survey, a dataset and the model structure. Included in the dataset was a binary variable indicating whether or not benefit recipients were referred to reemployment services. This binary variable allows us to test for endogeneity within our data and answer the question - does referral to reemployment services have an effect on the exhaustion of benefits?

Our first step was to try to replicate the given score using the data provided and the coefficients for the variables given. From the given data, we were able to derive all variables and categories used by DC in its model. We were able to replicate the SWA's profiling score. Our replicated score correlated with the provided score at .998.

We used the profiling scores provided to produce a decile table as shown below. The decile means are calculated by dividing the percentage of recipients that exhaust benefits for a given decile by 100. For example, in the first decile, our mean is 0.4163223, or approximately 41.6 percent, which indicates that approximately 42 percent of benefit recipients in this decile exhausted benefits.

Original score deciles	mean	se(mean)
1	.4163223	.0158521
2	.5010438	.0161627
3	.5333333	.0161099
4	.5426516	.0159791
5	.5977249	.015777
6	.5405128	.0159684
7	.5820106	.0160532
8	.5964361	.0158925
9	.643595	.0154016
10	.6494192	.0155135
Total	.5600624	.0050625

After testing for endogeneity, we found that referral to reemployment services did not have a significant impact on benefit exhaustion. There was no need to correct for endogeneity.

Using the dataset, we created three models – an updated, a revised, and a Tobit model – with new profiling scores which were ranked and divided into deciles. The table below shows the decile gradient for each of our models (detailing the mean for each decile) and includes the decile gradient for the original model for reference. From the table, we see that there was considerable improvement between the original and updated models and considerable improvement in the decile gradient between the updated and revised models.

Decile	Original score	Updated score	Revised score	Tobit score
1	.4163223	.3711019	.3409563	.3482328
2	.5010438	.4657676	.4693028	.4745057
3	.5333333	.4973931	.491684	.489605
4	.5426516	.5098855	.5109261	.5421436
5	.5977249	.5316719	.5602911	.539501
6	.5405128	.56639	.6024974	.5712799
7	.5820106	.6388309	.6070686	.6205821
8	.5964361	.635514	.628512	.6253902
9	.643595	.6690947	.6580042	.6632017
10	.6494192	.715625	.7315297	.7263267
Total	.5600624	.5600624	.5600624	.5600624

While there was considerable improvement between the original and updated and revised models. There was no significant improvement between the revised and the Tobit models. As such, the revised model appears to be the best model using the data available (see detail on revised model in Appendix D). Additionally, we tested the performance of each model using the following metric:

Percent exhausted of the top 56 percent of individuals in the score.

We used 56 percent because the exhaustion rate for benefit recipients in the District of Columbia dataset was 56 percent. This metric will vary from about 56 percent, for a score that is a random draw, to 100 percent for a score that is a perfect predictor of exhaustion. The scores for the four models are as follows:

Score	% exhausted of those with the top 56% of score	Standard error of the score
Original	60.25213	.66639
Updated	63.55366	.65585
Revised	63.76973	.65507
Tobit	62.93408	.65823

In the metric below, *"Exhaustion"* is the percentage of all benefit recipients in our sample that exhaust benefits. For the District of Columbia, *"Exhaustion"* is 56 percent since the exhaustion rate for all benefit recipients in the provided dataset was 56 percent. "Pr[*Exh*]" in our metric is determined by the model with the highest percentage of benefit exhaustees with profiling scores falling in the top X percent of the sample, where X percent is determined by the exhaustion rate for all benefit recipients in the sample. For the District of Columbia "Pr[*Exh*]" is represented by the revised model with a score of 63.77 for benefit recipients who exhaust benefits with scores falling in the top 56 percent.

$$\text{Metric: } 1 - \frac{100 - \Pr[Exh]}{100 - Exhaustion}$$

We used the numbers above to calculate a metric of 0.097 for the original profiling score and 0.176 for the revised score.

SWA	Profiling score	Control for endogeneity?	Exhaustion rate for the state	Number of individuals with the highest profiling score	Exhaustion rate for individuals with high profiling scores	Metric	Variance of the Metric	Standard Error of the metric
District of Columbia	original score	N**	56.0	5,385	60.3	0.097	2.277	0.021
District of Columbia	revised score	N**	56.0	5,385	63.8	0.176	2.057	0.020

These metrics show that the revised model is significantly better that the original score. The metrics also show a baseline on which other models can improve. Further analysis of the District of Columbia's model is in the expanded analysis section.

ANALYSIS OF FLORIDA PROFILING MODEL

Introduction:

In 2002, Florida removed probability scoring from the model, and the Regional Workforce Boards were authorized to determine who was most likely to exhaust benefits and need additional services. The Worker Profiling Reemployment Services (WPRS) model is run weekly against the claimant first payment records, and the results are sent from the mainframe legacy system to the One-Stop Management Information System (OSMIS) via File Transfer Protocol (FTP).

Data Collection Process:

Initial claims are filed by Iinternet (50 percent), by telephone (45 percent), and by mail (5 percent). O*Net is used as the occupational classification system, and the claimant's O*Net code is assigned by the initial claims taker. The industry code (NAICS) is also determined by the initial claims taker based on a review of the work history with the claimant. It is important to note that the occupational and industry codes of those individuals who are selected for profiling are reviewed by One-Stop intake staff and may be changed if inaccuracies are detected. Individuals not eligible for referral through WPRS include:

- Claimants whose program identification is other than intrastate UC, CWC, UCFE and UCX
- Claimants on recall status
- Interstate claimants
- Transitional claimants
- Seasonally unemployed claimants
- Partially unemployed claimants (claimants with earnings)
- Claimants with a first payment issued more than 42 days after the Benefit Year Beginning date (BYB)

One-Stop personnel may also exempt claimants from participation if, during the WPRS Orientation, they become aware that an individual has a return-to-work date or is in Workforce Investment Act (WIA) training.

Model Revisions:

The model was revised in 2002. The probability scoring was removed and a decision was made to allow the Regional Workforce Boards to determine who was most likely to exhaust benefits and need additional services.

Variables:

No variables are utilized in the Florida model. The pool consists of all individuals eligible for WPRS services.

Selection/Referral Process:

Individuals who are eligible for WPRS services are randomly assigned to a pool by the One-Stop area that serves the claimant's geographic area. The One-Stops determine the number to serve based on service capacity. These claimants are instructed to come into the One-Stop to participate in an orientation at which time available services, program requirements. etc., are described. During the orientation, additional claimant characteristics are evaluated and staff members determine which individuals should be referred to additional mandatory services. These additional characteristics include:

- Tenure at most recent employment
- Education level
- Total Unemployment Rate (TUR) in the local labor market
- Whether claimant's last occupation was in a declining industry (O*Net)

Profiling Model Performance:

Florida provided the model structure and dataset for data analysis but did not provide useable data for profiling score, tenure, education, unemployment rate, industry and occupation. We were not able to conduct any further analysis of the model.

ANALYSIS OF GEORGIA PROFILING MODEL

Introduction:

At the time the Georgia survey was completed, the state was in the process of programming and implementing a new linear probability profiling model estimated by ordinary least squares. The new model is being developed by the W.E. Upjohn Institute. The commentary below describes the model being replaced.

Georgia uses a statistical model, of which the functional form is logistic, to determine a claimant's Worker Profiling and Reemployment Services (WPRS) profiling score. The model is run at the time the initial claim is filed and, if found to be eligible for services, the candidate is informed of the requirement to participate if he/she receives a first payment. A list of profiled candidates is produced daily and sent to local Career Centers. Each Career Center Manager sets the cutoff score for candidates to be served based on the capacity of the center. All profiled candidates are referred to the Employment Service (ES) for registration and the ES staff can access the profiling list to determine who requires WPRS services. Candidates are served on a highest to lowest score basis, and all who score at or above the cutoff score are served.

This model was last revised in 1998. The first model was estimated in 1995 with a sample size of 10,000. It was last estimated (applied) in 1998 with a sample size of 77,000. The Upjohn review of the existing model determined it accurately predicted exhaustion at the upper and lower levels but was not as accurate in the mid-range

Data Collection Process:

Initial claims are filed in person. The claimant has the option of self-completing a computerized claim at the local center or being assisted by a claims taker. All claimant characteristic data are captured as part of the initial claim process. Wages and work history are reviewed for accuracy, and staff procedures detailing the profiling process are routinely reviewed for consistency. The claimant's occupational code is determined by the claims taker, or if the claim is filed electronically, is self-selected by the claimant from a drop-down list. The North American Industry Classification System (NAICS) code is determined by a review of wage records or work history depending on the manner of claims taking.

As the data are entered at claimant intake, the model is automatically run. The system excludes from referral to services the following categories of individuals:

- Those with union membership
- Claimants in training
- Those with a recall date

Profiling Model Structure:

The WPRS profiling model employed by Georgia utilizes a statistical model, of which the functional form is logistic, to estimate benefit exhaustion. The dependent variable is benefit exhaustion, defined as the payment of the maximum benefit amount. The independent variables used in the model are as follows:

- Education
- Job Tenure
- Local Unemployment
- Occupation
- Industry

Georgia currently uses 11 regional models corresponding to the original 11 Title III districts. The new model will utilize one statewide model.

Profiling Model Performance:

Georgia provided their model structure and a dataset for data analysis and possible model revision. From the given data, we were able to derive variables and categories for education, job tenure, county of residence unemployment rate, occupation code, and industry code. We were able to successfully replicate the provided profiling scores. We then ranked these profiling scores in ascending order, divided them into deciles and produce the decile table shown below. The decile means in this table are calculated by dividing the percentage of recipients that exhaust benefits for a given decile by 100. For example, in the first decile our mean is 0.2840939, or approximately 28.4 percent, which indicates that approximately 28 percent of benefit recipients in this decile exhausted benefits.

Decile	Mean	Standard Error (Mean)
1	.284	.0029731
2	.331	.0032492
3	.338	.0033743

4	.343	.003126
5	.347	.0033578
6	.366	.0035024
7	.387	.0037862
8	.394	.0039152
9	.405	.0034609
10	.403	.0037612
Total	.356	.0010847

Using the provided dataset and the offset variable to account for endogeneity, we continued our analysis of Georgia's profiling model by creating three models – updated, revised, and Tobit. For each of the models, new profiling scores were created, ranked, and divided into deciles. The table below shows the decile gradient for each of the models (detailing the mean for each decile), and it includes the decile gradient for the original model for reference. From the table, it is clear there was an improvement between the original and updated models and further improvement in the decile gradient between the updated and revised models.

Decile	Original Score	Adjusted Original score	Updated score	Revised score	Tobit score
1	.284	.269	.176	.174	.17
2	.331	.319	.231	.232	.234
3	.338	.312	.275	.275	.273
4	.343	.294	.317	.309	.309
5	.347	.285	.341	.344	.349
6	.366	.335	.376	.374	.379
7	.387	.336	.398	.401	.399
8	.394	.404	.436	.438	.437
9	.405	.486	.497	.499	.505
10	.403	.525	.518	.518	.509
Total	.356	.356	.356	.356	.356

While there were improvements between the adjusted original decile scores and all other models, the revised model appears to be the best model using the data available. Additionally, we tested the performance of each model using the following metric:

Percent exhausted of the top 35.7 percent of individuals in the score.

We used 35.7 percent because the exhaustion rate for benefit recipients in the dataset provided by Georgia was 35.7 percent. This metric value will vary from about 35.7 percent, for a score that is a random draw, up to 100 percent for a score that is a perfect predictor of exhaustion. The scores for the four models are as follows:

Score	% exhausted of those with the top 35.7% of score	Standard error of the score
Original	39.83	0.0018598
Updated	47.12	0.0018926
Revised	47.32	0.0018919
Tobit	47.14	0.0018925

In the metric below, *"Exhaustion"* is the percentage of all benefit recipients in the sample that exhaust benefits. We use 35.7 percent for "*Exhaustion*" because the exhaustion rate for all benefit recipients for Georgia was 35.7 percent. "Pr[*Exh*]" in our metric is determined by the model with the highest percentage of benefit exhaustees with profiling scores falling in the top X percent of the sample, where X percent is determined by the exhaustion rate for all benefit recipients in the sample. For Georgia, "Pr[*Exh*]" is represented by the revised model with a score of 47.32 percent for benefit recipients that exhaust benefits with scores falling in the top 35.7 percent.

$$\text{Metric:}\ \ 1 - \frac{100 - \Pr[Exh]}{100 - Exhaustion}$$

We used the numbers above to calculate a score of 0.129 for the original score (corrected for endogeneity) and 0.181 for the revised model score.

SWA	Profiling score	Control for endogeneity?	Exhaustion rate for the state	Number of individuals with the highest profiling score	Exhaustion rate for individuals with high profiling scores	Metric	Variance of the Metric	Standard Error of the metric
Georgia	original score	Y	35.7	75,994	44.0	0.129	1.017	0.004
Georgia	revised score	Y	35.7	75,994	47.3	0.181	0.976	0.004

These metrics show that the revised model is significantly better that the original score. The metrics also show a baseline on which other models can improve. Further analysis of Georgia's model is in the expanded analysis section.

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ANALYSIS OF HAWAII PROFILING MODEL

Introduction:

Hawaii uses a statistical model, of which the functional form is logistic, to determine a claimant's Worker Profiling and Reemployment Services (WPRS) profiling score. The model is run weekly against the claimant first payment records with a list of WPRS eligible claimants being sent in hard copy to Unemployment Insurance (UI), Workforce Development Division (WDD), and Research and Statistics Office (R&S). Claimants are ranked according to probability scores, and those with the highest scores are selected for WPRS.

The model was revised in 2001 to accommodate a conversion from the Dictionary of Occupational Titles (DOT) system to the Standard Occupational Classification (SOC) system. The computer program was revised to assign a default value for occupation to each claimant until the model could be reworked and new variable coefficients developed using SOC. When the model was developed, 14,000 benefit recipients were profiled with a Benefit Year Beginning (BYB) from September 1, 1993 to August 31, 1994.

Data Collection Process:

Initial claims are filed by telephone (90 percent) and in-person (10 percent). All claimant characteristics are captured when the initial claim is filed. A claimant's Social Security Number is verified daily through the State Verification Exchange System (SVES); alien status is verified with the Systematic Alien Verification for Entitlements (SAVE) as necessary; and employment information is verified against quarterly wage record information. Hawaii uses the Standard Occupational Classification (SOC) system as its occupational coding system, and the code is determined by the Workforce Development Worker. The following are not eligible to participate in WPRS:

- Claimants without a first payment within five weeks of filing an initial claim
- Union members affiliated with a hiring hall
- Claimants partially employed
- Interstate agent or liable claimants
- Claimants whose last separation is for other than a lack of work
- Claimants in local office 2100 – Lanai

Selection/Referral Process:

Individuals selected for WPRS are referred by hard copy listings. The number of individuals to be served is determined by the center based on available resources. Claimants are ranked according to probability scores with the highest scores being selected first. Workforce center staff can also manually select claimants from the list if openings exist.

Profiling Model Structure:

The WPRS profiling model employed by Hawaii utilizes a statistical model, of which the functional form is logistic, to estimate benefit exhaustion. The dependent variable is benefit exhaustion defined as the payment of the maximum benefit amount. The independent variables are as follows:

- Education
- Job Tenure
- Industry
- Occupation
- Local Unemployment Rate

Profiling Model Performance:

Hawaii provided their survey, a dataset and the model structure. Included in the dataset was a binary variable indicating whether or not benefit recipients were referred to reemployment services. This binary variable allows us to test for endogeneity within our data and answer the question - does referral to reemployment services have an effect on the exhaustion of benefits?

Our first step was to try to replicate the given score using the data provided and the coefficients for the variables given. From the given data, we were able to replicate the original score, creating a score that correlated with the provided score at 0.86. However, to do so we had to delete four cases with erroneous values for the profiling score.

We used the profiling scores provided to produce a decile table as shown below. The decile means are calculated by dividing the percentage of recipients that exhaust benefits for a given decile by 100. For example, in the first decile, our mean is 0.327, or approximately 33 percent, which indicates that approximately 33 percent of benefit recipients in this decile exhausted benefits.

prorigdec	mean	se(mean)
1	0.327	0.016
2	0.314	0.016
3	0.376	0.016
4	0.376	0.016
5	0.405	0.016
6	0.389	0.016
7	0.406	0.016
8	0.423	0.017
9	0.457	0.017
10	0.467	0.017
Total	0.394	0.005

After testing for endogeneity, we found that referral to reemployment services did have a significant impact on benefit exhaustion. In further analyses, we provided a correction for endogeneity.

Using the dataset, we created three models – an updated, a revised, and a Tobit model – with new profiling scores which were ranked and divided into deciles. The table below shows the decile gradient for each of our models (detailing the mean for each decile) and includes the decile gradient for the original model for reference. The second model is the original model corrected for endogeneity. From the table, we see that there was considerable improvement between the original and updated models and considerable improvement in the decile gradient between the updated and revised models.

Decile	Original score	Original score adapted for endogeneity	Updated mean	Revised mean	Tobit mean
1	.320356	.3273942	.2817372	.3084633	.3162584
2	.359375	.3143813	.3322185	.3188406	.3054627
3	.3489409	.3756968	.3730512	.3377926	.361204
4	.3534002	.3756968	.4129464	.3846154	.4024526
5	.4087432	.4046823	.386845	.3734671	.3723523
6	.3886364	.3886414	.4153675	.422049	.4053452
7	.4197121	.406015	.4292085	.4225195	.4158305
8	.4480088	.4229432	.3908686	.4180602	.4091416
9	.4366516	.4570792	.4424779	.4537347	.4537347
10	.4548495	.4671126	.4746907	.4994426	.4972129
Total	.3938921	.3938921	.3938921	.3938921	.3938921

While there was considerable improvement between the original and updated and revised models, there was no significant improvement between the revised and the Tobit models. As such, the revised model appears to be the best model using the data available (see detail on revised model in Appendix D). We tested the performance of each model using the following metric:

Percent exhausted of the top 39.4% of individuals in the score.

We used 39.4 percent because the exhaustion rate for benefit recipients in the Hawaii dataset was 39.4 percent. This metric will vary from about 39.4 percent, for a score that is a random draw, to 100 percent for a score that is a perfect predictor of exhaustion. The scores for the four models are as follows:

Score	% exhausted of those with the top 39.3% of score	Standard error of the score
Original	43.87408	.83581
Adapted	43.87408	.83581
Updated	43.2785	.83451
Revised	44.81293	.83737
TOBIT	44.36281	.83524

In the metric below, *"Exhaustion"* is the percentage of all benefit recipients in our sample that exhaust benefits. For Hawaii, "*Exhaustion*" is 39.4 percent since the exhaustion rate for all benefit recipients in the provided dataset was 39.4 percent. "Pr[*Exh*]" in our metric is determined by the model with the highest percentage of benefit exhaustees with profiling scores falling in the top X percent of the sample, where X percent is determined by the exhaustion rate for all benefit recipients in the sample. For Hawaii, "Pr[*Exh*]" is represented by the revised model with a score of 44.81 percent for benefit recipients who exhaust benefits with scores falling in the top 39.4 percent.

$$\text{Metric: } 1 - \frac{100 - \Pr[Exh]}{100 - Exhaustion}$$

We used the numbers above to calculate a score of 0.069 for the original profiling score (corrected for endogeneity) and a score of 0.085 for the revised score.

SWA	Profiling score	Control for endogeneity?	Exhaustion rate for the state	Number of individuals with the highest profiling score	Exhaustion rate for individuals with high profiling scores	Metric	Variance of the Metric	Standard Error of the metric
Hawaii	original score	Y	39.7	3,526	43.9	0.069	1.248	0.019
Hawaii	revised score	Y	39.7	3,526	44.8	0.085	1.232	0.019

These metrics show that the revised model is significantly better that the original score. The metrics also show a baseline on which other models can improve. Further analysis of Hawaii's model is in the expanded analysis section.

ANALYSIS OF IDAHO PROFILING MODEL

Introduction:

Idaho uses a characteristic screen to determine a claimant's eligibility for selection and referral to Worker Profiling and Reemployment Services (WPRS). The model is run weekly against the claimant first payment records with a list of WPRS eligible claimants sent to consultants in the 24 local offices. The consultants use the list to contact potential candidates and make a decision on how best to serve each candidate.

The model is updated annually, and a major revision was implemented in June, 2005 when independent variable relationships were analyzed and revised as necessary.

Data Collection Process:

Initial claims are filed in-person (5 percent), by telephone (6 percent) and Internet (89 percent). Claimant characteristics that determine an individual's eligibility for WPRS are captured at the same time the initial claim is taken. Claimants self-select the occupational code using the SOC classification system. UI wage records are checked to determine the claimant's industry code. Individuals not eligible for selection and referral to WPRS include:

- Claimants who are empolyer attached
- Claimants who are union hiring hall attached
- Claimants who are on a short-term layoff of 16 weeks or less

Selection/Referral Process:

The profiling candidate list is available for viewing online by staff in the 24 local centers. Claimants with a probability of exhaustion score of 50 percent or above are selected for services. Local offices have discretion on selection of the candidates within the 50 – 100 percent rankings. Each office's management staff, in conjunction with area managers and their chain of command, determines a target number of claimants to serve at the start of the year. That number is periodically reviewed and revised to ensure target groups and individuals are properly identified for referral to services.

Profiling Model Structure:

The WPRS profiling model employed by Idaho to estimate benefit exhaustion is a characteristic screen model called a "decision tree." The model's dependent variable is benefit exhaustion, defined as maximum benefits paid (i.e., when a claimant's remaining benefit balance is $40), and the independent variables examined in the screen are as follows:

- Potential Duration of Benefit Receipt
- NAICS (21 separate industries at the sector level are used)
- County of Residence/Local Office Federal Information Processing Standards (FIPS) Code
- Marital Status
- Job Tenure
- WBA
- Ratio of Total Wage to High Quarter Wage
- Number of Employers
- Education (years completed)
- Month of Filing

Records with missing values are kept and processed as missing, thus assuring that no qualifying records are excluded from the modeling process.

Profiling Model Performance:

Idaho provided both a dataset for data analysis and their model structure for revision. The Idaho model used 31 combinations of their independent variables to define groups of individuals to be selected for referral to reemployment services. For example, the first group was defined as individuals having a duration greater than 16; a principal industry of 1 (a NAICS of 0, or no reported industry); a county of residence of FIPS code 1, 19, 27, 35, 69, 75, or 79; and a ratio of total wage to high quarter wage of between 2.34 and 2.68. Individuals who belonged to any one of the 31 groups were selected for reemployment services. In the sample given, 73 percent of the individuals were selected.

This approach has both strengths and weaknesses. The model can be tailored to various subsets of applicants. That is, individuals with a principal industry of 2 are selected very differently from individuals with a principal industry of 7. However, the model also could leave out many individuals who are likely to exhaust and/or select individuals who are not likely to exhaust. For example, individuals with a principal industry of 1 are not selected on the basis of any variable except duration and county of residence. Inclusion of other variables in the selection process for individuals with a principal industry of 1 would probably improve the model.

The first step of our analysis is to calculate a new selection variable. The current selection variable takes a value of zero or one. We used the same variables in the decision tree to calculate a continuous selection variable. The higher values of this new selection variable would correspond to the "ones" of the original selection variable; lower values of this new selection variable would correspond to the "zeros" of the original selection variable.

Our method is to run a logistic regression model with the variables listed above as independent variables and the original selection variable as dependent variable. Due to collinearity problems, we eliminated principal industry 1, FIPS 1 (county 1), month 1, Duration (correlated at 0.9789 with RATIO), Weekly Benefit Amount (WBA) [correlated at 0.8572 with Total Benefit Amount (TBA)]. By taking the predictions of this model, ordering them and dividing them into deciles, and then for each decile, showing the actual exhaustion rate along with its standard error, we obtain the following table.

Decile	Mean	Standard Error (Mean)
1	.411	.0084416
2	.393	.0083795
3	.365	.0082577
4	.359	.0082334
5	.35	.0081812
6	.362	.0082434
7	.438	.0085133
8	.55	.0085327
9	.65	.0081812
10	.709	.0077873
Total	.459	.0027027

Note: the results above are adjusted for endogeneity. A thorough explanation of our methods for testing and adjusting for endogeneity is included in the expanded analysis included in our technical report.

This decile table is the basis for demonstrating the effectiveness of each model. The decile means are calculated by dividing the percentage of recipients that exhaust benefits for a given decile by 100. For example, in the first decile our mean is 0.411, which indicates that approximately 41 percent of benefit recipients in this decile exhausted benefits.

Using the Idaho dataset, we continued our analysis of the SWA's profiling model by creating three models – an updated, a revised, and a Tobit model. For each of the models, new profiling scores were created, ranked, and divided into deciles. The table below shows the decile gradient for each model (detailing the mean for each decile) and includes the decile gradient for the original model for reference. From the table, there was an improvement between the original and updated models and further improvement in the decile gradient between the updated and revised models.

Decile	Original score	Updated score	Revised score	Tobit score
1	.411	.219	.216	.227
2	.393	.304	.297	.319
3	.365	.353	.359	.353
4	.359	.389	.391	.393
5	.35	.435	.424	.418
6	.362	.444	.459	.446
7	.438	.504	.50	.502
8	.55	.566	.565	.552
9	.65	.643	.642	.634
10	.709	.729	.734	.741
Total	.459	.459	.459	.459

While there was improvement between the original and updated and revised models, there was no apparent improvement between the revised and the Tobit models. The revised model appears to be the best model using the data available (see Appendix D for information on revised model). Additionally, we tested the performance of each model using the following metric:

Percent exhausted of the top 45.9% of individuals in the score.

We used 45.9 percent because the exhaustion rate for benefit recipients in the dataset provided by Idaho was 45.9 percent. This metric will vary from about 45.9 percent, for a score that is a random draw, up to 100 percent for a score that is a perfect predictor of exhaustion. The scores for the four models are as follows:

Score	% exhausted of those with the top 45.9% of score	Standard error of the score
Original	56.1	0.39729
Updated	59.03	0.39367
Revised	59.26	0.39335
Tobit	58.82	0.39399

We note that the revised model performed better than the updated and Tobit models. The original model performed worst, and the Tobit model performed slightly worse than the updated model.

In the metric below, *"Exhaustion"* is the percentage of all benefit recipients in the sample that exhaust benefits. For Idaho, "Exhaustion" is 45.9 percent since the exhaustion rate for all benefit recipients in the provided dataset is 45.9 percent. "Pr[*Exh*]" in our metric is determined by the model with the highest percentage of benefit exhaustees with profiling scores falling in the top X percent of the sample, where X percent is determined by the exhaustion rate for all benefit recipients in the sample. For Idaho, "Pr[*Exh*]" is represented by the revised model with a score of 59.26 percent for benefit recipients that exhaust benefits with scores falling in the top 45.9 percent.

$$\text{Metric: } 1 - \frac{100 - \Pr[Exh]}{100 - Exhaustion}$$

We used the numbers above to calculate a metric of 0.189 for the estimated original profiling score (corrected for endogeneity) and a score of 0.247 for the revised score.

SWA	Profiling score	Control for endogeneity?	Exhaustion rate for the state	Number of individuals with the highest profiling score	Exhaustion rate for individuals with high profiling scores	Metric	Variance of the Metric	Standard Error of the metric
Idaho	estimated score*	Y	45.9	15,605	56.1	0.189	1.400	0.009
Idaho	revised score	Y	45.9	15,605	59.3	0.247	1.306	0.009

These metrics show that the revised model is significantly better that the estimated original score. The metrics also show a baseline on which other models can improve. Further analysis of Idaho's model is in the expanded analysis section below.

ANALYSIS OF ILLINOIS PROFILING MODEL

Introduction:

Illinois uses a statistical model, of which the functional form is logistic, to determine a claimant's Worker Profiling and Reemployment Services (WPRS) profiling score. The model is run weekly against the claimant first payment records, and a listing of WPRS eligible claimants is sent electronically or by fax to Local Workforce Investment Areas (LWIA). This list ranks the candidates in order from the highest probability of exhaustion to the lowest, and the LWIAs determine the number of profiling candidates to be served based on resources currently available. The model was updated in 1997 but has never been revised.

Data Collection Process:

Initial claims are filed in person (80 percent) and through the Internet (20 percent). Claimant characteristics data are captured at the time the initial claim is filed, and there are no further checks for accuracy. The initial claims taker assigns the claimant's occupational code using the Dictionary of Occupational Titles (DOT) system. The claimant's primary employer, used in assigning the industry code, is determined by a review of the claimant's wage records. The following claimants are not eligible for WPRS services:

- Claimants who do not receive a first payment
- Claimants registered with a union hiring hall
- Claimants with a return to work date
- Claimants who leave work voluntarily
- Claimants involved in a labor dispute

Selection/Referral Process:

A listing of WPRS eligible claimants is sent to LWIAs electronically or by fax. This list ranks the candidates in order from the highest probability of exhaustion to the lowest, and the LWIAs determine the number of profiling candidates to be served based on the resources available. LWIAs cannot "skip down the rank" in selecting candidates for services. The candidates must be served in order of their probability of exhaustion.

Profiling Model Structure:

The WPRS profiling model utilizes a statistical model, of which the functional form is logistic, to estimate benefit exhaustion. The dependent variable is exhaustion of benefits, defined as the payment of the maximum benefit amount. The independent variables are as follows:

- Reason for Unemployment
- Tenure
- Occupation
- Filing Lag

Profiling Model Performance:

Illinois did not provide a dataset for data analysis and/or model revision; therefore, we were unable to gauge the performance of its current model.

ANALYSIS OF INDIANA PROFILING MODEL

Introduction:

Indiana uses a statistical model, of which the functional form is logistic, to determine a claimant's Worker Profiling and Reemployment Services (WPRS) profiling score. The model is run weekly against the claimant first payment records, and a listing of WPRS-eligible claimants is produced at that time and electronically distributed to local office staff. Local office managers determine the number of eligible claimants to be served based on staffing resources. The listing ranks claimants in order from the highest to the lowest probability of exhaustion, and the local office cannot deviate from the listing. The model has never been updated or revised.

Data Collection Process:

Initial claims are filed in-person and by Internet. Claimant characteristics are captured at the time the initial claim is filed. Only the claimant's social security number is verified for accuracy. Both the occupational and industry codes are assigned based on the claimant's work history, and the following claimants are not eligible for WPRS services:

- Job Attached
- Union Members
- Claimants Filing Trade Adjustment Assistance Claims

Selection/Referral Process:

Claimants selected for WPRS are ranked from those with the highest probability of exhaustion to the lowest. A listing is produced that is distributed electronically to the local offices. Local office managers determine the number of WPRS candidates to be called in and served based on staff resources available. Claimants with the highest probability of exhaustion must be called in first.

Profiling Model Structure:

The WPRS profiling model employed by Indiana utilizes a statistical model, of which the functional form is logistic, to estimate benefit exhaustion. The dependent variable is benefit exhaustion, defined as the payment of the maximum benefit amount. The independent variables are as follows:

- Education
- Maximum Benefits
- Occupation
- Annualized County Unemployment Rate
- Months of Tenure

Extensive testing of several variables, including those listed above, occurred prior to model implementation. The variables found not to impact benefit exhaustion were industry, county growth rate, projected Standard Industrial Classification (SIC) growth rate, weekly benefit amount, claim balance remaining, and variations of occupational classification such as the projected Dictionary of Occupational Titles (DOT) growth rate.

Profiling Model Performance:

Indiana did not provide a dataset for data analysis and/or model revision; therefore, we were unable to gauge the performance of its current model.

ANALYSIS OF IOWA PROFILING MODEL

Introduction:

Iowa uses a statistical model, of which the functional form is logistic, to determine a claimant's Worker Profiling and Reemployment Services (WPRS) profiling score. The model is run weekly against the claimant first payment records. A listing of all profiled claimants is produced when claimants are selected for orientation to reemployment services. The number of individuals to be called in for services is determined by workforce center administrators based on staff resources and facility availability. Local regions have flexibility in this regard but are assigned an annual goal for the number of individuals to be served. This goal is set by Unemployment Insurance (UI) and Workforce Development administrators. The model has never been updated or revised.

Data Collection Process:

Initial claims are filed in-person (46 percent), by telephone (31 percent), through employer filed mass claims (4 percent) and via Internet (20 percent). Internet claims include those filed by claimants using local office resource room computers. Claimant characteristic data are collected at the time the initial claim is taken, and there are no checks on the accuracy of the information supplied by the claimant. Dictionary of Occupational Titles (DOT) system codes are assigned to claimants and are subsequently converted to Standard Occupational Classification (SOC) system codes that use a crosswalk when the model is run. The industry code is based on the claimant's last employer as indicated on the initial claim. Claimants ineligible for referral to services through profiling include:

- Claimants who are job attached (likely to return to last employer)
- Claimants on temporary layoff
- Claimants who refused to bump less senior employees
- Claimants who obtain work through a union hiring hall
- Work-share claimants
- Claimants with an out-of-state address

Workforce center staff may exempt claimants from participation in reemployment services if they:

- were referred in error (obtained work through a union hiring hall, definite date of recall with former employer)
- are currently participating in a similar service
- have completed reemployment services or a job training program in the last six months

- are currently attending training under a department approved training program

Selection/Referral Process:

A file of claimants eligible for WPRS services is generated at the time of first payment; however, a list of eligible claimants is not created until they are selected for a reemployment services orientation session. When there is a need to refer individuals to the workforce centers, a notice to appear is generated from the central office and a listing of notified individuals is sent to the local profiling coordinators. A statewide goal of the number of profiled candidates to be served is determined by UI and Workforce Development administrators. The goal is to distribute candidates to local regions based on their historic share of claimants who are not job attached. Local regions have flexibility in determining the size and frequency of candidate selection and their orientation sessions. These determinations are based on staff resources and facility availability.

Profiling Model Structure:

The WPRS profiling model utilizes a statistical model, of which the functional form is logistic, to estimate benefit exhaustion. The dependent variable is benefit exhaustion defined by payment of the maximum benefit amount. The independent variables are as follows:

- Education
- Job Tenure
- Twelve-month Statewide Industry Growth (based on published NAICS or SIC sectors)
- Growing/Declining Occupation (national one digit SOC)
- Local Region Unemployment Rate

Profiling Model Performance:

Iowa provided the model structure and dataset for data analysis but did not provide useable data for state industry growth, decreasing and increasing occupation factors, and regional unemployment rate. Therefore, we did not conduct an extended analysis for Iowa. We did calculate a decile table for Iowa with a correction for endogeneity. It is shown below.

prorigdec	mean	se(mean)
1	0.145	0.008
2	0.152	0.004
8	0.162	0.010
9	0.156	0.010
10	0.170	0.010
Total	0.154	0.003

Note that, due to large numbers of individuals with the same score, we were not able to separate the sample into 10 parts. We also calculated the metric that shows the effectiveness of Iowa's profiling score. It is shown below.

SWA	Profiling score	Control for endogeneity?	Exhaustion rate for the state	Number of individuals with the highest profiling score	Exhaustion rate for individuals with high profiling scores	Metric	Variance of the Metric	Standard Error of the metric
Iowa	original score	Y	15.4	2,456	16.2	0.010	0.368	0.012

The metric has a value of 0.010 and a standard error of 0.012. The metric is not really useful because it is not significantly greater than 0. However, further analysis may result in a better model. The metric provides a basis for comparison with other profiling models.

ANALYSIS OF KANSAS PROFILING MODEL

Introduction:

Kansas uses a statistical model, of which the functional form is logistic, to determine a claimant's Worker Profiling and Reemployment Services (WPRS) profiling score. The model is run daily against the claimant first payment records, and a listing of WPRS eligible claimants is mailed to local centers and provided on the Job Link website. This list ranks candidates in order from highest probability of exhaustion to lowest. There has been no update or revision to the model since its creation in 1995.

Data Collection Process:

Initial claims are filed by telephone (75 percent) and Internet (25 percent) with claimant characteristics captured at the time initial claims are filed. A Workforce Development worker assigns the occupation code using the Standard Occupational Classification (SOC) system derived from the O*Net classification system. For purposes of assigning North American Industrial Classification System (NAICS)/Standard Industrial Classification (SIC) system codes, the primary employer is determined by a review of the claimant's work history. Individuals not eligible for referral to services through WPRS include:

- Union Workers
- Claimants Awaiting Job Recall
- Claimants in Approved Training

Note: currently there are no checks on the accuracy of the information provided by the claimant and all incomplete records are ignored.

Selection/Referral Process:

The list of WPRS eligible candidates is produced at the same time that the profiling model is run. The list is mailed to the local centers and provided on the Job Link website. Workforce Development staff determine the number of candidates to call in based on their workload. Individuals are ranked from high to low probabilities of exhaustion and the ranked listings are provided to Workforce Development staff. Under no conditions does the local area skip candidates.

Profiling Model Structure:

The WPRS profiling model utilizes a statistical model, of which the functional form is logistic, to estimate benefit exhaustion. The dependent variable is benefit exhaustion defined as full payment of the maximum benefit amount. The independent variables include:

- Years of Experience
- County Total Unemployment Rate
- Wage Replacement Rate
- Metropolitan Statistical Area or Non-Metro Area
- One-digit SIC Code

The variables for years of experience, county total unemployment rate, and wage replacement amount are all categorical variables. They are:

- Four categories for years of experience: less than three years, three to four years, five to seven years, and eight or more years of experience
- Three categories for county total unemployment rate: 0 to 5 percent, 5.1 to 8 percent, and 8.1 percent or above
- Five categories for wage replacement rates: 0.0 to 0.0100, 0.0101 to 0.015, 0.0151 to 0.02, 0.0201 to 0.025, and 0.0251 and above

Profiling Model Performance:

Kansas did not provide a dataset for data analysis and/or model revision; therefore, we were unable to gauge the performance of its current model.

ANALYSIS OF KENTUCKY PROFILING MODEL

Introduction:

Kentucky uses a statistical model, of which the functional form is Tobit, to determine a claimant's eligibility for selection and referral to Worker Profiling and Reemployment Services (WPRS). In June, 1994, Kentucky was selected by the Employment and Training Administration to be a prototype state for the development of a system for profiling Unemployment Insurance (UI) claimants. The Center for Business and Economic Research (CBER) at the University of Kentucky developed a profiling system for the Department for Employment Services (DES). This system generated a single score for each claimant to measure the probability of a claimant exhausting his or her benefits. The model was updated in 1997 and has never been revised. It is run weekly against the claimant first payment file, and the resulting list of profiled claimants sent via an encrypted e-mail list to the local offices.

Data Collection Process:

Initial claims are filed by telephone and by Internet. Claimant characteristic data are captured at the time the claim is filed and is confirmed by Social Security Number through the State Verification and Exchange System (SVES). Employers and addresses are verified by mail, and the reason of separation is verified with the employer.

Selection/Referral Process:

The list of claimants eligible for WPRS is produced when the weekly WPRS model is run and is distributed to the Kentucky DES local offices via an encrypted e-mail. Eligible claimants are listed by office, and those claimants having the highest probability of exhaustion are at the top of the list. Claimants must be selected in descending order as there are no provisions for choosing claimants out of order. The Director of the Division for Workforce and Employment Services determines the number of eligible candidates to be called in weekly based on the service capacity of the office (i.e., after considering available space and staffing levels).

Profiling Model Structure:

The WPRS profiling model utilizes a Tobit functional form to estimate benefit exhaustion. The dependent variable is benefit exhaustion, defined as maximum benefits paid. The independent variables were created using five years of claimant data obtained from the UI computer mainframe database. Variables from the Enhanced National Data System (ENDS), the U.S. Bureau of Economic Analysis' Regional Economic Information System (REIS), the 1990 U.S. Census and the ES-202 database were also included in the analysis. Those ultimately selected include:

- Monetary Variables (annual wage, benefit amount, reservation wage)
- Demographic Variables (Does the worker have a phone? Is the worker economically disadvantaged? Is the worker on welfare? Does the worker hold a driver's license?)
- Industry Code (SIC codes)
- Education Variables (level of education)
- Occupation Variables (accessed from the ENDS database)
- Characteristics of Job Variables (tenure – also derived from the ENDS database)
- Prior UI Receipt Variables
- Variables to Capture Regional Economic Differences

Profiling Model Performance:

Kentucky did not provide a dataset for data analysis and/or model revision; therefore, we were unable to gauge the performance of its current model.

ANALYSIS OF LOUISIANA PROFILING MODEL

Introduction:

Louisiana uses a statistical model, of which the functional form is logistic, to determine a claimant's eligibility for referral to Worker Profiling and Reemployment Services (WPRS). The model is run weekly against the claimant first payment records with a list of WPRS eligible claimants made available to both Wagner-Peyser and Workforce Investment Act (WIA) staff by Job Center and Local Workforce Investment Area (LWIA). Claimants remain in the selection pool for four weeks before they are deleted.

Louisiana undertook a major revision of its profiling model in June, 2003. This revision included the following:

- Updating for changes in economic conditions since 1999
- Change from Dictionary of Occupational Titles (DOT) system to Standard Occupational Classification (SOC) system
- Change from the Standard Industrial Classification (SIC) to the North American Industry Classification System (NAICS) industry coding
- Change to a logit model, addition of new variables, and allowing for nonlinear relationships.

The revised model was developed by the Division of Economic Development and Forecasting at Louisiana State University. The model was developed based on a sample of 85,284 benefit recipients.

Data Collection Process:

Initial claims are filed in-person (5 percent) and by Internet (95 percent). Claimant characteristic data are captured at the time the claim is filed, and there are no further checks on the accuracy of the information. When the claim is filed by Internet, the claimant self-selects the occupational (SOC) and industrial codes [North American Industry Classification System (NAICS)]. When filing in-person, the claims taker assigns the occupational and industrial codes. O*Net occupational coding is used in the WIA One-Stops. The following individuals are not eligible for referral to WPRS:

- Union members
- Work attached claimants
- Interstate claimants
- Claimants in approved training

- Claimants who completed or are participating in similar services
- Claimants with justifiable cause
- Claimants who have received more than five weeks of benefits.

Selection/Referral Process:

The list is available on the mainframe through screens for Wagner-Peyser and WIA staff. Local staff determines the number of candidates to be served based on the type of services needed, available space and staff capacity. The listing is sorted in the order of those having the highest probability of exhaustion to lowest. Generally, the profiled claimants with the highest probabilities are called in and served first. Local staff persons have discretion to select at will, and may select claimants whom they determine need additional services even though the claimants have been seen previously. This occurs most frequently with claimants who are in the pool and their four week limitation is about to expire. The WIA One-Stops use O*Net occupational coding.

Profiling Model Structure:

The WPRS profiling model employed by Louisiana utilizes a logistic regression model to estimate benefit exhaustion. The dependent variable is benefit exhaustion, defined as maximum benefits paid. The independent variables are as follows:

- Occupation
- Industry
- Regional labor market unemployment rate
- Education
- Number of days between the separation from work date and the initial claim filing date
- Exhaustion of benefits on a prior claim
- Average unemployment compensation received
- Replacement ratio (ratio of benefits paid to average wage)
- Number of employers in the base period.

As noted above, four possible models were considered for adoption.

Profiling Model Performance:

Louisiana provided the model structure and dataset for data analysis but did not provide useable data for occupation, regional labor market unemployment rate, number of days between the separation from work date and the initial claim filing date, and number of employers in the base period. Therefore, we did not conduct an extended analysis for Louisiana. We did calculate a decile table with a correction for endogeneity. It is shown below.

prorigdec	mean	se(mean)
1	0.325	0.006
2	0.322	0.006
3	0.341	0.006
4	0.383	0.007
5	0.407	0.007
6	0.383	0.007
7	0.477	0.007
8	0.500	0.007
9	0.505	0.007
10	0.621	0.007
Total	0.426	0.002

We also calculated the metric that shows the effectiveness of Louisiana's profiling score. It is shown below.

SWA	Profiling score	Control for endogeneity?	Exhaustion rate for the state	Number of individuals with the highest profiling score	Exhaustion rate for individuals with high profiling scores	Metric	Variance of the Metric	Standard Error of the metric
Louisiana	original score	Y	42.6	22,825	51.9	0.161	1.282	0.007

The metric has a value of 0.161 and a standard error of 0.007. The metric is useful because it is significantly greater than 0. The metric provides a basis for comparison with other profiling models.

ANALYSIS OF MAINE PROFILING MODEL

Introduction:

Maine uses a statistical model, of which the functional form is logistic, to determine a claimant's profiling score for identification and referral to Worker Profiling and Reemployment Services (WPRS). The model is run weekly against the claimant first payment records, and with a list of WPRS eligible claimants is sent in hard copy to the Bureau of Employment Services for distribution to the One-Stop Centers. This list ranks candidates in order from highest probability of exhaustion to lowest. The One-Stops determine who is called in based on capacity and claimants with the highest likelihood of exhaustion.

The model was revised in 2000 and 2004. The first revision to the model was implemented on January 1, 2000. During this revision, the "Education," "Reason Unemployed," and "Ratio of High Quarter Wages to Base Period Wages" variables were eliminated, and the "Job Tenure" variable was added.

The second revision to the model was implemented on September 1, 2004. The changes were extensive and included:

- Change from Standard Industrial Classification (SIC) to North American Industry Classification System (NAICS) (industry change at 3-digit NAICS level by County)
- Binary Industry Variable at Super Sector Level
- Addition of an "Effective Quarter of Claim" variable
- Addition of a "Number of Base Period Employers" variable
- Addition of a "Separation Reason" variable
- Addition of a "Ratio of High Quarter Wages to Base Period Wages" variable
- Addition of an "Education" variable
- Removal of occupation variables

Data Collection Process:

Initial claims are filed by telephone, mail and Internet. Automated and manual records are used to assist in classifying individuals for WPRS, with claims takers determining the occupational codes of individuals filing telephonically and by mail; these codes are self-selected by claimants when filings are made via the Internet. The DOT code system is used to classify the occupational codes. The NAICS code is obtained from each claimant's wage record and is determined by their last employer. There are no further checks on the accuracy of information provided by the claimant. Individuals not eligible for referral to services through WPRS include:

- Interstate Claimants
- Claimants with a recall date; or those expecting to be recalled
- Claimants who obtain employment through a union hiring hall
- Claimants without a first payment

Selection/Referral Process:

Claimants eligible for services through WPRS are selected when they receive their first payment. They are then ranked with claimants with the highest probability of exhausting benefits appearing first. The list of eligible claimants is sent to the Bureau of Employment Services for distribution to the Career Centers (One-Stops) by interoffice mail. Each Career Center determines the number of profiled claimants that it can serve for a specified period of time. Those with the next highest exhaustion probability scores are selected until all of available slots are filled for each Center. The Centers are not given the option of who to serve; they must adhere to the ranking on the list. There are no feedback loops in place.

Profiling Model Structure:

The dependent variable is benefit exhaustion, defined as the payment of the maximum benefit amount. The revision of January 1, 2000 utilized a sample of 14,969 benefit recipients to determine the needed changes. The revision of September 1, 2004 utilized a sample of 17,537 benefit recipients to determine the needed changes. Prior to implementation, the original model was based on a sample of approximately 9,000 benefit recipients. The independent variables are as follows:

- NAICS Code (industry change at 3-digit NAICS level by county)
- Binary Industry Variable at Super Sector Level
- Effective Quarter of Claim
- Number of Base Period Employers
- Separation Reason
- Ratio of High Quarter Wages to Base Period Wages
- Years of Education

In order to select the independent variables when WPRS was initially implemented, a Statistical Analysis System (SAS) or National Council for Social Studies (NCSS) software package was used to evaluate the predictive factor of each variable. The variables analyzed and selected were based on the minimum requirements of the U. S. Department of Labor, ease of generating the variables when initial claims are filed, reliability of the data source, and overall fit in the equation. It is important to note that the occupation variables were removed from the current profiling model because of data quality limitations.

Claimants determined exempt from profiling were also excluded from the model estimation. Between 40 and 70 percent of the claimants were excluded during the initial model estimation. During the most recent revision, approximately 43 percent of the claimants were excluded - mostly due to recall status.

Maine is currently collecting data on the characteristics of claimants who exhaust benefits and plans to compare these data to the profiling data when time and resources become available.

Profiling Model Performance:

Maine provided the model structure and dataset for data analysis but did not provide useable data for county of residence, industry, effective date of claim, number of employers, and industry percent change. Therefore, we did not conduct an extended analysis for Maine. We did calculate a decile table with a correction for endogeneity. It is shown below.

prorigdec	mean	se(mean)
1	0.275	0.010
2	0.319	0.010
3	0.342	0.011
4	0.353	0.011
5	0.368	0.011
6	0.390	0.011
7	0.387	0.011
8	0.382	0.011
9	0.416	0.011
10	0.503	0.011
Total	0.373	0.003

We also calculated the metric that shows the effectiveness of Maine's profiling score. It is shown below.

SWA	Profiling score	Control for endogeneity?	Exhaustion rate for the state	Number of individuals with the highest profiling score	Exhaustion rate for individuals with high profiling scores	Metric	Variance of the Metric	Standard Error of the metric
Maine	original score	Y	37.3	7,346	42.6	0.084	1.121	0.012

The metric has a value of 0.084 and a standard error of 0.012. The metric is useful because it is significantly greater than 0. The metric provides a basis for comparison with other profiling models.

ANALYSIS OF MARYLAND PROFILING MODEL

Introduction:

Maryland uses a statistical model, of which the functional form is logistic, to determine a claimant's Worker Profiling and Reemployment Services (WPRS) profiling score. The model is run weekly against claimant first payment records, and a listing of eligible claimants is provided electronically to WPRS workshop facilitators. The facilitators determine the number of claimants that can be called in for services, and their determination is based on the availability of space as well as performance standards set at the state level. This list ranks candidates in order from highest probability of exhaustion to lowest. Maryland gives priority to candidates with scores of 0.40 and above an invitation to attend an orientation workshop. The goal is to serve all with scores 0.40 or higher first and then fill the workshops with individuals who have probability scores below 0.40.

The model was updated in 2000. In this update, 100 percent of the benefit recipients in 1998 were studied. In 2001, a subsequent study was conducted and only records with complete data from both UI and the Job Service were used. This subset represented approximately 20 percent of the total records available. Based on sampled comparisons, the analysis concluded that the estimation data were representative of the claimant population. The characteristics of those who exhausted did not change, so the current model was retained. In both 2003 and 2004, a complete review of claimants who exhausted benefits was undertaken and characteristics had not changed, and the model was not revised.

Data Collection Process:

Initial claims are filed by telephone and via the Internet. Claimant characteristics are captured at the time the claim is filed. Except for a review of the wage records to determine the industry code and name(s) of employers, no check on the accuracy of information is performed. The Standard Industrial Classification (SIC) is used as the industry code. The Dictionary of Occupational Titles (DOT) system coding is used to assign the occupational classification. The following individuals are not eligible for WPRS:

- Claimants who have a verified return-to-work date of 10 weeks or less
- Claimants attached to union hiring halls
- Interstate Claimants

Selection/Referral Process:

The listing of WPRS candidates is produced at the same time as the model is run, and the list is then sent electronically to the WPRS workshop facilitators. The listing is ranked with individuals with the highest probability of exhaustion first; Maryland does not skip down the listing. The facilitators determine the number of profiled claimants to be served based on the availability of space as well as performance standards (goals) that are set at the state level.

Profiling Model Structure:

The WPRS profiling model employed by Maryland utilizes both a characteristic screen and a logistic regression model to estimate benefit exhaustion. The dependent variable is benefit exhaustion, defined as receiving 26 weekly payments.

The model uses a mix of characteristic and data elements. The process is as follows:

1) Characteristic screens are applied.

Characteristic screens are:

- Claimant had not received an initial UI payment
- Claimant had a specific recall date
- Claimant had a union hiring hall agreement
- Claimant filed an interstate claim

2) Data elements are validated and converted to profiling categories.

The independent variables are:

- Education
- Job tenure
- Industry
- Occupation
- Workforce Investment Act (WIA) area unemployment rate (converted from FIPS code).

3) Default values are applied for missing data.

Profiling Model Performance:

Maryland provided the model structure and dataset for data analysis but did not provide useable data for education, occupation, and job tenure. In addition, Maryland did not provide coefficients needed to replicate their profiling score. We did calculate a decile table. Although Maryland provided a variable that indicated whether individuals were referred to reemployment services, its effect was not significant. No correction for endogeneity was needed. The decile table is shown below.

prorigdec	mean	se(mean)
1	0.527	0.007
2	0.546	0.004
7	0.441	0.011
8	0.424	0.010
9	0.435	0.009
10	0.410	0.012
Total	0.504	0.003

Note that due to many individuals having the same score, we were not able to separate the sample into 10 parts. We also calculated the metric that shows the effectiveness of Maryland's profiling score. It is shown below.

SWA	Profiling score	Control for endogeneity?	Exhaustion rate for the state	Number of individuals with the highest profiling score	Exhaustion rate for individuals with high profiling scores	Metric	Variance of the Metric	Standard Error of the metric
Maryland	original score	N**	50.4	18,974	54.1	0.075	1.877	0.010

The metric has a value of 0.075 and a standard error of 0.010. The metric is useful because it is significantly greater than 0. The metric provides a basis for comparison with other profiling models.

ANALYSIS OF MASSACHUSETTS PROFILING MODEL

Introduction:

Massachusetts uses a characteristic screen model to determine a claimant's Worker Profiling and Reemployment Services (WPRS) eligibility. By utilizing the characteristic model, Massachusetts uses screens which are based on current information. The model is run weekly against the first payment records, and the listing of profiled candidates is provided following screening of first payments. The file of WPRS eligible claimants is sent to the Employment Service (ES) system for tracking Workforce Investment Act (WIA) services and outcomes. Currently, all selected candidates are required to be served and to attend a seminar that provides information on connecting claimants to the workforce.

The latest revision to the WPRS model occurred in May 2005. Prior to that time, the screens included declining industries which identified those three digit Standard Industrial Classification (SIC) codes in which employment statewide had declined in the two most recent quarters over the same quarters the year before. The list of industries was updated each quarter from the latest Bureau of Labor Statistics Quarterly Census of Employment and Wages (QCEW) files. The model is able to be updated frequently using screens which are based on current conditions.

Data Collection Process:

Initial claims are taken principally by telephone with a small share taken in-person by staff at the Career Centers. Interstate liable claims have not yet been converted to telephone claims. Some claimant information is collected at the time the new initial claim is filed. Screening for WPRS is done at the time of first payment and includes information from employers submitted after the initial claim is taken. The initial claims taker currently codes only a 2 digit Standard Occupational Classification (SOC) system. Massachusetts will implement Autocoder later this year, and this will enable them to move to a 6 digit SOC. The coding is based on information provided by the claimant on his/her primary occupation. The North American Industry Classification System (NAICS) code of the most recent separating employer is used to determine the industry, and it is obtained from the Unemployment Insurance (UI) tax system. The following claimants are not eligible for WPRS services:

- Claimants who exclusively use a union hiring hall to register for work
- Claimants who have a definite return to-work-date
- Claimants who have received a written notice from the employer with a return to work date

- Claimants separated from an industry with a temporary or seasonal layoff
- Claimants separated from a temporary or seasonal occupation
- An employer has provided the claimant with a definite return to work date
- Interstate Claimants
- Claimants enrolled in a work sharing program
- Claimants approved to attend training during the claim
- Claimants who have a first payment more than 10 weeks into the claim (usually appeal reversals)
- Claimants with partial earnings deducted from the first compensable week (those not in total employment)

Selection/Referral Process:

The weekly listing of WPRS candidates is sent to the ES system for use in their system for tracking WIA services and outcomes. Currently, all WPRS eligible claimants are required to be served and to attend a seminar that provides information on connecting claimants to the workforce.

Profiling Model Structure:

The WPRS profiling model employed by Massachusetts utilizes a characteristic screen model to estimate benefit exhaustion. This characteristic screen eliminates all claimants that are ineligible for referral to reemployment services as detailed above. Accordingly, there are no true variables used in the profiling model employed by Massachusetts.

Profiling Model Performance:

Massachusetts did not provide a dataset for data analysis and/or model revision; therefore, we were unable to gauge the performance of its current model.

ANALYSIS OF MICHIGAN PROFILING MODEL

Introduction:

Michigan uses a statistical model, of which the functional form is linear regression, to determine a claimant's Worker Profiling and Reemployment Services (WPRS) profiling score. The model is run weekly against the claimant first payment records, and a list of WPRS eligible claimants is sent electronically to a Profiling Coordinator in each Workforce Development Area. This list ranks candidates in order from highest probability of exhaustion to lowest. Each Workforce Development Board determines the number of individuals to be called in for service based on resources and staffing. Candidates must be taken in order of their scores with those with a score of 0.40 or higher having mandatory attendance. If the Workforce Development Center has the capacity to service more claimants than those required to attend, other WPRS eligible individuals can be chosen to participate and are selected in any order.

The model is updated when needed. It was revised in June 2003 based on all claimants from October 2000 through December 2001. The following changes were made:

- Occupational coding was changed from the Dictionary of Occupational Titles (DOT) to the Standard Occupational Classification (SOC) system
- Industry coding was changed from the Standard Industrial Classification (SIC) to (NAICS) system
- Service Delivery Areas were replaced by Workforce Development Centers
- The Education Variable was changed from 3 to 5 levels

Data Collection Process:

Initial claims are filed by telephone, mail, Internet, and mass layoff notifications by employers. Claimant characteristics are captured at the time of the initial claim. Verification is performed using computer data and independent employer verification. The SOC system code is determined by the automated system, and it is based on the claimant's occupational title selected from a drop-down list. The NAICS is obtained from a review of Unemployment Insurance (UI) wage records. Individuals not eligible for referral to services through WPRS include:

- Claimants who are job attached
- Claimants on short-term layoff

- Interstate Claimants

Selection/Referral Process:

Claimants are selected to participate in WPRS when the model is run at the first payment. Mandatory ranks are established from highest to lowest probability of exhaustion. Candidates must be taken in order of their scores for those with those with scores of 0.40 or higher. If the Workforce Development Center has the capacity to service more than claimants in the mandatory category, these WPRS eligible individuals can be chosen to participate in any order. Each Workforce Development Center determines the number to be served based on their resources and staffing.

Profiling Model Structure:

The WPRS profiling model employed by Michigan utilizes a linear regression model to estimate benefit exhaustion. The dependent variable is benefit exhaustion, defined as receiving 26 weekly payments or a payment balance of zero if entitlement is less than 26 weeks. The independent variables are as follows:

- Occupational Code (SOC)
- Industry Code (NAICS)
- Workforce Development Center
- Education Level
- Base Period Wages
- Benefit Exhaustion Indicator on a Prior Claim
- Reason for Separation

During the initial claim application, these variables are entered (required fields). At this time, job attached waivers are assigned, but the claims are not included. Additionally, Interstate and Combined Wage Claims are not included.

Profiling Model Performance:

Michigan provided the model structure and dataset for data analysis but did not provide useable data for separation reason and SOC code. We did calculate a decile table corrected for endogeneity. It is shown below.

prorigdec	mean	se(mean)
1	0.536	0.005
2	0.559	0.005
3	0.525	0.005
4	0.433	0.005
5	0.434	0.005
6	0.476	0.005
7	0.500	0.005
8	0.541	0.005
9	0.580	0.005
10	0.690	0.004
Total	0.527	0.001

We also calculated the metric that shows the effectiveness of Michigan's profiling score. It is shown below.

SWA	Profiling score	Control for endogeneity?	Exhaustion rate for the state	Number of individuals with the highest profiling score	Exhaustion rate for individuals with high profiling scores	Metric	Variance of the Metric	Standard Error of the metric
Michigan	original score	Y	52.7	60,128	55.2	0.052	2.110	0.006

The metric has a value of 0.052 and a standard error of 0.006. The metric is useful because it is significantly greater than 0. The metric provides a basis for comparison with other profiling models.

ANALYSIS OF MINNESOTA PROFILING MODEL

Introduction:

Minnesota uses a statistical model, of which the functional form is logistic, to determine a claimant's Worker Profiling and Reemployment Services (WPRS) profiling score. The model is run daily against the claimant initial claim file. Eligible candidates are separated by ZIP code and assigned to area offices to be called in for services. Letters are sent informing claimants of the necessity for them to report. The top one-third of those most likely to exhaust benefits must be called in within the first two weeks of filing their claims. They are called in by designated Unemployment Insurance (UI) staff called Resource Area Coordinators (RAC) who access the database and schedule them for service. Staff may skip any person at any time.

The number of claimants to be served is affected by the number of individuals in the pool at any given time. Claimants will remain in the pool for six weeks and every attempt is made to call them in and provide them with services in a timely manner. Claimants who draw benefits for 12 weeks or more are also more likely to exhaust benefits, so they are added to the pool of claimants to be called in for services. For identification purposes, these individuals are classified with a "V" (voluntary) and are generally in the bottom two-thirds of candidates.

The latest revision of the WPRS model was undertaken in May 2005 when the coefficients were re-estimated using more recent data on claimants. The data used was for CY2004. Minnesota has used five different models since 1995 with revisions occurring in 1999, 2000, 2002, and 2004. The whole population of claimants was used in the 2004 revision.

Data Collection Process:

Initial claims are filed by telephone (55 percent), Internet (40 percent) and mail (5 percent). All of the claimant characteristics necessary to profile claimants are captured during the initial claim process. Social security numbers are verified through the Social Security Administration, and employment information is verified through wage detail. Claimants are assigned occupational codes through an automated process using the Standard Occupational Classification (SOC) system which has been in place since 2001. The claimant's primary employer is determined based on a review of work history with the claimant; or, in the case of internet applications, a review of the information in the application. The following individuals are not eligible for WPRS services:

- Claimants that may be determined to not be eligible based on their occupation and labor market conditions are coded "LM."
- Claimants who are temporarily deferred from employment (TD code; seasonal worker or temporary plant shutdown) and will be called back to their position.
- Claimants who are members of a union with an exclusive hiring hall and cannot look for work outside of that hall (coded UN).

Selection/Referral Process:

The model to generate a listing of profiled candidates is produced daily and is run against the initial claim records. Profiling candidates are identified according to their quotient from the model. Those that are highly likely to exhaust (generally the top one third of the scores) are immediately added to the pool through the mainframe data base and are to be called in within two weeks of filing their claims (these claimants are identified as M – Mandatory). Claimants selected for WPRS services are divided into sub-groups based on their ZIP codes and allocate to area offices. UI Resource Area Coordinators (RACs) then schedule them for profiling services. The number of claimants to be served is affected by the number of individuals in the pool at any given time. Claimants will remain in the pool for six weeks and every attempt is made to call them in and provide services in a timely manner. Claimants who draw benefits for 12 weeks or more are also likely to exhaust benefits. They are generally in the bottom two thirds of candidates. At 12 weeks, they are added to the pool of claimants to be called in for services. For identification purposes, these individuals are classified with a "V" (voluntary). Staff may skip any person at any time.

Profiling Model Structure:

The WPRS profiling model employed by Minnesota utilizes a logistic regression model to estimate benefit exhaustion. The dependent variable is benefit exhaustion, defined as maximum benefits paid. The independent variables are as follows:

- Education Level
- Occupational Code
- Industry Code
- Geographical Region

- Area Office Location
- County Unemployment Rate
- County Unemployment Rate Change
- Occupational Employment Projections
- Perceived Separation
- Wait Period to File
- Month Claim Filed
- Number of Employers
- Weekly Benefit Amount
- Replacement Wage
- Past Claim History

Profiling Model Performance:

Minnesota provided the model structure and dataset for data analysis but did not provide useable data for industry, wait period and geographic region. We did calculate a decile table corrected for endogeneity. It is shown below.

prorg2dec	mean	se(mean)
1	0.152	0.003
2	0.227	0.004
3	0.262	0.004
4	0.307	0.004
5	0.353	0.004
6	0.366	0.004
7	0.385	0.005
8	0.398	0.004
9	0.439	0.005
10	0.492	0.005
Total	0.336	0.001

We also calculated the metric that shows the effectiveness of Minnesota's profiling score. It is shown below.

SWA	Profiling score	Control for endogeneity?	Exhaustion rate for the state	Number of individuals with the highest profiling score	Exhaustion rate for individuals with high profiling scores	Metric	Variance of the Metric	Standard Error of the metric
Minnesota	original score	Y	33.6	37,395	43.5	0.150	0.922	0.005

The metric has a value of 0.150 and a standard error of 0.005. The metric is useful because it is significantly greater than 0. The metric provides a basis for comparison with other profiling models.

ANALYSIS OF MISSISSIPPI PROFILING MODEL

Introduction:

Mississippi uses a statistical model, of which the functional form is logistic, to operate its WPRS Program. The model is run weekly against claimant first payment records. The listing of candidates is produced the next day from a nightly batch process, and the list is sent to a Workforce Development Staff Person in the Central Office. This individual determines the number of claimants to be selected and referred for services depending on local office staffing and workload. The model has never been updated or revised. The list is ranked in descending order and begins with the claimants with the highest probability of exhaustion. There are no provisions to skip down the list.

Data Collection Process:

Claims are filed by telephone, Internet, and in-person. Claimant characteristics are captured during the initial claims filing interview and from agency files during nightly batch processing. Employment verification is conducted by reviewing the base period information provided by the claimant with information in the wage record system. Occupational classification is determined based on the type of work the individual performed and/or desires using the Standard Occupational Classification (SOC) system. The following individuals are not eligible for WPRS services:

- Claimants that are job attached
- Claimants that have seasonal claims
- Interstate Claimants

Selection/Referral Process:

The listing of WPRS-eligible candidates is based on the claimant first payment file; it is run as a batch job overnight and available the next day. The list is transmitted to a Workforce Development Worker in the central office through an online Customer Information Control System (CICS) transaction and then to the local WINS Job Centers through a subsequent online transaction. The staff person determines the number of individuals to be selected and referred based on local office staffing and workload. The list is ranked with those with the highest probability of exhaustion to the lowest. Candidates with the highest score are selected first, and there are no provisions to select individuals out-of-order on the list.

Profiling Model Structure:

The dependent variable used in the WPRS equation is benefit exhaustion. The independent variables are based on Mathematica's Statistical Model Requirements and include:

- Maximum duration = maximum benefit amount divided by weekly benefit amount
- Industry
- Occupation
- Education
- Potential duration = 26 weeks
- Job experience = number of months to a maximum of 99 months
- Last day worked = valid date
- WBA = actual monetary amount allowed

The selection of the independent variables was based on information available and probability of exhaustion.

Profiling Model Performance:

Mississippi provided the model structure and dataset for data analysis but did not provide enough information on variable definition and model construction for us to replicate the profiling score. Mississippi did not provide a variable indicating referral for reemployment services. We did calculate a decile table that was not corrected for endogeneity. It is shown below.

prorigdec	mean	se(mean)
1	0.457	0.012
2	0.431	0.012
3	0.443	0.012
4	0.436	0.012
5	0.429	0.012
6	0.451	0.012
7	0.455	0.012
8	0.489	0.012
9	0.481	0.012
10	0.478	0.012
Total	0.455	0.004

We also calculated the metric that shows the effectiveness of Mississippi's profiling score. It is shown below.

SWA	Profiling score	Control for endogeneity?	Exhaustion rate for the state	Number of individuals with the highest profiling score	Exhaustion rate for individuals with high profiling scores	Metric	Variance of the Metric	Standard Error of the metric
Mississippi	original score	N	45.5	8,208	47.3	0.033	1.620	0.014

The metric has a value of 0.033 and a standard error of 0.014. The metric is useful because it is significantly greater than 0. The metric provides a basis for comparison with other profiling models.

ANALYSIS OF MISSOURI PROFILING MODEL

Introduction:

Missouri uses a statistical model, of which the functional form is logistic, to determine a claimant's Worker Profiling and Reemployment Services (WPRS) profiling score. The WPRS model is run daily against the claimant first payment records, and a listing of eligible candidates is produced and sent via mainframe disk dataset and hardcopy to the Department of Economic Development. This list ranks candidates in order from highest probability of exhaustion to lowest and local areas cannot skip down the list. Local agencies then request candidates to attend orientation sessions and referral to services based upon resource availability.

A major revision of the model was implemented in December 2004. The revision included a new mix of variables, and the types of variables used were different. Initial model analysis was performed on samples taken from the pool of eligible claimants. The final model run in each case was performed on all eligible claimants, currently approximately 35,000. The sample size in determining the latest model was 11,000, but the original model was built on all eligible claimants. Data for both were built on claimants who actually received a week of benefits. Union members and claimants with a recall date were not included in the estimation database.

Data Collection Process:

Initial claims are filed by telephone (84 percent) and Internet (16 percent). Claimant characteristics are captured at the time the initial claim is filed. Claimant wage information is verified with the employer. The initial claims taker assigns the occupational code for claims taken by telephone. A claimant chooses the occupational codes from a drop down list if filed by internet. The Dictionary of Occupational Titles (DOT) is currently used to classify a claimant's occupation. Programming to create an O*Net / Standard Occupational Classification (SOC) Autocoder is to begin soon. A claimant's primary employer is determined by a review of work history with the individual and a review of wage records. The following individuals are not eligible for WPRS:

- Union Members
- Claimants With a Recall Date

Selection/Referral Process:

The listing of individuals selected for WPRS is produced at the same time the model is run against the first payment file. The list is sent to staff in the Department of Economic Development via mainframe disk dataset and paper printout. Local agencies request candidates based upon their service capability. The list is sorted by those with the highest probability of exhaustion to the lowest, and local areas cannot skip down the list. Those with the highest probability of exhaustion must be served first.

Profiling Model Structure:

The dependent variable used in the WPRS model equation is benefit exhaustion. Missouri uses a different definition of benefit exhaustion than most states. The 2004 model uses 21 weeks of benefits as the basis for benefit exhaustion. The original model used the more traditional definition of exhaustion of the maximum benefit amount. The independent variables are as follows:

- Education Level
- Wage Replacement Rate
- Average Weekly Wage
- Rate Effect
- Tenure Category
- Industry
- Reason for Leaving
- Weekly Benefit Amount
- Number of Employers
- Filing Delay
- Ratio of the High Quarter to Total Base Period Wages.

Profiling Model Performance:

Missouri provided the model structure and dataset for data analysis but did not provide useable variables for education, industry, total unemployment rate, number of employers, delay in filing, ratio of high quarter to base period wages, and a binary variable for lack of work. We did calculate a decile table that was corrected for endogeneity. It is shown below.

prorigdec	Mean	se(mean)
1	0.364	0.008
2	0.410	0.007
3	0.448	0.008
4	0.472	0.008
5	0.483	0.008
6	0.512	0.008
7	0.542	0.008
8	0.557	0.008
9	0.611	0.008
10	0.694	0.008
Total	0.506	0.003

We also calculated the metric that shows the effectiveness of Missouri's profiling score. It is shown below.

SWA	Profiling score	Control for endogeneity?	Exhaustion rate for the state	Number of individuals with the highest profiling score	Exhaustion rate for individuals with high profiling scores	Metric	Variance of the Metric	Standard Error of the metric
Missouri	original score	Y	50.6	18,727	58.3	0.156	1.726	0.010

The metric has a value of 0.156 and a standard error of 0.010. The metric is useful because it is significantly greater than 0, and it provides a basis for comparison with other profiling models.

ANALYSIS OF MONTANA PROFILING MODEL

Introduction:

Montana uses a statistical model, of which the functional form is logistic, to determine a claimant's Worker Profiling and Reemployment Services (WPRS) profiling score. The model is run weekly against the claimant first payment records, and a list of WPRS eligible claimants is produced and sent electronically to the Workforce Services system. This list ranks candidates in order from highest probability of exhaustion to lowest, and those with higher rankings are scheduled to receive services first. Workforce Services Division management determines the number of appointments for each local office based upon each office's budget and staff levels. Claimant ranking has limited influence on selections during the summer and fall when 75 percent of the 23 local job service offices have two or fewer claimants in their profiling pool. The model has never been updated or revised. When the model was designed, it was based on all benefit recipients residing in Montana.

Data Collection Process:

Initial claims are filed by telephone (75 percent) and via the Internet (25 percent). Claimant characteristics are captured at the time the initial claim is taken. The social security number is verified online with the Social Security Administration, and employment dates are verified with employers. Otherwise, Montana relies on the claimant to provide appropriate information. The Standard Occupational Classification (SOC) system is used as the occupational coding system; the system will be converted to Autocoder in 2007. The code is based on work history or last employment. Some exceptions are permitted in assigning an occupational code for individuals needing an occupational change. The claimant's primary employer is based on a review of work history with the claimant and a check of wage records. The following claimants are not eligible for WPRS services:

- Claimants who are job attached
- Union members who obtain employment through a union hiring hall
- Out-of-state claimants
- Monetarily ineligible claimants
- Disqualified claimants
- Seasonally employed claimants (i.e., Forest Service and National Park employees who do not wish to change their occupation)

Selection/Referral Process:

The list of eligible candidates is produced at the same time as the profiling model is run against claimant first payment records. As a result, a list of appointments is electronically transferred from the UI computer system to the Workforce Services computer system. Workforce Services Division management determines the number of appointments for each local office based upon each office's budget and staff levels, and Workforce Services staff can access their appointment lists. Local offices cannot skip down the ranking to bypass claimants and select other individuals for service because the UI system automatically schedules the clients based on probability of exhaustion. Rankings have limited influence on selections during summer and fall when approximately 75 percent of the 23 local Job Service offices have two or fewer claimants in their profiling pool. This results in an "automatic" selection to fill a profiling appointment.

Profiling Model Structure:

Montana uses a statistical model, of which the functional form is logistic, to operate its WPRS Program. The dependent variable is benefit exhaustion, defined as maximum benefits paid. The independent variables:

- Weeks of Benefit Eligibility
- Number of Employers
- Job Tenure
- County Unemployment Rate
- Industry Growth
- Educational Attainment
- Month in Which Initial Claim is Filed

The variables were selected using the National Prototype Model.

Profiling Model Performance:

Montana provided the model structure and dataset for data analysis but did not provide a coefficient for the variable industry growth. Therefore, we were not able to replicate the profiling score. We did calculate a decile table that was corrected for endogeneity. It is shown below.

prorigdec	Mean	se(mean)
1	0.419	0.028
2	0.479	0.028
3	0.463	0.028
4	0.508	0.028
5	0.527	0.028
6	0.505	0.028
7	0.567	0.028
8	0.570	0.028
9	0.624	0.027
10	0.678	0.026
Total	0.534	0.009

We also calculated the metric that shows the effectiveness of Montana's profiling score. It is shown below.

SWA	Profiling score	Control for endogeneity?	Exhaustion rate for the state	Number of individuals with the highest profiling score	Exhaustion rate for individuals with high profiling scores	Metric	Variance of the Metric	Standard Error of the metric
Montana	original score	Y	53.4	1,678	58.0	0.100	2.051	0.035

The metric has a value of 0.100 and a standard error of 0.035. The metric is useful because it is significantly greater than 0 and provides a basis for comparison with other profiling models.

ANALYSIS OF NEBRASKA PROFILING MODEL

Introduction:

Nebraska uses a statistical model, of which the functional form is logistic, to determine a claimant's Worker Profiling and Reemployment Services (WPRS) profiling score. It is run daily against the claimant first payment file, and a list of selected candidates is produced and sent electronically to the Labor Reemployment System (LRS) where it is automatically uploaded. The list is sorted so that claimants having the highest probabilities of exhaustion are listed first, and those with lowest probabilities are listed last.

The model was "remodeled" in 2000 when it changed from one statewide model to three - separate models for Lincoln, Omaha and Greater Nebraska. This undertaking was a joint effort between Sandy Wegner, Lead Program Analyst in Nebraska and Scott Gibbons of ETA. Many variables were analyzed and many statistical regression analyses were run on data used to develop the models. It is important to note that Nebraska has not experienced any problems with the Office of Workforce Security (OWS)/LRS coordinated program that actually offers services for WPRS selected individuals.

Data Collection Process:

Initial claims are filed by telephone (80 percent) and Internet (20 percent). All of the characteristics necessary to determine eligibility for WPRS are captured at the time of the initial claim. The initial claims taker determines and assigns the claimant's occupational code using the SOC (Standard Occupational Classification) coding system. The primary employer of the claimant is determined through a review of wage records. The following claimants are not eligible for WPRS services:

- Trade Readjustment Act (TRA) Claimants
- Disaster Unemployment Assistance (DUA) Claimants
- Union Attached Claimants
- Claimants With a Job Recall
- Interstate Claimants
- Ex-service Members (UCX) Claimants
- Ex-Federal Employee (FE) Claimants

Selection/Referral Process:

The list of WPRS eligible candidates is produced at the same time that the model is run against the first payment file. It is sent electronically to the Labor Reemployment System (LRS) where it is automatically uploaded. The OWS staff determines the number of profiled candidates to be served. The decision is based on daily output printouts, available funding, and staff resources. The model ranks in descending order individuals with the highest probabilities of exhaustion to the lowest. Claimants are selected on sampling criteria and are not pre-selected by names or Social Security Number. The local offices can choose claimants out-of-order when there are no claimants in the pool that fit the selection characteristics of the model. The model can be adjusted to meet the needs of those out-of order claimants, and the local office has staff and money to provide services to additional claimants.

Profiling Model Structure:

Nebraska uses a statistical model, of which the functional form is logistic, to operate its WPRS Program. The dependent variable is benefit exhaustion, defined as 90 percent of a claimant's benefit credit exhausted. The independent variables equation:

- FIPS Code (determines if claimant is from Omaha, Lincoln, or elsewhere)
- NAICS Industry Code
- Number of Employers
- Education
- Base Period Wages
- Job Tenure
- Delay in Filing
- Weekly Benefit Amount
- Maximum Benefit Amount

The analysis included a review of the characteristic screens used in the predictive equations. The 2000 model used a sample of 2,813 benefit recipients in the Omaha area, 1,102 in the Lincoln area, and 5,704 in Greater Nebraska. During the building of the 2000 model, many statistical regression analyses were run to refine the datasets and develop the data ranges for the model. Data were screened prior to building the models. Categorical variables were used for missing data to ensure accurate model building.

Nebraska has confidence that its WPRS model is working properly because of the internal controls and data range checks it put in place. As a result, they have not experienced any problems with the

OWS/LRS coordinated program that actually offers services for the claimants selected for WPRS services.

Profiling Model Performance:

Nebraska provided the model structure and dataset for data analysis but did not provide coefficients for the variables in the model. Therefore, we were not able to replicate the profiling score. We also note that in the sample provided, 95 percent of the individuals had exhausted benefits, or had drawn more UI benefits than their maximum benefit allowance. We did calculate a decile table that was not corrected for endogeneity. It is shown below.

prorigdec	Mean	se(mean)
1	0.915	0.004
2	0.933	0.004
3	0.934	0.004
4	0.932	0.004
5	0.952	0.003
6	0.963	0.003
7	0.966	0.003
8	0.970	0.003
9	0.974	0.002
10	0.984	0.002
Total	0.952	0.001

We also calculated the metric that shows the effectiveness of Nebraska's profiling score. It is shown below.

SWA	Profiling score	Control for endogeneity?	Exhaustion rate for the state	Number of individuals with the highest profiling score	Exhaustion rate for individuals with high profiling scores	Metric	Variance of the Metric	Standard Error of the metric
Nebraska	original score	N***	95.2	44,098	95.5	0.054	36.698	0.029

*** Nebraska had possible data problems, with 95 percent of the sample having more benefits paid than mba(maximum benefit allowance).

The metric has a value of 0.054 and a standard error of 0.029. The metric is useful because it is significantly greater than 0. The metric provides a basis for comparison with other profiling models; however, the comparability of this sample may be limited due to possible data problems.

ANALYSIS OF NEVADA PROFILING MODEL

Introduction:

Nevada uses a statistical model, of which the functional form is logistic, to determine a claimant's Worker Profiling and Reemployment Services (WPRS) profiling score. It is run weekly against the claimant first payment file, and a list is developed that ranks candidates in order from highest probabilities of exhaustion to lowest. The SWA has a policy that 10 WPRS candidates will be selected to be served in each JobConnect Office every other week. All claimants with 22 or less lag weeks are included in the profiling pool. A letter inviting those selected is generated centrally and JobConnect offices cannot deviate from the order on the listing. When the initial model was built, it was based on a sample of 12,000 benefit recipients. The model has never been updated or revised.

Data Collection Process:

Initial claims are filed by telephone (84 percent) and Internet (16 percent). Claimant characteristics necessary to determine an individual's eligibility to receive WPRS services are obtained when the initial claim is filed. The occupational classification is not included in the model. The industry code is obtained through a review of the UI wage records. The following claimants are not eligible for referral:

- Union members who obtain work through a hiring hall
- Temporarily laid-off workers
- Interstate Claimants

Selection/Referral Process:

The SWA has a policy that 10 WPRS candidates will be selected to be served in each JobConnect Office every other week. Candidates are selected based on the probabilities of exhausting their benefits, and those with the highest probabilities are ranked first. The list generated is also sorted by ZIP code, and the local offices cannot skip down the list. Selected individuals are notified via letter generated centrally at the time of first payment.

Profiling Model Structure:

The WPRS profiling model employed by Nevada utilizes a logistic regression model to estimate benefit exhaustion. The dependent variable is benefit exhaustion, defined as receipt of 95 percent of the maximum benefit amount. The independent variables are as follows:

- Local Area Unemployment Rate
- Education
- Annual Changes in Industrial Employment
- Number of Quarters Worked in the Last Seven Quarters
- Job Tenure
- Maximum Benefit Amount

Profiling Model Performance:

Nevada did not provide a dataset for data analysis and/or model revision; therefore, we were unable to gauge the performance of its current model.

ANALYSIS OF NEW HAMPSHIRE PROFILING MODEL

Introduction:

New Hampshire uses a statistical model, of which the functional form is logistic, to determine a claimant's Worker Profiling and Reemployment Services (WPRS) profiling score. The model is run weekly against the database of continued claims for benefits for the first time in a benefit year, and a list is produced and sent electronically to the 13 local offices. The list ranks candidates in order from highest probability of exhaustion to lowest. Claimants are selected when they claim their first week in the benefit year. The local office cannot skip individuals on the list with the exception of veterans who are served by the Local Veterans Employment Representative (LVER) and/or Disabled Veterans Outreach Person (DVOP).

The model has never been revised but has been updated with the most recent update taking place effective April 4, 2005. In updating the model, the SWA compared the predicted exhaustion rate versus the actual exhaustion rate in the old model and to the updated model. Regular and transitional benefit recipients whose first payment were for a week of total unemployment were included in the data extract. Episodic and claimants who filed special program claims were not included in the extract. A total of 20,405 benefit recipients were include in the most recent sample

Data Collection Process:

All initial claims are filed on the internet. Claimant characteristics necessary to determine an individual's eligibility for WPRS services are obtained at the time a first payment is claimed. Claimants are selected at the time they claim their first week of benefits. Accuracy of the data provided by the claimant is verified daily by claims certifying officers. O*Net is used as the occupational classification system, and the claimant self-selects his/her code from a listing of skills sets. The North American Industry Classification System (NAICS) is used as the industry classification system, and coding is assigned based on the last employer. If the claimant separated from two employers simultaneously, the classification would be assigned based on the employer that the employee worked on for the greatest period of time. The following individuals are not eligible to receive WPRS services:

- Claimants who obtain employment through a union hiring hall
- Claimants who expect to be recalled to their previous employers
- Claimants who voluntary quit their last jobs

Selection/Referral Process:

Claimants are selected for participation in the WPRS program when they claim their first week of the benefit year. A listing of candidates is produced and is distributed to the 13 local offices. The listing is arrayed by probability of exhaustion with those most likely to exhaust listed first. The local office cannot skip individuals on the list, except for veterans who are served by the Local Veterans Employment Representative (LVER) and/or Disabled Veterans Outreach Person (DVOP). Local office managers determine the number and frequency of eligible individuals to be served based on staff availability and workloads.

Profiling Model Structure:

The WPRS profiling model employed by New Hampshire utilizes a logistic regression model to estimate benefit exhaustion. The dependent variable is benefit exhaustion, defined as maximum benefits available in a benefit year. The independent variables include:

- Long Delay - defined as a delay in filing an initial claim for benefits over 90 days from the date of separation from employment
- Education
- Wage Replacement Rate
- Industry
- Total Wages in the Base Period
- Reason for Separation

Profiling Model Performance:

New Hampshire did not provide a dataset for data analysis and/or model revision; therefore, we were unable to gauge the performance of its current model.

ANALYSIS OF NEW JERSEY PROFILING MODEL

Introduction:

New Jersey uses a statistical model, of which the functional form is logistic, to determine a claimant's Worker Profiling and Reemployment Services (WPRS) profiling score. The model is run daily against the claimant first payment records with a batch program feeding the data to a mainframe system which can be accessed by Workforce New Jersey (WNJ) staff. Claimants are listed by highest probability of exhaustion to lowest. For each One-Stop Center, the WNJ Manager determines a standard number of WPRS eligible candidates to be served weekly.

The model was last revised effective January 1, 2004, when three changes were made. An administrative directive requires the model to be updated at least every three years. It may be updated more frequently if circumstances such as accuracy indicate that an update is needed. The updates include updated coefficients and may involve changes in the form of the model if warranted by the statistical analysis. In the most recent revision, three changes were made to the model, including:

- New categorical industry variables were added based on the North American Industry Classification System (NAICS) coding system. Prior to that, industry was temporarily dropped from the model during the transition from the Standard Industrial Classification (SIC) classification system to NAICS.
- The dummy variable "some college" was added (in addition to "college graduate") because it had become statistically significant.
- The variable "recall" was dropped from the model because it had become insignificant. This variable represented claimants who expected to be recalled by their former employers, but the recall was not definite so claimants were not screened out of profiling.

The sample size for this update was 12,404 benefit recipients. It is estimated that the sample size was less than 1,500 benefit recipients when the model was first estimated in 1994.

Data Collection Process:

Initial claims for benefits are filed by telephone (70 percent), internet (25 percent) and in-person (5 percent). All claimant characteristics are captured at the time the initial claim is taken. The social security number is verified through a batch process (Veris). The initial claims taker determines the claimant's occupational code using OES (Occupational Employment Statistics). Later, the DOT code is used for claimants receiving services at One-Stop Centers. This is part of the One-Stop Operating System (OSOS) database and is added to the UI (unemployment insurance) database (replacing the OES code) through an interface. The claimant's primary employer is assigned based on the employer for whom the claimant worked the most weeks in the base year. The following individuals are not eligible for referral to WPRS services:

- Claimants with partial first payments
- Claimants with first payments more than 35 days after they filed their claims
- Claimants using approved union hiring halls
- Claimants in "definite recall" status (have a definite recall date, or their employer, industry or occupation have an established historical pattern of recall)
- Interstate Claimants

Selection/Referral Process:

The daily listing of WPRS eligible individuals is produced at the same time the model is run. A batch job feeds the data to a mainframe system which can be assessed by WNJ staff. For each One-Stop Center the WNJ Manager determines a standard number of claimants to be selected weekly based on office space and staff resources. Candidates are ranked from highest to lowest in probabilities of exhaustion, and those with the highest scores are selected for referral by the automated system. This prevents the Centers from skipping individuals on the listing because candidates are automatically selected and notified that they have been selected for WPRS.

Profiling Model Structure:

The WPRS profiling model employed by New Jersey utilizes a logistical regression model to estimate benefit exhaustion. The dependent variable is defined as exhaustion of the maximum benefit amount. The independent variables are as follows:

- College Graduate
- Job Tenure
- Temporary Layoff
- Log of Base Year Earnings
- Potential Duration of Benefits

- County Unemployment Rate
- Claimant Selected for Reemployment Services
- Occupational Group
- Industry Group

The selection of variables was determined by:

- Variables available at the time of first payment
- Statistical significance
- Improvement in overall model diagnostics
- Reasonableness (expected to be related to reemployment difficulty and have the expected sign)

Variables other than those selected were also examined and different functional forms were also tested (e.g., continuous vs. categorical groupings). Different versions of similar variables were also tested.

Profiling scores are computed using data from the UI database which are then passed to the profiling database after processing. Edit checks are done on UI data when they are entered into the UI database to prevent certain invalid data and to ensure that required data are entered. Some additional checks are done by the profiling program to identify invalid data and check for missing values.

There are three differences between the data quality procedures used in estimating the model and running it. In estimating the model:

1. Some additional records are deleted because they have data values considered invalid that remain in the data. One example is claimants who did not receive any benefits. This generally would occur because the claimants were later found to be ineligible and their payments were voided in the data. (UI data on the profiling database are refreshed weekly by current data from the UI database.)
2. Additional range checks are done to eliminate extreme values that might unduly affect the coefficients. Specified ranges are set to exclude outliers, and out-of-range values are set to the limits of these ranges.
3. Because of a formatting error on the profiling database, there are substantially more invalid occupational codes when the model is estimated than in the regular profiling of UI claims.

Profiling Model Performance:

New Jersey provided its survey, a dataset and the model structure. Included in the dataset was a binary variable indicating whether or not benefit recipients were referred to reemployment services. This binary variable allows us to test for endogeneity within our data and answer the question - does referral to reemployment services have an effect on the exhaustion of benefits?

Our first step was to try to replicate the given score using the data provided and the coefficients for the variables given. From the given data, we were able to replicate the original score, creating a score that correlated with the provided score at 0.956.

We used the profiling scores provided to produce a decile table as shown below. The decile means are calculated by dividing the percentage of recipients that exhaust benefits for a given decile by 100. For example, in the first decile, our mean is 0.499, or approximately 50 percent, which indicates that approximately 50 percent of benefit recipients in this decile exhausted benefits.

prorigdec	mean	se(mean)
1	.4994117	.0037426
2	.5670739	.0037091
3	.5924552	.0036845
4	.6079857	.0036509
5	.6290051	.0036219
6	.6438648	.0035828
7	.6527864	.0035666
8	.6694806	.003529
9	.6911517	.0034598
10	.6901045	.0034657
Total	.6242945	.0011471

After testing for endogeneity, we found that referral to reemployment services did have a significant impact on benefit exhaustion. In further analyses, we provided a correction for endogeneity.

Using the dataset, we created three models – an updated, a revised, and a Tobit model – with new profiling scores which were ranked and divided into deciles. The table below shows the decile gradient for each of our models (detailing the mean for each decile) and includes the decile gradient for the original model for reference. The second model is the original model corrected for endogeneity. From the table, we see that there was considerable improvement between the original and updated models and considerable improvement in the decile gradient between the updated and revised models.

Decile	Original score	Original score adapted for endogeneity	Updated mean	Revised mean	Tobit mean
1	.4994117	.4994117	.4900629	.480631	.4800696
2	.5670739	.5670739	.5616754	.5402279	.5432036
3	.5924552	.5924552	.5835719	.5652125	.5648756
4	.6079857	.6079857	.5846059	.5819672	.5875814
5	.6290051	.6290051	.6087811	.6119252	.6106339
6	.6438648	.6438648	.6176173	.6307338	.6306777
7	.6527864	.6527864	.6467352	.6434988	.6491691
8	.6694806	.6694806	.6689125	.6756499	.6667228
9	.6911517	.6911517	.7070911	.7161866	.7088316
10	.6901045	.6901045	.7740161	.7970355	.8013026
Total	.6242945	.6242945	.6243059	.6243059	.6243059

While there was considerable improvement between the original and updated and revised models, there was only marginal improvement between the revised and the Tobit models. We tested the performance of each model using the following metric:

Percent exhausted of the top 62.4 percent of individuals in the score.

We used 62.4 percent because the exhaustion rate for benefit recipients in the New Jersey dataset was 62.4 percent. This metric will vary from about 62.4 percent, for a score that is a random draw, to 100 percent for a score that is a perfect predictor of exhaustion. The scores for the four models are as follows:

Score	% exhausted of those with the top 62.4% of score	Standard error of the score
Original	66.07	.14%
Adapted	66.04	.14%
Updated	66.04	.14%
Revised	67.58	.14%
TOBIT	67.46	.14%

In the metric below, *"Exhaustion"* is the percentage of all benefit recipients in our sample that exhaust benefits. For New Jersey, "*Exhaustion*" is 62.4 percent since the exhaustion rate for all benefit recipients in the provided dataset was 62.4 percent. In our metric, "Pr[*Exh*]" is determined by the model with the highest percentage of benefit exhaustees with profiling scores falling in the top X percent of the sample, where X percent is determined by the exhaustion rate for all benefit recipients in the sample. For New Jersey, "Pr[*Exh*]" is represented by the revised model with a score of 67.58 percent for benefit recipients who exhaust benefits with scores falling in the top 62.4 percent.

$$\text{Metric: } 1 - \frac{100 - \Pr[Exh]}{100 - Exhaustion}$$

We used the numbers above to calculate a score of 0.096 for the original profiling score (corrected for endogeneity) and a score of 0.137 for the revised score.

SWA	Profiling score	Control for endogeneity?	Exhaustion rate for the state	Number of individuals with the highest profiling score	Exhaustion rate for individuals with high profiling scores	Metric	Variance of the Metric	Standard Error of the metric
New Jersey	original score	Y	62.4	67,030	66.0	0.096	2.947	0.007
New Jersey	revised score	Y	62.4	67,030	67.6	0.137	2.789	0.006

These metrics show that the revised model is significantly better that the original score. The metrics also show a baseline on which other models can improve. Further analysis of New Jersey's model is in the expanded analysis section.

ANALYSIS OF NEW MEXICO PROFILING MODEL

Introduction:

New Mexico uses a statistical model, of which the functional form is logistic, to determine a claimant's Worker Profiling and Reemployment Services (WPRS) profiling score. It is run weekly against the claimant first payment file, and a file of eligible candidates is produced and sent to Office of Workforce Security (OWS) One-Stop Offices to be invited into the office. The listing is sorted with those having the highest probabilities of exhaustion listed first. The One-Stop initiates the process of selecting profiled claimants to attend workshops. The number of profiled candidates served depends on the availability of staff and meeting room size. Local staff can skip down the list as candidates are exempted.

The model was updated in 2004. At that time, it was determined that the updated model correctly predicts about 70 percent of claimants likely to exhaust benefits. The model is currently being tested in the new system, and instances of inaccurate data are being investigated.

Data Collection Process:

Initial claims are filed by telephone and via the Internet. Claimant characteristics necessary to profile the claimant are obtained during the initial claims filing process by the claims taker. The Dictionary of Occupational Titles (DOT) system is used to assign the occupational code, and it is based on an interview with the claimant and a review of wage records. Social Security validations are performed to guarantee that Date of Birth and Social Security Number belong to the claimant. Employers are contacted by mail to validate separation issues.

Profiling Model Structure:

The WPRS profiling model employed by New Mexico utilizes a statistical model, of which the functional form is logistic, to estimate benefit exhaustion. The dependent variable is either exhaustion of benefits or receipt of 26 weeks of benefits. The independent variables are as follows:

- Industry
- Occupational Code
- Claim Month
- Education

- Weekly Benefit Amount
- Replacement Ratio
- Months in Last Job
- County Code
- Local Unemployment Rate

Profiling Model Performance:

New Mexico has not yet put its model into production. The SWA did not provide a dataset for data analysis and/or model revision; therefore, we were unable to gauge the performance of its current model.

ANALYSIS OF NEW YORK PROFILING MODEL

Introduction:

New York uses a characteristic screen that utilizes a contingency table to estimate claimants' likelihood of benefit exhaustion. The model is run weekly against the claimant first payment file; however, the list of eligible candidates is not run until an orientation roster request is submitted by an orientation provider. Selection for participation in orientation is automated and claimants are ranked providing scores with those most likely to exhaust UI benefits being higher ranked.

The model is updated every two to three years with the most recent revision occurring in June 2003 when the North American Industry Classification System (NAICS) replaced the Standard Industrial Classification (SIC) system. Revision to the model are decided jointly by the Unemployment Insurance Division, the Division of Employment Services (DOES), the Division of Planning and Technology (P&T), and the Division of Research and Statistics (R&S).

Data Collection Process:

Initial claims are filed in-person, by telephone, by mail, and via the Internet. Claimant characteristics necessary to determine an individual's eligibility for WPRS services are captured at the time of the initial claim filing. Checks for accuracy are performed through the rescoring process and informally by DOES staff members.

New York uses the Dictionary of Occupational Titles (DOT) system occupation coding, and the coding is determined by claimant if filing by phone, mail, or internet, or it is determined by a claims taker if filed in-person. Industry classification, for purposes of assigning NAICS codes, is based on the claimant's work history and wage records. Individuals not eligible for referral to WPRS services include:

- Union members who receive jobs through a hiring hall
- Temporary layoffs
- Out-of-state residents

Profiling Model Structure:

The WPRS profiling model employed by New York uses a characteristic screen along with a contingency table to estimate the likelihood of a claimant exhausting benefits. This approach has both strengths and weaknesses and can be tailored to various subsets of applicants. For example, individuals with a NAICS code of 221, which corresponds with employment in the utilities industry, are selected differently from individuals with a NAICS code of 516 (Internet Publishing and Broadcasting). However, the model also probably leaves out many individuals who are likely to exhaust and/or selects individuals who are not likely to exhaust.

The dependent variable is benefit exhaustion, defined as the total number of days receiving benefits. For New York, there is a maximum allowance of 26 weeks for receipt of benefits. Four working days correspond to one week, resulting in a total of 104 days for the maximum allowance of 26 weeks of benefits.

The independent variables are:

- Mass Layoff – a binary variable indicating whether claimant was part of a mass layoff from previous employer
- Education – defined by numbers of years of education completed
- Job Tenure – defined by numbers of years with previous employer
- Industry – 3 digit NAICS code of last employer
- Occupation – 1 digit DOT code of last employer

Profiling Model Performance:

New York did not provide sufficient details of its contingency table methodology to enable us to replicate its profiling scores. We did have sufficient data to calculate a decile table that was corrected for endogeneity. It is shown below.

prorigdec	Mean	se(mean)
1	0.143	0.002
2	0.223	0.002
3	0.283	0.002
4	0.353	0.002
5	0.397	0.002
6	0.434	0.002

7	0.492	0.002
8	0.531	0.002
9	0.570	0.002
10	0.639	0.002
Total	0.404	0.001

We also calculated the metric that shows the effectiveness of New York's profiling score. It is shown below.

SWA	Profiling score	Control for endogeneity?	Exhaustion rate for the state	Number of individuals with the highest profiling score	Exhaustion rate for individuals with high profiling scores	Metric	Variance of the Metric	Standard Error of the metric
New York	original score	Y	40.4	205,729	55.5	0.253	1.073	0.002

The metric has a value of 0.253 and a standard error of 0.002. The metric is useful because it is significantly greater than 0, and it provides a basis for comparison with other profiling models.

ANALYSIS OF NORTH CAROLINA PROFILING MODEL

Introduction:

North Carolina uses a statistical model, of which the functional form is logistic, to determine a claimant's Worker Profiling and Reemployment Services (WPRS) profiling score. The model is run daily against the claimant first payment file, and a list of eligible candidates is produced and available to all staff via the mainframe system. The list ranks all candidates in order from highest probability of exhaustion to lowest with those with higher rankings scheduled to receive services first.

Local Office Managers determine the number of individuals to be served based on available staffing; claimants with probability scores exceeding 50 percent are selected for reemployment services. In selecting candidates for reemployment services, local offices cannot skip individuals on the list. The model has never been updated or revised.

Data Collection Process:

Initial claims are filed in-person, by telephone, and via the Internet. All claimant characteristics necessary to determine eligibility for WPRS services are obtained during the initial claims filing with no check for accuracy of data provided. In cases where the claim is filed in-person or by the telephone, the claims taker assigns the occupational code using the Dictionary of Occupational Titles (DOT) system. When filing by Internet, the claimant self-selects the occupational code. For purposes of assigning North American Industrial Classification System (NAICS)/Standard Industrial Classification (SIC) system codes, the primary employer is based on a review of work history with the claimant. Individuals not eligible for referral to services through WPRS include:

- Job Attached Claimants
- Interstate Claimants
- Claimants receiving first payments five weeks or later after benefit year beginning date
- Longshoremen

Individuals who received more than five weeks of benefits prior to selection for reemployment services are excluded from the sample for future profiling. Additionally, missing values are assigned default values as determined through a statistical process as defined by North Carolina.

Selection/Referral Process:

Claimants are selected for WPRS services when the model is run against the first payment file. The file is available for all staff via the mainframe. Candidates with the highest probability of exhaustion are listed first and those with lowest last. Local Office Managers determine the number of individuals to be served based on staffing. Candidates with a probability of exhaustion in excess of 50 percent are expected to be served. Local offices cannot skip individuals on the list.

Profiling Model Structure:

The WPRS profiling model employed by North Carolina utilizes a statistical model, of which the functional form is logistic, to estimate benefit exhaustion, defined as full payment of the maximum benefit amount. The independent variables are as follows:

- Industry Code
- DOT Occupation Code
- Job Tenure
- Level of Education
- Local Office

Profiling Model Performance:

North Carolina did not provide a dataset for data analysis and/or model revision; therefore, we were unable to gauge the performance of its current model.

ANALYSIS OF NORTH DAKOTA PROFILING MODEL

Introduction:

North Dakota uses a statistical model, of which the functional form is logistic, to determine a claimant's Worker Profiling and Reemployment Services (WPRS) profiling score. The model is run daily against the initial claims data to produce a referral list. The list is stratified by individuals most likely to least likely to exhaust, and it is sent electronically to the local workforce offices who determine the number to be served and called in for possible referral to reemployment services. The center staff cannot skip down the list; the candidates must be served in a high to low probability order.

The model is updated yearly with the last update occurring in September 2005. The last revisions to the model took place in 2002/2003; it included moving from use of Dictionary of Occupational Titles (DOT) and Standard Industrial Classification (SIC) codes to Standard Occupational Classification (SOC) and North American Industry Classification System (NAICS).

Data Collection Process:

Initial claims are filed by telephone (80 percent) and internet (20 percent). All claimant characteristic data are captured during the initial claim process. Identity is verified but other data are not routinely validated. The occupation code is assigned by the claims taker for telephonic initial claims and is self-selected by the claimant for internet claims. The industry code is determined by the claims taker. Individuals not eligible for referral for services through WPRS include:

- Job Attached Claimants
- Students
- Interstate Claimants
- Disaster Unemployment Assistance (DUA) and Trade Readjustment (TRA) Claimants
- Combined Wage Claimants

The exclusions result in 86 percent of all claimants being excluded from referral for services. In North Dakota, nearly two thirds of all claimants are considered job attached.

Selection/Referral Process:

The listing of WPRS candidates is produced at the same time the model is run and sent electronically to local One-Stop Career Centers. The listing is ranked with individuals with the highest probability of exhaustion first to the lowest, with exemptions made on a case-by-case basis. The local One-Stop Centers decide the number of profiled claimants that will be served.

Profiling Model Structure:

While other independent variables (education, weekly benefit amount, BYE date) were considered the percentage of amount paid for NAICS, SOC, and County of residence were determined to be most representative. The dependent variable is benefit exhaustion and the independent variables are as follows:

- Ratio of high quarter wages to base period wages
- NAICS average percentage: the sum of the amount paid/maximum benefit amount of all claimants with the same NAICS code divided by the number of claimants with that NAICS code.
- SOC average percentage: the sum of the amount paid/maximum benefit amount of all claimants with the same SOC divided by the number of claimants with that SOC.
- County average percentage: the sum of the amount paid/maximum benefit amount of all claimants with the same county (residence) code divided by the number of all claimants with that county code.

The numerical values for the estimated coefficients and the standard error rates were readily available and included in the survey response. Records with missing data are assigned numeric averages.

Profiling Model Performance:

North Dakota provided a dataset and the model structure used for analysis of its current profiling model but did not provide a profiling score. Therefore, we were not able to calculate decile tables or a model metric.

ANALYSIS OF OHIO PROFILING MODEL

Introduction:

Ohio uses characteristic screen models to operate its Worker Profiling and Reemployment Services (WPRS) Program. The model is run weekly against the claimant first payment file with a list of WPRS candidates produced at that time by the Unemployment Insurance (UI) software system. This list of WPRS candidates is then made available to State Merit Staff by county within the UI software system. The number of profiled candidates to be served is determined by district coordinators and local staff based on staff availability and One-Stop room capacity. Only in cases where a staff member knows of a return to work date or other exemption prior to claimant selection, may a claimant be skipped in the profiling pool.

The characteristic screen models were last updated in 2000 and have never been revised. Any revision would be based on a declining industry update through the Bureau of Labor Market Information. Currently, because of a lack of funding, Ohio has not been able to evaluate the accuracy of their profiling model in properly predicting benefit exhaustion of claimants.

Data Collection Process:

Initial claims are filed by telephone (75 percent) and Internet (25 percent) with claimant characteristics necessary to determine an individual's eligibility for WPRS services being obtained at that time. Accuracy of information is checked through the wage record system and confirmed with the employer. The occupational code is selected by the claimant when applying for benefits on the Internet, or by the initial claims taker and/or workforce development when applying by telephone. Standard Occupational Classification (SOC) system and O*Net codes are used to classify the occupation of individuals filing claim. For purposes of assigning North American Industrial Classification System (NAICS)/Standard Industrial Classification (SIC) system codes, a review of work history with the claimant is used to determine his/her primary industry. Individuals not eligible for referral to services through WPRS include:

- Claimants who are work attached
- Claimants who have a justifiable cause that would last longer than four weeks
- Claimants who have received the same or similar service within the past 12 months

Note, currently there is no procedure for Ohio for dealing with claimants with incomplete records or records with missing variables.

Selection/Referral Process:

The WPRS model is run weekly against the claimant first payment file, and candidates are selected for participation in WPRS at that time. The list is produced in the UI software system and made available to State Merit Staff by County. The only time someone may be skipped within the profiling pool is if the staff member knows of a return to work date or exemption that applies PRIOR to selection of the candidate. District coordinators and local staff decide the number of profiled claimants to service based on staff availability and room capacity in the One-Stop.

Profiling Model Structure:

The WPRS profiling model employed by Ohio utilizes a characteristic screen model to estimate benefit exhaustion, defined as full payment of the maximum benefit amount. The characteristic screens used in the model are as follows:

- Claimant received a first payment
- Claimant is receiving benefits under the regular Ohio UI Program, Unemployment Compensation for Federal Employees (UCFE), Unemployment Compensation System (UCS), or Combined Wage Claim (CWC) claims under Ohio law
- Claimant is an Ohio resident filing for benefits through an Ohio local office or Telephone Registration Center
- Claimant is totally unemployed (no income or earnings for the first UI week paid)
- Claimant is not job attached and has no hiring hall (i.e., “Required” work search assignment)
- Claimant was last employed in a declining industry

Profiling Model Performance:

Ohio did not provide a dataset for data analysis and/or model revision; therefore, we were unable to gauge the performance of its current model.

ANALYSIS OF OKLAHOMA PROFILING MODEL

Introduction:

Oklahoma uses a statistical model, of which the functional form is linear, to determine a claimant's Worker Profiling and Reemployment Services (WPRS) profiling score. The model is run weekly against the claimant first payment records, but a listing of WPRS candidates is not produced at that time. The list is compiled electronically in each local office which conducts profiling screening when individuals are scheduled to receive services. This list ranks candidates in order from highest probability of exhaustion to lowest. The local office cannot skip down the listing, except to waive claimants who have returned to work. The model has never been updated or revised.

Data Collection Process:

Initial claims are filed by Internet (51 percent), telephone (46 percent) and employer filed mass and/or partial claims (3 percent). All of the characteristics necessary to profile claimants are obtained at the time the initial claim is taken. The O*Net SOC (Standard Occupational Classification) system is used and the initial claims taker assigns the code which is based on the claimant's past work history. The primary employer is determined during the same interview. Claimants not eligible for referral to WPRS services include:

- Claimants who have a definite return-to-work date
- Claimants who are union members

Profiling Model Structure:

The dependent variable used in the WPRS model equation is benefit exhaustion. Independent variables were not identified.

Profiling Model Performance:

Oklahoma did not provide a dataset for data analysis and/or model revision; therefore, we were unable to gauge the performance of its current model.

ANALYSIS OF OREGON PROFILING MODEL

Introduction:

Oregon uses a statistical model, of which the functional form is logistic, to determine a claimant's Worker Profiling and Reemployment Services (WPRS) profiling score. The model is run weekly against the claimant first payment records, and with a list of WPRS eligible claimants, is produced and sent electronically to local Business and Employment Services offices. The profiling scores determine which claimants will receive enhanced service. Those claimants with a score of 44 or higher are deemed likely to exhaust benefits and given priority. Local Business and Employment Services offices then determine the number of claimants that can be served based on capacity. If the number of candidates meeting the threshold score is not great enough to meet the local capacity, those with lower scores can be served.

On July 3, 2003, the model was last updated; it has never been revised. It is tested for accuracy on a continuous basis, and, if the accuracy of the model declines, it is reviewed and revised.

Data Collection Process:

Initial claims are filed by telephone, by mail, and via the Internet. All characteristic data are captured at the time of initial claim with a quality control procedure in place within the Unemployment Insurance (UI) operation that systematically monitors the data being entered. The North American Industry Classification System (NAICS) code is assigned based on the information provided at the initial claim. Claims with the following indicators are screened out of the dataset prior to the analysis and computation of the profiling scores:

- Claimants who were never issued a first payment
- Claimants who are employer attached
- Denied Claimants
- Claimants who have specific separation reasons
    - Leave of Absence
    - Labor Dispute
    - Other
    - Still Working
    - 00
    - FR

- Claimants who have dislocated worker codes
    - Union Attached
    - Employment Services Offered by Another Organization
    - SEA Program Referral
- Claimants who have a maximum benefit amount less than 20 times the weekly benefit amount

Profiling Model Structure:

The WPRS profiling model employed by Oregon utilizes a statistical model, of which the functional form is logistic, to estimate benefit exhaustion. The dependent variable is benefit exhaustion, defined as maximum benefits paid. The independent variables include the following:

- Education
- Occupation Code
- Industry Code
- Reason for Separation
- Log of Base Year Wages
- County Code
- Previous Experience
- Prior Benefits Exhaustion

Variables were selected based on previous studies, federal recommendations, and UI data availability in Oregon's UI data system.

Profiling Model Performance:

Oregon did not provide a dataset for data analysis and/or model revision; therefore, we were unable to gauge the performance of its current model.

ANALYSIS OF PENNSYLVANIA PROFILING MODEL

Introduction:

Pennsylvania uses a statistical model, of which the functional form is logistic, to determine a claimant's Worker Profiling and Reemployment Services (WPRS) profiling score. The model is run weekly against the claimant first payment records, and a list of WPRS eligible claimants is produced and sent electronically to the local workforce office which determines the number to be served and called them in for interviews. This list ranks candidates in order from highest probabilities of exhaustion to lowest. A revised model was developed in 2004, but it has not been implemented. The revision will be incorporated in the Unemployment Insurance (UI) Modernization Project, which is in its early phases.

Pennsylvania uses a characteristic screen to determine whether or not individuals are eligible for referral for services through WPRS. In 2003, one of four questions was changed on the initial characteristic screen with the modified screen requesting a yes/no response to whether the claimant received a definite date of recall from any of his/her past employers. The prior version was too restrictive because it required the claimant to provide an actual date of recall. This is the model upon which we conducted the data analysis.

Data Collection Process:

Initial claims are filed by telephone (69 percent), Internet (30 percent) and mail (1 percent). Initial claims questions capture the characteristic information necessary to make profiling decisions. The occupation code is not used as a variable within the WPRS model due to unreliability of the data. The employer code is obtained from the UI wage records. Individuals not eligible for referral for services through WPRS include:

- Claimants separated from employment as a result of direct involvement in a labor dispute
- Claimants who expect to be recalled by a past employer
- Claimants who obtain employment through a union hiring hall
- Claimants who are employed in some capacity
- Claimants who reside out-of-state

Claimants eligible for services through profiling are selected when they receive their first payment. They are ranked in order by workforce area with the claimants with the highest probabilities of exhaustion (highest scores) listed first on the list that is generated when they are profiled. If a claimant has passed five weeks after the filing of a claim, he/she is also not eligible for referral to WPRS. The automated list is sent via electronic link to the CareerLink system where staff in the local CareerLink office accesses the lists. The determination of the number of profiled candidates to select for services is determined by local office personnel based on the capacity to provide services. Staff cannot skip down the list in selecting claimants to be called in for service with the exception of those on the list that are exempted from mandatory participation. These include:

- Claimants who are currently enrolled in approved training [WIA, TAA/NAFTA (North American Free Trade Agreement), or any other UC Training]
- Claimants receiving or who have completed similar reemployment services
- Inappropriately profiled –used when union hiring, work stoppage/labor dispute, or filing partials were missed during the initial claims filing process
- Claimants moved and are now filing on an interstate basis
- Claimants received a return-to-work date or working part-time prior to PREP call-in
- Claimants returned to work after WPRS program call-in or participation
- Claimants had other justifiable causes

There are feedback systems in place for the local workforce office to provide information to the UI Service. Fifty-two percent of the claimants are determined not eligible for referral or subsequently exempted from WPRS.

Selection/Referral Process:

Claimants eligible for services through profiling are selected when they receive their first payment. They are ranked in order by workforce area with the claimants with the highest probabilities of exhaustion (highest scores) listed first on the list that is generated when they are profiled. If a claimant has passed five weeks after the filing of a claim, he/she is not eligible for referral to WPRS. The automated list is sent via electronic link to the CareerLink system, where local CareerLink office staff members can access the list. The determination of the number of profiled candidates to select for services is determined by the local office personnel based on the capacity to provide services. Fifty-two percent of the claimants are determined as not eligible for referral or subsequently exempted from WPRS.

Profiling Model Structure:

The WPRS profiling model employed by Pennsylvania utilizes a statistical model, of which the functional form is logistic, to estimate benefit exhaustion. The dependent variable in the WPRS model is benefit exhaustion, defined as maximum benefits paid. The independent variables are as follows:

- Job tenure with the most recent employer is less than three years
- Education is less than 12 years
- Education is 16 years or more
- Primary base period employer's industry employment is projected to decline in the state by 19 percent or more over the next 10 years
- Benefit replacement rate is less than or equal to 35 percent average weekly wage in high quarter
- Benefit replacement rate is greater than or equal to 55 percent average weekly wage in high quarter
- Ten-year historical exhaustion rate of primary base year employer's industry
- Total unemployment rate 12-month moving average for the labor market area

Profiling Model Performance:

A revised statistical model concept was developed in 2004 that included the modification of some variables (education, job tenure, industry, wage replacement), the elimination of one (unemployment rate), and the addition of another (previous UI experience). The revised model has not been implemented due to constraints in altering the SWA's WPRS that limit the ability to include North American Industry Classification System (NAICS) codes, occupational codes, and previous UI experience. These changes will occur as part of the UI Modernization Project, which is in its early stages.

Pennsylvania provided the model structure and a dataset for analysis. The original model used by Pennsylvania for predicting the exhaustibility scores was a logistic regression model that produced a range of scores from 0.1665 to 0.5974. Included in the dataset was a binary variable indicating whether or not benefit recipients were referred to reemployment services. This binary variable allows us to test for endogeneity within the data and answer the question - does referral to reemployment services have an effect on the exhaustion of benefits?

After testing for endogeneity, we found that referral to reemployment services did have a significant impact on benefit exhaustion. To correct for this endogeneity, we generated an offset variable to account for the impact. Using this offset variable and the original scores provided by Pennsylvania, we generated the predicted profiling scores (i.e., probabilities of benefit exhaustion). After generating these predicted profiling scores, we then divided them into deciles (including means and standard errors) as detailed in the table below:

Original Score	Mean	Standard Error (Mean)
1	.326	.003
2	.393	.0033
3	.417	.0033
4	.455	.0033
5	.479	.0033
6	.489	.0033
7	.508	.0033
8	.493	.0033
9	.516	.0033
10	.540	.0033
Total	.461	.0011

Using the dataset and the offset variable to account for endogeneity, we continued our analysis of Pennsylvania's profiling model by creating three models – an updated, revised, and a Tobit model. For each of the models, new profiling scores were created, ranked, and divided into deciles. The table below shows the decile gradient for each of our models (detailing the mean for each decile) and includes the decile gradient for the original model for reference. From the table, we see that there was considerable improvement between the original and updated models and considerable improvement in the decile gradient between the updated and revised models.

Decile	Original score	Original score corrected for endogeneity	Updated score	Revised score	Tobit score
1	.326	0.326	.312	.283	.282
2	.393	0.394	.362	.378	.385
3	.417	0.417	.429	.426	.425
4	.455	0.456	.45	.458	.449
5	.479	0.479	.476	.47	.479
6	.489	0.490	.484	.49	.482
7	.508	0.508	.489	.487	.503
8	.493	0.494	.521	.515	.508
9	.516	0.517	.528	.533	.527
10	.540	0.541	.567	.577	.578
Total	.461	0.461	.461	.461	.461

There was improvement over the original models with the updated and revised, or models, especially past the 7th decile. The Tobit model allows only marginal improvement over the revised model. Thus, the revised model appears to be the best model for the available data (see Appendix D for information on the revised model). Additionally, we tested the performance of each model using the following metric.

Percent exhausted of the top 46.1 percent of individuals in the score.

We used 46.1 percent because the exhaustion rate for benefit recipients in the dataset provided by Pennsylvania was 46.1 percent. This metric value will vary from about 46.1 percent, for a score that is a random draw, up to 100 percent for a score that is a perfect predictor of exhaustion. The scores for the four models are as follows:

Score	% exhausted of those with the top 46.1% of score	Standard error of the score
Original	49.33	0.15727
Updated	52.29	0.15493
Revised	52.48	0.15547
TOBIT	52.39	0.15542

In the metric below, *"Exhaustion"* is the percentage of all benefit recipients in the sample that exhaust benefits. For Pennsylvania, *"Exhaustion"* is 46.1 percent since the exhaustion rate for all benefit recipients in the provided dataset was 46.1 percent. In our metric, "Pr[*Exh*]" is determined by the model with the highest percentage of benefit exhaustees with profiling scores falling in the top X percent of the sample, where X percent is determined by the exhaustion rate for all benefit recipients in the sample. For Pennsylvania, "Pr[*Exh*]" is represented by the revised model with a score of 52.48 percent for benefit recipients that exhaust benefits with scores falling in the top 46.1 percent.

$$\text{Metric: } 1 - \frac{100 - \Pr[Exh]}{100 - Exhaustion}$$

We used the numbers above to calculate a score of 0.095 for the original profiling score (corrected for endogeneity) and a score of 0.118 for the revised score.

Pennsylvania	original score	Y	46.1	103,172	51.2	0.095	1.564	0.004
Pennsylvania	revised score	Y	46.1	103,172	52.5	0.118	1.527	0.004

These metrics show that the revised model is significantly better that the original score. The metrics also show a baseline on which other models can improve. Further analysis of Pennsylvania's model is in the expanded analysis section below.

ANALYSIS OF PUERTO RICO PROFILING MODEL

Introduction:

Puerto Rico uses a characteristic screen to determine a claimant's Worker Profiling and Reemployment Services (WPRS) profiling score. The model is run weekly against the claimant first payment records, and a list of WPRS eligible claimants is produced and sent via their Interempleo System to the local offices. This list ranks candidates in order from highest probabilities of exhaustion to lowest with those with higher rankings scheduled to receive services first. Local Office Managers determine the number of candidates to be served based upon the personnel available to perform the WPRS tasks. Unlike most SWAs, if delays have deferred payments for two weeks, claimants are not selected for WPRS. The model has never been updated or revised.

Data Collection Process:

All initial claims are taken in-person. All characteristics necessary to include an individual in the profiling model are captured during the initial claims taking process. The occupational code is determined jointly using the Dictionary of Occupational Titles (DOT) system and O*Net. The claimant's primary employer is determined in a review of work history with the claimant. The following individuals are not eligible for referral to WPRS:

- Claimant who have returned, or are returning to work
- Claimants who are receiving outside similar services or received similar services in the past
- Claimants who are in training
- Claimants referred to existing job openings
- Claimant who have a hardship
- Claimants who have a delay in first payment for two or more weeks

Selection/Referral Process:

WPRS candidates are selected when the model is run against the claimant first payment records. Candidates are selected for services based on their probabilities of exhaustion score, with individuals with the highest probabilities of exhaustion selected first. The list is sent to the local offices by means of the Interempleo System. Local Office Managers determine the number of candidates to be served based upon the personnel available to perform the WPRS tasks.

Profiling Model Structure:

The WPRS profiling model employed by Puerto Rico utilizes a characteristic screen model to estimate benefit exhaustion. The model's dependent variable is duration of benefits, defined as full payment of the maximum benefits amount. However, as indicated on their WPRS survey, Puerto Rico was not able to provide the independent variables used in their characteristic screen model.

Profiling Model Performance:

Puerto Rico did not provide a dataset for data analysis and/or model revision; therefore, we were unable to gauge the performance of its current model.

ANALYSIS OF RHODE ISLAND PROFILING MODEL

Introduction:

Rhode Island (RI) uses a statistical method with a linear functional form to determine a claimant's Worker Profiling and Reemployment Services (WPRS) profiling score. The model is run daily against the claimant first payment file; however, the list of eligible candidates, which is run weekly, is posted on a web server for staff access in three RI One-Stop offices that do profiling. The other three One-Stop offices are participating in the Reemployment Eligibility and Assessment (REA) Program. The model was last updated in 2000; however, it has never been revised.

Data Collection Process:

Initial claims are filed by telephone (65 percent) and Internet (35 percent). Claimant characteristics are captured at the time the initial claim is filed. The North American Industry Classification System (NAICS) is used as the industry classification and is assigned by the agency based on the claimant's last base period employer. This is the only characteristic assigned and verified by the agency. O*NET is used as the occupational classification system. Codes are assigned by staff when the claim is filed by telephone, and when a claimant uses the Internet to file a claim, the codes are self-selected using the O*NET auto coder. The claimant's occupational code is considered to be the occupation in which the claimant is qualified and seeking employment, which is not necessarily the occupational classification of the last job held. The following individuals are not eligible for selection and referral to WPRS:

- Claimants with a definite return-to-work date within 12 weeks of the last day of work
- Claimants collecting partial benefits
- Claimants affiliated with a union hiring hall

Selection/Referral Process:

The list of profiling candidates is placed weekly on a web server and can be accessed by staff at the three RI One-Stop offices that conduct profiling. Local office managers and staff determine the number of candidates to be served. This number is determined by the maximum number of individuals who can be accommodated for an orientation to WPRS. The list is arrayed in rank order with those claimants having the highest likelihood of exhausting benefits at the top of the list. The rankings influence the selection of individuals since these individuals are most likely to need intensive reemployment services to shorten their duration of unemployment. Employment counselors usually select the candidates according to the ranking system. They may skip down the list if they find individuals are “seasonal” (returning to work with the same employer for at least three years).

<u>Profiling Model Structure</u>:

The model’s dependent variable is benefit exhaustion, defined as receipt of maximum benefits paid. Independent variables were not identified.

<u>Profiling Model Performance</u>:

Rhode Island did not provide a dataset for data analysis and/or model revision; therefore, we were unable to gauge the performance of its current model.

ANALYSIS OF SOUTH CAROLINA PROFILING MODEL

Introduction:

South Carolina uses a statistical model, of which the functional form is logistic, to determine a claimant's Worker Profiling and Reemployment Services (WPRS) profiling score. The model is run daily against the initial claims file, and a list of WPRS-eligible claimants is produced and sent to the local offices. The probabilities of exhaustion are computed daily, but the list of candidates, which is sorted by probability of exhaustion, is sent to the local offices weekly. Eligible individuals with a score of 0.40 or higher are also sorted by separation status (e.g., lack of work, voluntary quit, and discharge). Selection listings are arranged in descending order by probabilities of exhaustion; individuals can only be selected or exempted according to their ranking (to be exempted, they must have received similar services in the last 12 months). The model is updated yearly with the last update occurring in March, 2005. The 2006 update is in progress.

The model has never been revised; however, it is updated annually. A 20 percent sample has been consistently used in updating the model. South Carolina has also consistently used exhaustion in its updates, which is defined as maximum benefits paid (i.e., no money remaining in a claimant's benefit year).

Data Collection Process:

Initial claims are filed in-person, by telephone and by Internet. Claimant characteristics data needed for profiling purposes are captured at the time the initial claim is taken. The initial claims taker also assigns the occupational code using the SOC (Standard Occupational Classification) system. The occupational code is based on the broadest work history of the claimant, not necessarily the most recent job. The primary employer is determined through a review of work history with the claimant. The following individuals are not eligible for referral to WPRS services:

- Unemployment Compensation Ex-service Members (UCX) Claimants
- Unemployment Compensation for Federal Employees (UCFE) Claimants
- Claimants who are Job Attached

Selection/Referral Process:

The model is run daily against the claimant initial claim file. Profiling scores are calculated, and they are sent to the local offices weekly (the Monday following the week in which the initial claim is filed). Claimants are sorted by probabilities of exhaustion and reason for separation (lack of work, voluntary quit, and discharge). Candidates for WPRS services can only be selected or exempted (to be exempted, they must have received similar services in the last 12 months) based on their ranking; and they cannot be skipped.

Profiling Model Structure:

The WPRS profiling model employed by South Carolina utilizes a statistical model, of which the functional form is logistic, to estimate benefit exhaustion. The dependent variable is benefit exhaustion, defined as the payment of the maximum benefit amount. The independent variables are as follows:

- Weekly Benefit Amount
- Job Tenure
- Delay in Filing
- Wage Replacement Rate
- Potential Duration of Benefits
- County Unemployment Rate
- Education
- Industry Code
- Occupation Code

Profiling Model Performance:

South Carolina provided the model structure and dataset for data analysis but did not provide useable variables for county unemployment rate and did not provide data that would enable us to calculate exhaustion of benefits. Therefore, we were not able to construct decile tables or model metrics.

ANALYSIS OF SOUTH DAKOTA PROFILING MODEL

Introduction:

South Dakota uses a statistical model, of which the functional form is logistic, to determine a claimant's Worker Profiling and Reemployment Services (WPRS) profiling score. The model is run weekly against the first payment records, and a list of WPRS eligible claimants is created at that time. This list ranks candidates in order from highest probabilities of exhaustion to lowest; local areas cannot skip down the list. All claimants who receive a first payment, regardless of the lag time since filing the initial claim, are included in the model. The list is sent to a Management Analyst in the Administrative Office for distribution to the local offices. The model has never been updated or revised.

Data Collection Process:

Initial claims are filed by telephone and Internet with WPRS eligibility characteristics being captured at that time, except for education and months of work experience. They are retrieved later from Employment Service records. The claimant's occupational code is determined using the Standard Occupational Classification (SOC) system, and the primary employer is determined through a review of Unemployment Insurance (UI) wage records. Individuals not eligible for referral to WPRS services include:

- Claimants who are job attached
- Union members

Selection/Referral Process:

Candidates for the WPRS Program are selected weekly when the model is run against the claimant first payment file. A computer printout is sent to a Management Analyst in the Administrative Office who then distributes it to the appropriate local offices. The list is arrayed by probability of exhaustion. Each local office determines the number of candidates it can serve. The local offices cannot skip individuals on the list.

Profiling Model Structure:

The WPRS profiling model employed by South Dakota utilizes a statistical model, of which the functional form is logistic, to estimate benefit exhaustion. The dependent variable is benefit exhaustion, defined as the payment of the maximum benefit allowance. The independent variables include the following:

- Local Office (coefficient determined by model table)
- County Code (coefficient determined by model table is multiplied by -0.7274)
- County Unemployment Rate and Local Office Cross-term
- Delay in Filing
- O*Net Code
- O*Net and County Code Cross-term
- Standard Industrial Classification (SIC) Code (coefficient is multiplied by 0.25)
- Level of Education
- Years of Experience
- County Unemployment Rate and SIC Cross-term (multiplied by -0.0074)

Profiling Model Performance:

South Dakota provided the model structure and dataset for data analysis but did not provide useable variables for years of experience and local office. South Dakota did provide a variable for referral to reemployment services, but it was not significant, so we did not correct for endogeneity. We calculated a decile table, shown below.

prorigdec	Mean	se(mean)
1	0.130	0.014
2	0.165	0.015
3	0.174	0.016
4	0.180	0.014
5	0.168	0.016
6	0.191	0.020
7	0.166	0.015
8	0.174	0.016
9	0.220	0.018
10	0.288	0.019
Total	0.185	0.005

We also calculated the metric that shows the effectiveness of South Dakota's profiling score. It is shown below.

SWA	Profiling score	Control for endogeneity?	Exhaustion rate for the state	Number of individuals with the highest profiling score	Exhaustion rate for individuals with high profiling scores	Metric	Variance of the Metric	Standard Error of the metric
South Dakota	original score	N**	18.5	1,107	25.6	0.087	0.475	0.021

** SWA provided data indicating individuals who were referred, but the effect was insignificant.

The metric has a value of 0.087 and a standard error of 0.021. The metric is useful because it is significantly greater than 0. The metric provides a basis for comparison with other profiling models.

ANALYSIS OF TENNESSEE PROFILING MODEL

Introduction:

Tennessee uses a statistical model, of which the functional form is logistic, to determine a claimant's Worker Profiling and Reemployment Services (WPRS) profiling score. The model is run weekly against first claimant payment files, and a report of eligible claimants is produced and sent to local job center offices, both electronically and in paper form. The number of candidates to be called in is coordinated between the Job Service and Field Operations staff based upon staffing resources and the number of candidates identified. The score and rank of the individuals are used to determine order of service, without deviation. The model is updated every two or three years; the last update took place in October 2003. The model has not been revised since its implementation.

Data Collection Process:

Initial claims are filed in-person, by telephone, by Internet, or by mail. The survey response did not provide estimates of percentages for each method of filing; however, a review of their website suggests that telephone and in-person filings are the two most significant filing methods. All claimant characteristics required for the WPRS process are captured as part of the initial claim process. There are no checks on the accuracy of the data.

The occupational code is determined by the initial claims taker or a workforce development worker and, if assigned by the UI claims taker, will be a 3-digit Dictionary of Occupational Title (DOT) code. If assigned by a workforce development worker, the entire DOT code will be assigned. The assigned DOT code is matched to a Standard Occupational Classification (SOC) code during the overnight batch process. The occupational code is not used as a variable by the profiling model. A review of UI wage records is performed to determine the industry classification. The following claimants are not eligible for participation in WPRS services:

- Job attached
- Interstate claimants
- Transitional new claims
- Claimants not receiving a first payment

The number of individuals to be called in is determined by the Field Operations staff in conjunction with Job Service staff. The number to be called depends upon (1) the number of candidates on the listing and (2) the number of field staff available at each location. The order of service is determined by the score and rank of the individuals, and it is strictly observed.

<u>Selection/Referral Process</u>:

The WPRS model is run weekly against claimant first payment records. Claimants whose first payments are more than five weeks from the initial claim date are not considered. The listing produced is arrayed with individuals ranked from most likely to least likely to exhaust. The list is sent in paper form to the local job center offices; it is also available in electronic format to both the central and local centers. The number of individuals to be called in is determined by the Field Operations staff in conjunction with Job Service staff. The number to be called in is dependent upon (1) the number of candidates on the listing and (2) the number of field staff available at each location. The order of service is determined by the score and rank of the individuals, without deviation.

<u>Profiling Model Structure</u>:

The WPRS profiling model employed by Tennessee utilizes a statistical model, of which the functional form is logistic, to estimate benefit exhaustion. The dependent variable is benefit exhaustion, defined as maximum benefits paid. The independent variables are as follows:

- Job Tenure
- Month of Claim Initiation
- Category (not defined, assume type of claim)
- Wage Replacement Rate
- Enrollment Period (not defined)
- Vehicle Availability
- Method of Transportation

Profiling Model Performance:

Tennessee provided the model structure and dataset for data analysis, but did not provide coefficients for its variables, so we could not replicate its profiling score. We calculated a decile table, controlled for endogeneity. It is shown below.

prorigdec	Mean	se(mean)
1	0.404	0.007
2	0.460	0.007
3	0.464	0.007
4	0.482	0.007
5	0.488	0.007
6	0.496	0.007
7	0.503	0.007
8	0.524	0.007
9	0.536	0.007
10	0.616	0.007
Total	0.497	0.002

We also calculated the metric that shows the effectiveness of Tennessee's profiling score. It is shown below.

SWA	Profiling score	Control for endogeneity?	Exhaustion rate for the state	Number of individuals with the highest profiling score	Exhaustion rate for individuals with high profiling scores	Metric	Variance of the Metric	Standard Error of the metric
Tennessee	original score	Y	49.7	26,299	53.5	0.075	1.830	0.008

The metric has a value of 0.075 and a standard error of 0.008. The metric is useful because it is significantly greater than 0. The metric provides a basis for comparison with other profiling models.

ANALYSIS OF TEXAS PROFILING MODEL

Introduction:

Texas uses a statistical model, of which the functional form is logistic, to operate its WPRS Program. The model is run weekly against the claimant first-payment file. The list of eligible candidates is produced at that time and is refreshed automatically at the state level and made available to the Local Workforce Development Boards (Boards) via the Rapid Reemployment Services (RRES) computer system. The Boards may access their lists of candidates through a secure access system. The model was both updated and revised in 2003 in coordination with RRES.

Data Collection Process:

Initial claims are filed principally by telephone and Internet. They may also be filed by mail, but that method is rarely used. All of the characteristics necessary to determine eligibility for WPRS are captured at the time of the initial claim. The initial claims taker determines and assigns the claimant's occupational code using the SOC (Standard Occupational Classification) coding system. The primary employer of the claimant is determined through a review of the tax database, and it is determined by whomever the claimant names as the last employer (LEU) in the claim. There are a number of checks that verify the accuracy of information that claimants provide when filing an initial claim, including:

- All claimants must provide their name, date of birth, sex and Social Security account number when filing an Unemployment Insurance (UI) claim. This information is automatically cross-matched with the Social Security Administration (SSA) records to verify that the information provided by the claimant matches the SSA records. If a discrepancy is discovered through the cross-match, an investigation will be initiated to determine the validity of the claim. A claimant will not be paid benefits until the SSA verifies the accuracy of the information provided by the claimant or the Texas Workforce Commission (TWC), or the claimant corrects errors in the record.
- All claimants are asked to provide their Texas Driver's License (TDL) or Texas Identification (TID) number when filing an initial claim. The information is not required to file a claim, but if it is provided, the name, date of birth and TDL or TID number are automatically cross-matched with the Texas Department of Public Safety (DPS) records to verify the accuracy and authenticity of the information provided by the claimant. TWC will initiate an investigation to determine the validity of the identity of the claimant when the DPS cross-match indicates a discrepancy.

- All individuals filing claims are asked if they are citizens of the United States (US). Individuals who are not citizens are required to submit documentation from the Immigration and Naturalization Service (INS) that they have entered the US legally for the purposes of employment. The INS registration number provided by the non-citizen claimant is cross-matched with INS records to verify its authenticity and the claimants' legal status to work in the US. Any discrepancies in the INS registration number and/or records will initiate an investigation into the accuracy of the information provided by the claimant and the validity of the claim.
- Claimants are required to provide a mailing address when filing an initial claim. The address information is verified through a cross-match with the United States Postal Service (USPS) records. The cross-match verifies that the address is a standardized or valid address according to USPS records.
- Claimants list the name of the person or entity that they last worked for prior to filing the initial claim. A notice of application for benefits is mailed to the LEU named by the claimant. The notice to the employer includes the dates that the claimant worked and the reason for separation. The employer has an opportunity to either confirm or dispute any employment information provided by the claimant.

The following individuals are not eligible for WPRS services:

- Claimants who are not required to perform work search
- Claimants have union hall status
- Claimants have a definite return-to-work date

<u>Selection/Referral Process</u>:

The list of WPRS eligible candidates is produced at the same time that the model is run against the first payment file. The list is refreshed automatically at the state level and made available to the Local Workforce Development Boards (Boards) via the RRES computer system. Boards have access to it through a secure network. Each Board chooses the number of profiled candidates to be served based on the capacity of the workforce centers. The model ranks individuals beginning with the highest to lowest probabilities of exhaustion. Boards must select candidates with the highest score and work down the list in descending order.

Profiling Model Structure:

Texas uses a statistical model, of which the functional form is logistic, to operate its WPRS Program. The dependent variable is benefit exhaustion, defined as maximum benefits paid. The independent variables are:

- Potential Duration of Benefits
- Job Tenure
- Delay in Filing
- Metroplex Economic Region
- Log of Weekly Benefit Amount
- Log of Average Weekly Wage
- COG-level Unemployment Rate
- Need for Public Transportation
- Industry Code
- Occupation Code

Profiling Model Performance:

Texas provided the model structure and dataset for data analysis. Our first step in analyzing both the model used and the data was to order the provided profiling scores into a decile table as shown below. The decile means (the average for each group representing 10 percent) in this table are calculated by dividing the percentage of recipients that exhaust UI benefits for a given decile by 100. For example, in the first decile our mean is 0.3120462, which indicates that approximately 31 percent of benefit recipients in this decile exhausted benefits.

Decile	Mean	Standard Error (Mean)
1	.312	.0023265
2	.379	.0024018
3	.415	.0024895
4	.426	.0024906
5	.461	.0025132
6	.478	.0024786
7	.511	.0025492
8	.547	.0024834
9	.596	.0024753
10	.678	.0023531
Total	.480	.0007935

After creating this decile table, we attempted to replicate these scores using the data and coefficients for the variables given in the document "Rapid Reemployment Model." We were able to identify all variables from the dataset provided. However, there were two factors that limited our ability to replicate the given profiling score. First, there was no constant provided with the model. To address this, through trial and error of picking constant values, we estimated a constant for the model to be 0.2775. This enabled us to replicate the profiling scores for most cases. Second, there were 433 cases, out of a sample of 396,447, for which data were missing. Therefore, our analysis will be based on the 396,014 cases for which we have complete information.

Even for the cases with complete information, our replication of the SWA profiling score was significantly different from that which the SWA provided; there may be two reasons for this difference. First, the given coefficients were rounded off to two or three significant digits. For a model with 19 variables, this rounding could, in some cases, make a large difference in the estimated profiling score. However, there remained some cases with large differences. Second, there may be cases for which data were not accurate. Therefore, we assume that some individuals may have inaccurate information for at least one variable.

Texas included a binary variable indicating whether or not benefit recipients were referred to reemployment services; therefore, we were able to test for endogeneity within the data regarding whether referral to reemployment services had an effect on the exhaustion of benefits. We proceed with the assumption that the given profiling score is what Texas used in its WPRS referral system for 2003.

By adjusting our original scores with a control variable for endogeneity, we estimated the true exhaustion rate for the original score. Taking the predictions of the model, ordering them and dividing into deciles, and then for each decile, showing the actual exhaustion rate, with its standard error, we obtain the following table. This decile table demonstrates the effectiveness of each model.

Decile	Mean	Standard Error (Mean)
1	.312	.0023235
2	.378	.0024286
3	.416	.0024553
4	.426	.0025116
5	.461	.0025031
6	.479	.0024943
7	.51	.0025307

8	.546	.0024918
9	.597	.0024683
10	.677	.0023529
Total	.48	.0007935

The decile means are calculated by dividing the percentage of recipients that exhaust benefits for a given decile by 100. For example, in the first decile our mean is 0.312, which indicates that approximately 31 percent of benefit recipients in this decile exhausted benefits.

Using the dataset provided, we continued our analysis of Texas' profiling model by creating three models – an updated, a revised, and a Tobit model. For each of the models, new profiling scores were created, ranked, and divided into deciles. The table below shows the decile gradient for each of our models (detailing the mean for each decile) and includes the decile gradient for the original model for reference. From the table, we see that there was no improvement between the original and updated models in terms of decile gradient changes.

Decile	Original Score	Original score (Adjusted for Endogeneity)	Updated score	Revised score	Tobit score
1	.312	.312	.316	.308	.312
2	.379	.378	.374	.367	.37
3	.415	.416	.406	.404	.405
4	.426	.426	.435	.434	.434
5	.461	.461	.456	.463	.463
6	.478	.479	.482	.486	.484
7	.511	.51	.513	.513	.509
8	.547	.546	.543	.542	.542
9	.596	.597	.597	.598	.595
10	.678	.677	.676	.682	.685
Total	.48	.48	.48	.48	.48

In addition, we tested the performance of each model using the following metric:

Percent exhausted of the top 48 percent of individuals in the score.

We used 48 percent because the exhaustion rate for benefit recipients in the dataset provided by Texas was 48 percent. This metric value will vary from about 48 percent, for a score that is a random draw, up to 100 percent for a score that is a perfect predictor of exhaustion. The scores for the four models are as follows:

Score	% exhausted of those with the top 48% of score	Standard error of the score
Original	56.57	0.0011353
Updated	56.65	0.001136
Revised	56.87	0.0011353
TOBIT	56.73	0.0011357

In the metric below, *"Exhaustion"* is the percentage of all benefit recipients in our sample that exhaust benefits. For Texas, "Exhaustion" is 48 percent since the exhaustion rate for all benefit recipients in the dataset was 48 percent. In our metric, "Pr[*Exh*]" is determined by the model with the highest percentage of benefit exhaustees with profiling scores falling in the top X percent of the sample, where X percent is determined by the exhaustion rate for all benefit recipients in the sample. For Texas, "Pr[*Exh*]" is represented by the revised model with a score of 56.87 percent for benefit recipients that exhaust benefits with scores falling in the top 48 percent.

$$\text{Metric:}\ \ 1 - \frac{100 - \Pr[Exh]}{100 - Exhaustion}$$

We used the numbers above to calculate a score of 0.165 for the original profiling score (corrected for endogeneity) and a score of 0.170 for the revised score.

SWA	Profiling score	Control for endogeneity?	Exhaustion rate for the state	Number of individuals with the highest profiling score	Exhaustion rate for individuals with high profiling scores	Metric	Variance of the Metric	Standard Error of the metric
Texas	original score	Y	48.0	190,270	56.6	0.165	1.555	0.003
Texas	revised score	Y	48.0	190,270	56.9	0.170	1.545	0.003

These metrics show that the revised model is significantly better that the original score. The metrics also show a baseline on which other models can improve. Further analysis of Texas' model is in the expanded analysis section.

ANALYSIS OF UTAH PROFILING MODEL

Introduction:

Utah uses a statistical model, of which the functional form is logistic, to determine a claimant's Worker Profiling and Reemployment Services (WPRS) profiling score. The model is run weekly against the claimant first payment records, and a list of WPRS eligible claimants is produced and sent to a UI Specialist in the Administrative Office through the web-based reporting tool called "Actuate." This list ranks candidates in order from highest probabilities of exhaustion to lowest, and claimants are selected for services by their probability score compared to other claimants in the same geographical region. The number of candidates selected to be served is determined by the Unemployment Insurance (UI) Director based on the number of Employment Counselors in the local office so that they each receive six per year.

A revised model was implemented in April 2004. It has not been updated since then. It replaced an "antiquated" method of referring claimants for UI profiling services. The number of claimants included in the sample for the latest revision is not available. When the model was first estimated, 46,644 benefit recipients were included in the sample. Senior staff in Utah worked with Scott Gibbons in the ETA National Office to develop a logistic regression model that calculates an exhaustion formula based on several customer characteristics. The data warehouse sorts claimants within the program to identify 40 claimants most likely to exhaust benefits.

Data Collection Process:

Initial claims are filed by telephone and via the Internet. All of the claimant characteristics essential to determine an individual's eligibility for WPRS services are captured at the time of the initial claim. The UI automated system checks the accuracy of the claimant's name, date of birth, Social Security account number and wages. The occupational code is assigned by the initial claims taker using the Standard Occupational Classification (SOC) classification system. The industry code is based on a review of wage records. Individuals not eligible for WPRS services include:

- Claimants who have a potential duration of less than 20 weeks
- Claimants who are union attached
- Claimants who are in recall status
- Claimants who are non-Utah residents
- Claimants who have filed additional or reopened claims

Profiling Model Structure:

The WPRS profiling model employed by the Utah utilizes a statistical model, of which the functional form is logistic, to estimate benefit exhaustion. The dependent variable is exhaustion of benefits, defined as claimants who have received their maximum benefits. Independent variables were selected based principally on statistical significance. There were several possible variables that were examined that proved less significant to the model, and they were dropped from consideration. Variables that were selected include:

- Education
- Job Tenure
- Wage Replacement Rate
- High Quarter Earnings Rate
- Claim Filing Time Lapse (delay)
- Industry
- Severance Status
- Month of Filing

Profiling Model Performance:

Utah did not provide a dataset for data analysis and/or model revision; therefore, we were unable to gauge the performance of Utah's current model.

ANALYSIS OF VERMONT PROFILING MODEL

Introduction:

Vermont uses a statistical model, of which the functional form is logistic, to determine a claimant's Worker Profiling and Reemployment Services (WPRS) profiling score. The model is run weekly against the claimant first payment file, and the list of eligible candidates is distributed to the Job Service Offices in hard copy. This list ranks candidates in order from highest to lowest probabilities of exhaustion. The Job Service District Office determines the number to be served, and it cannot skip individuals with higher scores to service those with lower scores.

The model was last revised in March 2005. At that time, the occupational classification system in use was changed to the Standard Occupational Classification (SOC) system and the Weekly Benefit Amount (WBA) was removed as a variable. Initial claimants totaling 27,087 were used as the sample in the revision. In the revision of the model in 2001, 11,291 initial claims filers were included in the sample.

Data Collection Process:

All initial claims are filed by telephone. Claimant characteristics necessary to determine an individual's eligibility for WPRS services are obtained by the initial claims taker who also determines and assigns the occupational code using the SOC classification system. The industry code is obtained from the tax data base. Claimants with a return to work date are not eligible for referral to WPRS services.

Selection/Referral Process:

The WPRS model is run against the claimant first payment file and a list of eligible candidates is produced at that time. Claimants are listed by probability of exhaustion. The list is distributed in hard copy to the Job Service Offices. The Job Service District Office determines the number to be served. Local Office Staff cannot skip individuals with higher scores to service those with lower ones.

Profiling Model Structure:

The WPRS profiling model employed by Vermont utilizes a statistical model, of which the functional form is logistic, to estimate benefit exhaustion. The dependent variable is exhaustion of benefits, defined as maximum benefits paid. The independent variables are as follows:

- Claimant Previously Profiled
- Number of Lag Weeks Since Filing of Initial Claim
- Job Tenure
- Education
- SOC Classification
- Industry Code
- High Quarter Wages

Profiling Model Performance:

Vermont provided the model structure and dataset for data analysis but did not provide coefficients for the variables in its profiling model, so we could not replicate its profiling score. Vermont provided data on referral to reemployment services, but its effect was not significant. We did not control for endogeneity. We calculated a decile table for the original score. It is shown below.

prorigdec	Mean	se(mean)
1	0.219	0.037
2	0.172	0.033
3	0.277	0.039
4	0.252	0.038
5	0.258	0.039
6	0.228	0.037
7	0.326	0.041
8	0.258	0.039
9	0.392	0.044
10	0.457	0.044
Total	0.283	0.013

We also calculated the metric that shows the effectiveness of Vermont's profiling score. It is shown below.

SWA	Profiling score	Control for endogeneity?	Exhaustion rate for the state	Number of individuals with the highest profiling score	Exhaustion rate for individuals with high profiling scores	Metric	Variance of the Metric	Standard Error of the metric
Vermont	original score	N**	28.3	359	37.9	0.133	0.756	0.046

The metric has a value of 0.133 and a standard error of 0.046. The metric is useful because it is significantly greater than 0. The metric provides a basis for comparison with other profiling models.

ANALYSIS OF VIRGINIA PROFILING MODEL

Introduction:

Virginia uses a statistical model, of which the functional form is logistic, to determine a claimant's Worker Profiling and Reemployment Services (WPRS) profiling score. The model is run weekly against the claimant first payment records, and a list of WPRS eligible claimants is sent to local offices via mainframe screens. This list ranks candidates in order from highest probabilities of exhaustion to lowest. All claimants, regardless of probabilities of exhaustion, are shown on the list along with their rankings. In certain cases, local office staff may select candidates with lower rankings who have been posted in the pool for four weeks (they will drop off the list if they are not selected for services). These candidates may be selected before candidates with higher rankings who have just entered the pool and will likely remain in the pool long enough to be called in for services.

The model is currently undergoing its first revision since its inception. It has not been updated to generate new statistical parameters. However, tables containing the explanatory variables of unemployment rate by Service Delivery Area (SDA) and industry growth or decline are updated as Virginia's Economic Information System deems appropriate.

Data Collection Process:

Initial claims are filed in-person, by telephone and by Internet. The initial claims taker assigns the claimant's occupational code using the DOT (Dictionary of Occupational Titles) classification system unless the claim is filed on the Internet. In that case, the claimant self-selects his/her occupational code based on a pop-up list of codes. The industry code is also assigned by claims takers using the SIC (Standard Industrial Classification) system. Previous job position, length of time employed salary, etc., are verified with the employer by use of a "separation statement." Individuals not eligible for referral to WPRS services include:

- Claimants with specific recall dates
- Claimants with union hiring agreements
- Claimants not residing in Virginia

Selection/Referral Process:

The WPRS model is run weekly against the claimant first payment file, and a list of eligible candidates is produced at that time. The list is organized by local office and made available via mainframe screen to all local offices and the central office. Each local office determines the number of claimants that can be served in that office with the gateway service of RSO. While each office strives to serve all eligible candidates, the number of candidates notified depends on the availability of staff and facility resources. Regional coordinators review this activity monthly and quarterly. Claimants with the highest rankings (most likely to exhaust benefits) are selected first. Those with rankings beneath the minimum selection threshold are shown on the list along with their rankings, but they are not part of the pool and thus are not selected for WPRS services. In certain cases, local office staff may select candidates with lower rankings who have been posted in the pool for four weeks and will drop off the list if they are not selected for RSO.

Profiling Model Structure:

The WPRS profiling model employed by Virginia utilizes a statistical model, of which the functional form is logistic, to estimate benefit exhaustion. The dependent variable is benefit exhaustion, defined as maximum benefits paid. The independent variables are as follows:

- Job Tenure (continuous)
- Education
- Occupation
- Unemployment Rate in Local Area
- Industry Growth at the Division Level in the Local Area

Profiling Model Performance:

Virginia provided the model structure and dataset for data analysis but did not provide variables for local unemployment rate and local industry growth, so we could not replicate its profiling score. We calculated a decile table for the original score, controlled for endogeneity. It is shown below.

prorigdec	Mean	se(mean)
1	0.146	0.004
2	0.180	0.004
3	0.243	0.005
4	0.242	0.005
5	0.240	0.004
6	0.236	0.004
7	0.243	0.005
8	0.249	0.005
9	0.217	0.004
10	0.340	0.005
Total	0.233	0.001

We also calculated the metric that shows the effectiveness of Virginia's profiling score. It is shown below.

SWA	Profiling score	Control for endogeneity?	Exhaustion rate for the state	Number of individuals with the highest profiling score	Exhaustion rate for individuals with high profiling scores	Metric	Variance of the Metric	Standard Error of the metric
Virginia	original score	Y	23.3	21,186	27.7	0.057	0.611	0.005

The metric has a value of 0.057 and a standard error of 0.005. The metric is useful because it is significantly greater than 0. The metric provides a basis for comparison with other profiling models.

ANALYSIS OF THE VIRGIN ISLANDS PROFILING MODEL

Introduction:

The Virgin Islands uses characteristic screening to determine a claimant's eligibility for referral to Worker Profiling and Reemployment Services (WPRS). The model is run weekly against the claimant first payment file. First payment claimants are added to a pool of potential profiling candidates on a daily basis. Claimants with the highest probability of exhaustion of benefits are selected for services first. The model has never been updated or revised.

Data Collection Process:

All initial claims are filed in-person. Claimant characteristics essential to determine an individual's eligibility to participate in WPRS services is captured at the initial claim. Individuals must produce suitable identification. A separation notice is obtained from the employer, and the initial claim is checked for accuracy to verify the information provided by the claimant. The occupational code using the Standard Occupational Classification (SOC) system is assigned by a Workforce Development Worker. The claimant's primary employer is assigned based on a review of the claimant's work history. The following individuals are not eligible for participation in WPRS services:

- Job Attached Claimant
- Interstate Claimants
- Claimants on Definite Recall

Selection/Referral Process:

Claimants are selected for participation in the WPRS program when the weekly first payment file is matched with eligible claimants who are added to the pool daily. Claimants with the highest probability of exhaustion must be selected for participation first. The only exception occurs in cases where there may be unresolved non-monetary issues. The UI Service determines the number of candidates to be served by the Reemployment Service based on a Memorandum of Understanding (MOU) between the two services.

Profiling Model Structure:

The WPRS profiling model employed by the Virgin Islands utilizes a characteristic screen model to estimate benefit exhaustion. This characteristic screen eliminates all claimants that are ineligible for referral to reemployment services. The characteristics used to select candidates include:

- Education
- Job Tenure
- Occupation or Industry

Profiling Model Performance:

The Virgin Islands did not provide a dataset for data analysis and/or model revision; therefore, we were unable to gauge the performance of The Virgin Islands' current model.

ANALYSIS OF WASHINGTON PROFILING MODEL

Introduction:

Washington State uses a statistical model, of which the functional form is logistic, to determine a claimant's Worker Profiling and Reemployment Services (WPRS) profiling score. The model is run weekly against the claimant first payment records, and a list of WPRS-eligible claimants is produced and sent to the WorkSource One-Stop Offices using an electronic transfer from GUIDE (General Unemployment Insurance Development Effort) to SKIES (Services, Knowledge and Information Exchange System), which is Washington's One-Stop case management system. This list ranks candidates in order from highest to lowest probabilities of exhaustion, and each WorkSource office determines the number of candidates to be selected. Claimants who have received and/or are participating in the same or similar services are exempt from participation, as are those who have returned to work date or expectation of recall.

The model was last revised in July, 2004. The SWA would like to revise the model annually; however, resources may not always be available to make the revisions. All initial claims filers were included in the most recent model revision sample. This was equal to 321,925 (80 percent) of the initial claims.

Data Collection Process:

Initial claims are filed in-person, by mail, by telephone and via the Internet. Claimant characteristics essential to determine a claimant's eligibility for WPRS are captured at the time the initial claim is filed. Most of the characteristics are obtained from the GUIDE system, thus ensuring greater accuracy of the data. The Dictionary of Occupational Titles (DOT) system, with a crosswalk to O*Net, is used as the occupational classification system. The initial claims taker assigns the occupational code. The following individuals are not eligible to participate in the WPRS Program:

- Claimants who are partially unemployed
- Claimants who are participating in the Shared Work Program
- Claimants on standby
- Claimants who are on full referral to jobs through a union
- Claimants participating in Commissioner Approved Training (CAT)
- Claimants who are on Total Temporary Disability

Profiling Model Structure:

The WPRS profiling model employed by Washington utilizes a statistical model, of which the functional form is logistic, to estimate benefit exhaustion. The dependent variable is benefit exhaustion, defined as maximum benefits paid. Independent variables were not identified.

Profiling Model Performance:

Washington State did not provide a dataset for data analysis and/or model revision; therefore, we were unable to gauge the performance of Washington's current model.

ANALYSIS OF WEST VIRGINIA PROFILING MODEL

Introduction:

West Virginia uses a statistical model, of which the functional form is logistic, to determine a claimant's Worker Profiling and Reemployment Services (WPRS) profiling score. The model is run weekly against the claimant first payment file and candidates are selected and placed on a list for participation at that time. The list is sent to staff in the Administrative Office who have oversight responsibility for the WPRS Program and Local Office staff who receive a paper report listing the claimants selected for participation, including the date of their scheduled interview, etc.

During the third quarter of 2001, a new profiling model was implemented. The prior model used six independent variables but consisted of several individual models. The model now in use has 10 predictive variables that have been condensed into one model. In this revision, a sample of 69,612 benefit recipients was used. Two-thirds of the benefit recipients were used to build the model and the other one-third was used to test and verify the outcomes. In conducting the revision, in addition to analyzing historical independent variables, other potential ones, including Workforce Investment Act (WIA) regions and wage replacement rates, were also reviewed and analyzed.

Data Collection Process:

Initial claims are taken in-person. Claimant characteristics necessary to determine an individual's eligibility for WPRS services are obtained during the initial claims taking process. Several of the characteristics provided by the claimant are able to be checked for accuracy, including:

- Social Security numbers (SSN) through a crossmatch with the Social Security Administration
- North American Industry Classification System (NAICS) code through a check with the UI Wage Record System
- Also, several of the characteristics must be entered in order for the claim to be posted to the UI System.

The initial claims taker assigns the individual's occupational code using the Standard Occupational Classification (SOC) system classification system. The NAICS classification system is used to determine the claimant's proper industry, and it is based on an interview with the individual and a review of the UI Wage Records. The following individuals are not eligible for referral to WPRS services:

- Claimants who obtain work through a union hiring hall.

- Claimants who have a definite recall date
- Claimants who have been selected and offered a Personal Reemployment Account (PRA)
- Claimants who have a partial claim
- Claimants who have been profiled within the last 270 days

Selection/Referral Process:

At the same time that the WPRS model was being revised, it was decided that Job Service offices will use the Resource Allocation method when scheduling claimants for profiling services. This serves a two-fold purpose. First, the 50 percent exhaustion probability threshold has been eliminated which allows everyone scored to be placed in the pool. Secondly, this requires each office to specify the number of candidates to be served each week.

The profiled list is provided on a paper report showing the claimants who were selected along with their interview date, etc. These reports are usually printed automatically in each local office, but if necessary, they can be printed in the central office. Claimants are ranked by probability of exhaustion, and they are selected in that order automatically – staff cannot bypass individuals on the list. Job Service Offices determine the number of candidates to be called-in each week, based on workload and capacity and input the number into the automated system.

Profiling Model Structure:

West Virginia uses a statistical model, of which the functional form is logistic, to estimate benefit exhaustion. The dependent variable is benefit exhaustion, defined as maximum benefits paid. The independent variables include:

- Weekly benefit amount
- Wage base*
- Tenure
- Reopens*
- SOC – 3 digit (formerly occupation with former employer)
- NAICS – 3 digit (formerly industry of former employer)
- Education
- Benefit Year Begin Month (old model had only January seasonal factor)

- File lag*
- Other income*

* - New variables in the 2001 model

Profiling Model Performance:

West Virginia provided the model structure and dataset for data analysis. Our first step in analyzing both the model used and the data was to order the provided profiling scores into a decile table as shown below. The decile means (the average for each group representing 10 percent) in this table are calculated by dividing the percentage of recipients that exhaust UI benefits for a given decile by 100. For example, in the first decile our mean is 0.2116, which indicates that approximately 21 percent of benefit recipients in this decile exhausted benefits.

Decile	Mean	Standard Error (Mean)
1	.2116266	.0069132
2	.2552277	.0073801
3	.3091898	.0078209
4	.3562428	.0081051
5	.37611	.0081997
6	.4039508	.0083036
7	.4428531	.0084082
8	.4696101	.0084516
9	.4801031	.0084545
10	.5611923	.0084024
Total	.3865895	.0026062

After creating this decile table, we replicated the original profiling scores. We were able to identify all variables from the dataset provided. Our replicated SWA profiling score was correlated with the original score at 0.9277.

West Virginia included a binary variable indicating whether or not benefit recipients were referred to reemployment services; therefore, we were able to test for endogeneity within the data regarding whether referral to reemployment services had an effect on the exhaustion of benefits.

By adjusting our original scores with a control variable for endogeneity, we estimated the true exhaustion rate for the original score. Taking the predictions of the model, ordering them and dividing into deciles, and then for each decile, showing the actual exhaustion rate, with its standard error, we obtain the following table. This decile table demonstrates the effectiveness of each model.

Decile, original score corrected for endogeneity	Mean	Standard Error (Mean)
1	.2124857	.0069234
2	.25666	.0073937
3	.3070979	.007805
4	.3553009	.0081026
5	.382235	.0082267
6	.3981667	.0082862
7	.4372852	.0083956
8	.4743626	.0084525
9	.4800917	.0084569
10	.5623031	.0083977
Total	.3865895	.0026062

We continued our analysis of West Virginia's profiling model by creating two models – an updated and a revised model. We could not create a Tobit model because there was no way to calculate the proportion of benefits remaining in individuals' UI benefit accounts. For each of the models, new profiling scores were created, ranked, and divided into deciles. The table below shows the decile gradient for each of our models (detailing the mean for each decile) and includes the decile gradient for the original model for reference. From the table, we see that there was significant improvement between the original and updated models but no improvement for the revised model.

Decile	Original Score	Original score (Adjusted for Endogeneity)	Updated score	Revised score
1	.2160804	.2135395	.175957	.1796508
2	.2632411	.2686275	.2437878	.259906
3	.3236351	.3225689	.2971793	.3270651
4	.3774373	.3756047	.3399395	.3557272
5	.3924802	.3968833	.3895232	.3841504
6	.4150641	.4106452	.4308261	.4378778
7	.4629278	.4558684	.4662412	.4685925
8	.4799627	.4879032	.5238415	.5063801
9	.4918478	.4909475	.5815984	.5503694
10	.5734245	.5737608	.6536782	.6328519
Total	.4102495	.4102495	.4102495	.4102495

In addition, we tested the performance of each model using the following metric:

Percent exhausted of the top 41 percent of individuals in the score.

We used 41 percent because the exhaustion rate for benefit recipients in the dataset provided by West Virginia was 41 percent. This metric value will vary from about 41 percent, for a score that is a random draw, up to 100 percent for a score that is a perfect predictor of exhaustion. The scores for the four models are as follows:

Score	% exhausted of those with the top 41% of score	Standard error of the score
Original	.50692	.0045245
Adapted	.5070042	.0045252
Updated	.5536899	.0044991
Revised	.5373904	.0045126

In the metric below, *"Exhaustion"* is the percentage of all benefit recipients in our sample that exhaust benefits. For West Virginia, "Exhaustion" is 41 percent since the exhaustion rate for all benefit recipients in the dataset was 41 percent. In our metric, "Pr[*Exh*]" is determined by the model with the highest percentage of benefit exhaustees with profiling scores falling in the top X percent of the sample, where X pecent is determined by the exhaustion rate for all benefit recipients in the sample. For West Virginia, "Pr[*Exh*]" is represented by the updated model with a score of 55.37 percent for benefit recipients that exhaust benefits with scores falling in the top 41 percent.

$$\text{Metric: } 1 - \frac{100 - \Pr[Exh]}{100 - Exhaustion}$$

We used the numbers above to calculate a score of 0.164 for the original profiling score (corrected for endogeneity) and a score of 0.243 for the updated score.

SWA	Profiling score	Control for endogeneity?	Exhaustion rate for the state	Number of individuals with the highest profiling score	Exhaustion rate for individuals with high profiling scores	Metric	Variance of the Metric	Standard Error of the metric
West Virginia	original score	Y	41.0	12,209	50.7	0.164	1.205	0.010
West Virginia	updated score	Y	41.0	12,209	55.4	0.243	1.109	0.010

These metrics show that the updated model is significantly better that the original score. The metrics also show a baseline on which other models can improve. Further analysis of West Virginia's model is in the expanded analysis section.

ANALYSIS OF WISCONSIN PROFILING MODEL

Introduction:

Wisconsin uses a statistical model, of which the functional form is logistic, to determine a claimant's Worker Profiling and Reemployment Services (WPRS) profiling score. The model is run weekly against the claimant first payment file with selection for participation made centrally when requested by local centers. The resulting list ranks candidates in order from highest to lowest probabilities of exhaustion and local areas have no input or influence in the selection. The model has never been updated or revised. It has been in use since 1994, when WPRS was initiated.

Data Collection Process:

Initial claims are filed by telephone and Internet. Claimant characteristics necessary to determine an individual's eligibility for WPRS services are obtained during the initial claims taking process. Student status, union hiring hall (in good standing), and early recall with an employer are verified. The initial claims taker determines the occupational code using the Standard Occupational Classification (SOC) system. A review of UI wage records is performed to determine the industry classification. The following individuals are not eligible for participation in WPRS services:

- Union hiring hall
- Student status
- Partially employed
- Recall pending

Selection/Referral Process:

Individuals are determined eligible for WPRS services when the model is run weekly against the claimant first payment file. Selection is made centrally by profiling score in the One-Stop site ZIP code area. The only decision local staff can make is the number and frequency of group sessions that can be accommodated. This is principally determined by staff and facility availability.

Profiling Model Structure:

The WPRS profiling model employed by Wisconsin utilizes a statistical model, of which the functional form is logistic, to estimate benefit exhaustion. The dependent variable is benefit exhaustion, defined as maximum benefits paid. The independent variables are as follows:

- Tenure with Primary Employer
- Total Unemployment Rate in County
- Occupation
- Education
- Industry

Profiling Model Performance:

Wisconsin provided the model structure and dataset for data analysis but did not provide coefficients for the variables used in their model, so we could not replicate its profiling score. Wisconsin did not provide a variable for referral to reemployment services, so we could not control for endogeneity. We calculated a decile table for the original score. It is shown below.

prorigdec	Mean	se(mean)
1	0.375	0.011
2	0.422	0.011
3	0.433	0.011
4	0.437	0.011
5	0.457	0.011
6	0.446	0.011
7	0.473	0.011
8	0.508	0.011
9	0.434	0.008
Total	0.442	0.003

Note that there were some individuals with the same profiling score, so we were not able to generate 10 separate categories. We also calculated the metric that shows the effectiveness of Wisconsin's profiling score. It is shown below.

SWA	Profiling score	Control for endogeneity?	Exhaustion rate for the state	Number of individuals with the highest profiling score	Exhaustion rate for individuals with high profiling scores	Metric	Variance of the Metric	Standard Error of the metric
Wisconsin	original score	N	44.2	8,991	46.2	0.036	1.533	0.013

The metric has a value of 0.036 and a standard error of 0.013. The metric is useful because it is significantly greater than 0. The metric provides a basis for comparison with other profiling models.

ANALYSIS OF WYOMING PROFILING MODEL

<u>Summary</u>:

Wyoming uses a statistical model with a discriminant analysis functional form to select individuals for participation in the WPRS Program. The model is run weekly against the initial claim file, and a list of eligible candidates is produced at that time. The list is then sent to the profiling coordinator in the SWA claims center for review and distribution to the local offices. The model is revised every two or three years. As part of the 2001 revision, the logistic regression previously used was changed to a discriminant analysis statistical model. In July, 2005, the most recent update occurred when the coefficients were updated with more current database information to reflect current economic conditions.

<u>Data Collection Process</u>:

Initial claims are filed in-person, by telephone, by mail, and by Internet. The most prevalent method is telephone filing with 82 percent of the claimants using it. Claimant characteristics are captured at the time the initial claim is taken. The initial claims taker assigns the occupational code using the SOC classification system. The primary employer is determined based on information provided by the claimant and then verified through the wage record system. Additional checks on the accuracy of information provided by the claimant are done through a crossmatch with the Social Security Administration. Following a notification to the employer that a former employee has filed a claim, Benefit Accuracy Measurement (BAM) reviews, and benefit payment control crossmatch. The following individuals are not eligible for referral to WPRS services:

- The claimant is a member of a union or hiring hall or is job attached
- The claimant is filing an interstate claim which is not Wyoming liable
- The claimant worked for his/her last employer for less than 52 weeks
- The claimant is filing a continued or additional claim
- The claimant with any of the variables requested by the model equals zero

<u>Selection/Referral Process</u>:

Candidates for referral to WPRS services are selected weekly when the model is run against the initial claims payment file. A list of individual candidates is provided to the profiling coordinator in the SWA claims center who reviews it prior to distributing it to local offices. In the review, the coordinator may exclude and delete from the list, the following claimants:

- Individuals who have received similar services
- Individuals who have returned to work
- Individuals who have moved out of state
- Individuals who are monetarily not eligible or not likely to become eligible

The list is arrayed by probability of exhaustion ranked from highest to lowest. Claimants are included in the pool when their probability of exhaustion equals or exceeds 60 percent.

Profiling Model Structure:

The WPRS profiling model employed by Wyoming utilizes a statistical model with a discriminant analysis functional form to estimate benefit exhaustion. The dependent variable is benefit exhaustion, which is determined by a final payment indicator flag that is set for the initial claimant. The independent variables are as follows:

- Natural Log of Job Tenure
- Natural Log of Delay in Filing
- Number of Employers
- Weeks Eligible for Benefits
- Unemployment Rate for Industry
- Whether Claimant was Employed in a Declining Industry
- Month Claim is Filed
- NAICS Industry Code
- Total Unemployment Rate in County

Profiling Model Performance:

Wyoming provided the model structure and dataset for data analysis. We were able to replicate the original profiling score, but the sample size was too small (N=107) to merit further analysis. Wyoming did provide a variable for referral to reemployment services, but its effect was insignificant. There was no need to control for endogeneity. We calculated a decile table for the original score. It is shown below.

prorigdec	N	mean	se(mean)
1	8	0.500	0.189
2	12	0.333	0.142
3	10	0.300	0.153
4	10	0.500	0.167
5	14	0.500	0.139
6	8	0.375	0.183
7	12	0.500	0.151
8	9	0.667	0.167
9	11	0.273	0.141
10	13	0.462	0.144
Total	107	0.439	0.048

We also calculated the metric that shows the effectiveness of Wyoming's profiling score. It is shown below.

SWA	Profiling score	Control for endogeneity?	Exhaustion rate for the state	Number of individuals with the highest profiling score	Exhaustion rate for individuals with high profiling scores	Metric	Variance of the Metric	Standard Error of the metric
Wyoming	original score	N**	43.9	47	46.8	0.051	1.497	0.178

** SWA provided data indicating individuals who were referred, but the effect was insignificant.

The metric has a value of 0.051 and a standard error of 0.178. The metric is not useful because it is not significantly greater than 0. The metric provides a basis for comparison with other profiling models. A better model would generate a higher metric.

APPENDIX D: EXPANDED ANALYSES FOR 9 SWAS

In this section, we provide detailed analysis that includes all the elements described above in the Chapter on extended data analysis. These analyses represent our best attempt to improve upon the methodology for generating effective profiling scores.

We include here extended analyses for all SWAs for which we could replicate the given profiling score and exhaustion status. That means the SWA provided data for all variables used in its profiling score and all coefficients for variables, and that SWAs provided data on whether the individuals exhausted benefits. There is one exception to this rule: Wyoming. Because Wyoming only had 107 individuals with full information, there were not enough degrees of freedom to conduct a useful analysis.

Included here are extended analyses for:

- Arkansas
- District of Columbia
- Georgia
- Hawaii
- Idaho
- New Jersey
- Pennsylvania
- Texas
- West Virginia

The analyses and statistics are described above. Our analyses minimize the text. They are very table-intensive.

Decile Tables for 28 SWAs

The Table below contains decile tables for 28 SWAs. The tables were formed by first ranking all individuals in the sample by profiling score and then dividing the sample into 10 equal groups. For each group, we calculated the mean rate of exhaustion of UI benefits for the group. The tables include the standard error of each exhaustion rate. For most SWAs, the table includes only the original score, and if possible, the score was corrected for endogeneity. For nine states for which we conducted expanded analyses, we include two decile tables: one for the original score and one for the best other score that we calculated – usually the revised model score.

Arizona

prorigdec	mean	se(mean)
1	0.350	0.006
2	0.330	0.006
3	0.348	0.006
4	0.346	0.006
5	0.341	0.006
6	0.375	0.006
7	0.373	0.006
8	0.400	0.006
9	0.418	0.007
10	0.508	0.007
Total	0.379	0.002

Arkansas

Original score

scoredec	mean	se(mean)
1	0.379	0.007
2	0.462	0.007
3	0.467	0.007
4	0.484	0.007
5	0.472	0.007
6	0.491	0.007
7	0.496	0.007
8	0.522	0.007
9	0.577	0.007

Revised score

prrevdec	mean	se(mean)
1	0.326	0.006
2	0.414	0.007
3	0.426	0.007
4	0.471	0.007
5	0.477	0.007
6	0.503	0.007
7	0.535	0.007
8	0.552	0.007
9	0.606	0.007

10	0.647	0.007
Total	0.499	0.002

10	0.685	0.006
Total	0.499	0.002

Delaware

Estimated score

predscoredec	mean	se(mean)
1	0.350	0.014
2	0.318	0.014
3	0.419	0.015
4	0.383	0.015
5	0.365	0.015
6	0.375	0.015
7	0.394	0.015
8	0.404	0.015
9	0.415	0.015
10	0.475	0.015
Total	0.390	0.005

District of Columbia

Original score

scoredec	mean	se(mean)
1	0.416	0.016
2	0.501	0.016
3	0.533	0.016
4	0.543	0.016
5	0.598	0.016
6	0.541	0.016
7	0.582	0.016
8	0.596	0.016
9	0.644	0.015
10	0.649	0.016
Total	0.560	0.005

Revised score

prrevdec	mean	se(mean)
1.000	0.341	0.015
2.000	0.469	0.016
3.000	0.492	0.016
4.000	0.511	0.016
5.000	0.560	0.016
6.000	0.602	0.016
7.000	0.607	0.016
8.000	0.629	0.016
9.000	0.658	0.015
10.000	0.732	0.014
Total	0.560	0.005

Georgia

Original score

prorigdec	mean	se(mean)
1	0.269	0.003
2	0.319	0.003
3	0.313	0.003
4	0.294	0.004
5	0.286	0.003
6	0.336	0.003
7	0.336	0.003
8	0.404	0.004
9	0.487	0.004
10	0.526	0.004
Total	0.357	0.001

Revised score

prrevdec	mean	se(mean)
1	0.175	0.003
2	0.233	0.003
3	0.276	0.003
4	0.309	0.003
5	0.345	0.003
6	0.374	0.003
7	0.402	0.003
8	0.438	0.004
9	0.499	0.004
10	0.518	0.004
Total	0.357	0.001

Hawaii

Original score

prorigdec	mean	se(mean)
1	0.327	0.016
2	0.314	0.016
3	0.376	0.016
4	0.376	0.016
5	0.405	0.016
6	0.389	0.016
7	0.406	0.016
8	0.423	0.017
9	0.457	0.017
10	0.467	0.017
Total	0.394	0.005

Revised score

prrevdec	mean	se(mean)
1	0.308	0.015
2	0.319	0.016
3	0.338	0.016
4	0.385	0.016
5	0.373	0.016
6	0.422	0.016
7	0.423	0.017
8	0.418	0.016
9	0.454	0.017
10	0.499	0.017
Total	0.394	0.005

Idaho

Estimated score

prorigdec	mean	se(mean)
1	0.412	0.008
2	0.394	0.008
3	0.365	0.008

Revised score

prrevdec	mean	se(mean)
1	0.216	0.007
2	0.297	0.008
3	0.359	0.008

4	0.360	0.008
5	0.350	0.008
6	0.362	0.008
7	0.439	0.009
8	0.550	0.009
9	0.650	0.008
10	0.710	0.008
Total	0.459	0.003

4	0.392	0.008
5	0.425	0.008
6	0.459	0.009
7	0.500	0.009
8	0.566	0.009
9	0.642	0.008
10	0.734	0.008
Total	0.459	0.003

Iowa

prorigdec	mean	se(mean)
1	0.145	0.008
2	0.152	0.004
8	0.162	0.010
9	0.156	0.010
10	0.170	0.010
Total	0.154	0.003

Louisiana

prorigdec	mean	se(mean)
1	0.325	0.006
2	0.322	0.006
3	0.341	0.006
4	0.383	0.007
5	0.407	0.007
6	0.383	0.007
7	0.477	0.007
8	0.500	0.007
9	0.505	0.007
10	0.621	0.007
Total	0.426	0.002

Maine

prorigdec	mean	se(mean)
1	0.275	0.010
2	0.319	0.010
3	0.342	0.011

4	0.353	0.011
5	0.368	0.011
6	0.390	0.011
7	0.387	0.011
8	0.382	0.011
9	0.416	0.011
10	0.503	0.011
Total	0.373	0.003

Maryland

prorigdec	mean	se(mean)
1	0.527	0.007
2	0.546	0.004
7	0.441	0.011
8	0.424	0.010
9	0.435	0.009
10	0.410	0.012
Total	0.504	0.003

Michigan

prorigdec	mean	se(mean)
1	0.536	0.005
2	0.559	0.005
3	0.525	0.005
4	0.433	0.005
5	0.434	0.005
6	0.476	0.005
7	0.500	0.005
8	0.541	0.005
9	0.580	0.005
10	0.690	0.004
Total	0.527	0.001

Minnesota

prorg2dec	mean	se(mean)
1	0.152	0.003
2	0.227	0.004

3	0.262	0.004
4	0.307	0.004
5	0.353	0.004
6	0.366	0.004
7	0.385	0.005
8	0.398	0.004
9	0.439	0.005
10	0.492	0.005
Total	0.336	0.001

Mississippi

prorigdec	mean	se(mean)
1	0.457	0.012
2	0.431	0.012
3	0.443	0.012
4	0.436	0.012
5	0.429	0.012
6	0.451	0.012
7	0.455	0.012
8	0.489	0.012
9	0.481	0.012
10	0.478	0.012
Total	0.455	0.004

Missouri

prorigdec	mean	se(mean)
1	0.364	0.008
2	0.410	0.007
3	0.448	0.008
4	0.472	0.008
5	0.483	0.008
6	0.512	0.008
7	0.542	0.008
8	0.557	0.008
9	0.611	0.008
10	0.694	0.008
Total	0.506	0.003

Montana

prorg2dec	mean	se(mean)
1	0.419	0.028
2	0.479	0.028
3	0.463	0.028
4	0.508	0.028
5	0.527	0.028
6	0.505	0.028
7	0.567	0.028
8	0.570	0.028
9	0.624	0.027
10	0.678	0.026
Total	0.534	0.009

Nebraska

prorigdec	mean	se(mean)
1	0.915	0.004
2	0.933	0.004
3	0.934	0.004
4	0.932	0.004
5	0.952	0.003
6	0.963	0.003
7	0.966	0.003
8	0.970	0.003
9	0.974	0.002
10	0.984	0.002
Total	0.952	0.001

New Jersey

Original score

Decile	Mean	se(mean)
1	0.499	0.004
2	0.567	0.004
3	0.592	0.004
4	0.608	0.004
5	0.629	0.004
6	0.644	0.004
7	0.653	0.004

Revised score

Decile	Mean	se(mean)
1	0.481	0.004
2	0.540	0.004
3	0.565	0.004
4	0.582	0.004
5	0.612	0.004
6	0.631	0.004
7	0.643	0.004

8	0.669	0.004
9	0.691	0.003
10	0.690	0.003
Total	0.624	0.001

8	0.676	0.004
9	0.716	0.003
10	0.797	0.003
Total	0.624	0.001

New York

prorigdec	mean	se(mean)
1	0.143	0.002
2	0.223	0.002
3	0.283	0.002
4	0.353	0.002
5	0.397	0.002
6	0.434	0.002
7	0.492	0.002
8	0.531	0.002
9	0.570	0.002
10	0.639	0.002
Total	0.404	0.001

Pennsylvania

Original score

prorigdec	mean	se(mean)
1	0.326	0.003
2	0.394	0.003
3	0.417	0.003
4	0.456	0.003
5	0.479	0.003
6	0.490	0.003
7	0.508	0.003
8	0.494	0.003
9	0.517	0.003
10	0.541	0.003
Total	0.461	0.001

Revised score

prrevdec	mean	se(mean)
1	0.284	0.003
2	0.378	0.003
3	0.426	0.003
4	0.459	0.003
5	0.470	0.003
6	0.490	0.003
7	0.488	0.003
8	0.515	0.003
9	0.533	0.004
10	0.577	0.003
Total	0.461	0.001

South Dakota

prorigdec	mean	se(mean)
1	0.130	0.014

2	0.165	0.015
3	0.174	0.016
4	0.180	0.014
5	0.168	0.016
6	0.191	0.020
7	0.166	0.015
8	0.174	0.016
9	0.220	0.018
10	0.288	0.019
Total	0.185	0.005

Tennessee

prorigdec	mean	se(mean)
1	0.404	0.007
2	0.460	0.007
3	0.464	0.007
4	0.482	0.007
5	0.488	0.007
6	0.496	0.007
7	0.503	0.007
8	0.524	0.007
9	0.536	0.007
10	0.616	0.007
Total	0.497	0.002

Texas

Original score

prorigdec	mean	se(mean)
1	0.313	0.002
2	0.378	0.002
3	0.416	0.002
4	0.426	0.003
5	0.462	0.003
6	0.479	0.002
7	0.510	0.003
8	0.547	0.002
9	0.597	0.002
10	0.678	0.002
Total	0.480	0.001

Revised score

prrevdec	mean	se(mean)
1	0.309	0.002
2	0.368	0.002
3	0.404	0.002
4	0.434	0.002
5	0.463	0.003
6	0.486	0.003
7	0.514	0.003
8	0.543	0.003
9	0.599	0.002
10	0.683	0.002
Total	0.480	0.001

Vermont

scoredec	mean	se(mean)
1	0.219	0.037
2	0.172	0.033
3	0.277	0.039
4	0.252	0.038
5	0.258	0.039
6	0.228	0.037
7	0.326	0.041
8	0.258	0.039
9	0.392	0.044
10	0.457	0.044
Total	0.283	0.013

Virginia

prorigdec	mean	se(mean)
1	0.146	0.004
2	0.180	0.004
3	0.243	0.005
4	0.242	0.005
5	0.240	0.004
6	0.236	0.004
7	0.243	0.005
8	0.249	0.005
9	0.217	0.004
10	0.340	0.005
Total	0.233	0.001

West Virginia

Original score

prorigdec	mean	se(mean)
1	0.214	0.008
2	0.269	0.009
3	0.323	0.009
4	0.376	0.009
5	0.397	0.009
6	0.411	0.009
7	0.456	0.009

Updated score

prupdec	mean	se(mean)
1	0.176	0.007
2	0.244	0.008
3	0.297	0.008
4	0.340	0.009
5	0.390	0.009
6	0.431	0.009
7	0.466	0.009

8	0.488	0.009
9	0.491	0.009
10	0.574	0.009
Total	0.410	0.003

8	0.524	0.009
9	0.582	0.009
10	0.654	0.009
Total	0.410	0.003

Wisconsin

prorigdec	mean	se(mean)
1	0.375	0.011
2	0.422	0.011
3	0.433	0.011
4	0.437	0.011
5	0.457	0.011
6	0.446	0.011
7	0.473	0.011
8	0.508	0.011
9	0.434	0.008
Total	0.442	0.003

Wyoming

prorigdec	N	mean	se(mean)
1	8	0.500	0.189
2	12	0.333	0.142
3	10	0.300	0.153
4	10	0.500	0.167
5	14	0.500	0.139
6	8	0.375	0.183
7	12	0.500	0.151
8	9	0.667	0.167
9	11	0.273	0.141
10	13	0.462	0.144
Total	107	0.439	0.048

Expanded Analyses of Arkansas Profiling Data

ANALYSIS OF ARKANSAS PROFILING DATA

Reported Profiling Model

Arkansas uses a linear (multiple regression) statistical model to select individuals for participation in the WPRS Program. The original model has been updated only for routine system maintenance and for the year 2000 updating (i.e., Y2K). Only those individuals receiving benefits were included in the original sample and in the sample provided for our analysis. We used a logistic regression model to predict exhaustibility instead of the linear multiple regression model.

Our first step was to attempt replicating the given scores using the data and coefficients for the variables given. From these data, we identified the variables used in the model, including potential duration of receipt of unemployment benefits, ratio of weekly benefit allowance to maximum benefit allowance, service delivery area code, industry code, actual change and percentage change in the industry, occupation code, level of education, and a binary variable for the claim taker's indication of insufficient job preparation. No check for endogeneity was possible because there was no record of referral to reemployment services.

To show the performance of the original profiling score, we ordered individuals into deciles and calculated the exhaustion rate for each decile along with the standard error. This decile table is how we demonstrate the effectiveness of each model. The decile means are calculated by dividing the percentage of recipients that exhaust benefits for a given decile by 100. For example, in the first decile our mean is 0.3785118, which indicates that approximately 38 percent of benefit recipients in this decile exhausted benefits.

Profiling Means and Standard Error of Means by Decile

Decile	Mean	Standard Error (Mean)
1	.3785118	.006683
2	.4620468	.0068514
3	.4667939	.0068926
4	.4835645	.0068891
5	.4718697	.0068714
6	.4905732	.0068994
7	.4956274	.0068945
8	.5221189	.0068834
9	.5768281	.0068096
10	.6467123	.00659
Total	.4994397	.0021791

Updated Profiling Model

The updated model has the same form as the original model that was used to predict the profiling score, except that the updated coefficients are generated using 2003 data. We include diagnostic statistics to show how well the model works, including a classification table that looks at the top 49.9 percent of cases because that was Arkansas' exhaustion rate.

Updated Model Results

Logistic regression	Number of observations	=	52651
	LR chi2(18)	=	1906.66
Log likelihood = -35541.532	Prob > chi2	=	0.0000

exhaust	Coefficient	Standard error	z	P>z	[95% Conf.	Interval]
potential duration	-.0819982	.002063	-39.75	0.000	-.0860417	-.0779548
rtowbo	.5388585	.0373369	14.43	0.000	.4656795	.6120376
sda4	-.0255161	.0289362	-0.88	0.378	-.0822301	.0311979
sda5	-.0106963	.0304194	-0.35	0.725	-.0703172	.0489246
sda7	.0617819	.0344517	1.79	0.073	-.0057422	.1293061
ind1	-.0740481	.0677025	-1.09	0.274	-.2067425	.0586462
ind3	.0109159	.0373679	0.29	0.770	-.0623239	.0841556
ind4	.2263391	.027691	8.17	0.000	.1720657	.2806126
ind6	.2826363	.0486872	5.81	0.000	.1872111	.3780615
ind7	.2906381	.0318738	9.12	0.000	.2281666	.3531097
ind9	.2267198	.0350733	6.46	0.000	.1579773	.2954623
Ind. Emp. % change	-.008558	.0012343	-6.93	0.000	-.0109772	-.0061388
ind. emp. actual change	.0000188	2.25e-06	8.37	0.000	.0000144	.0000232
occ2	.3968615	.0481549	8.24	0.000	.3024796	.4912435
occ5	.3283993	.0831143	3.95	0.000	.1654983	.4913003
occ9	.1235428	.0356024	3.47	0.001	.0537634	.1933222
low education	-.1394604	.0667148	-2.09	0.037	-.270219	-.0087017
nsuf	-.0878458	.1461535	-0.60	0.548	-.3743015	.1986098
_cons	1.407504	.050807	27.70	0.000	1.307924	1.507084

	--------	True	--------	
Classified	D		~D	Total
+	12628		9324	21952
-	13668		17031	30699
Total	26296		26355	52651

Classified + if predicted Pr(D) >= .499
True D defined as exhaust != 0

Sensitivity		Pr(+ D)	48.02%	
Specificity		Pr(-~D)	64.62%	
Positive predictive value		Pr(D +)	57.53%	
Negative predictive value		Pr(~D -)	55.48%	
False + rate for true ~D		Pr(+~D)	35.38%	
False - rate for true D		Pr(- D)	51.98%	
False + rate for classified	+	Pr(~D +)	42.47%	
False - rate for classified	-	Pr(D -)	44.52%	
Correctly classified				56.33%

number of observations	=	52651
area under ROC curve	=	0.5977

The decile table for the updated model is as follows:

Decile	Mean	Standard Error (Mean)
1	.3459716	.0065501
2	.4210428	.0067501
3	.4550377	.0069257
4	.474924	.0068835
5	.4869896	.0068891
6	.4913907	.0068774
7	.5020019	.0069045
8	.5352327	.0068743
9	.588604	.0067824
10	.6940171	.0063515
Total	.4994397	.0021791

From the original score to the updated model, there was a significant improvement. The decile gradient, which ranged from a low of 0.38 to a high of 0.65 for the original model, improved to a low of 0.35 to a high of 0.69 for the updated model.

Revised Model

While the revised model is similar to the updated model, it incorporates more of the information in the dataset. We included additional variables such as benefit quarter in which the claim was filed and a binary variable indicating whether a claims taker thought the claimant was insufficiently prepared for a job search. We included second-order terms to capture nonlinear and discontinuous effects and dropped the variable for actual change in industry employment because it duplicates the information in the percentage change in industry employment variable. Moreover, the revised model includes the following variables:

- Categorical variables for benefit quarter, occupation, all one-digit SIC industries, and service delivery area
- Binary variable indicating whether a claims taker thought claimant was insufficiently prepared for a job search
- Continuous variables for potential duration of receipt of unemployment benefits, ratio of weekly benefit allowance to maximum benefit amount, percentage change in industry employment, and number of years of education
- Second-order variables for potential duration, ratio of WBA to MBA, percent change in industry employment, and education
- Four interaction variables for all possible interactions between the continuous variables

The second-order terms were created by first centering the variables, then subtracting their mean, and finally squaring them. The interaction variables were created by centering and multiplying the six second-order combinations. The means for the four continuous variables are shown below.

Variable	Potential Duration	Ratio of WBA to MBA	Percent Change in Employment	Education
Mean	23.14558	0.6272432	13.16632	12.29585

The logistic regression model results for the revised model are as follows.

Logistic regression	Number of observations	=	52651
	LR chi2(43)	=	2337.53
	Prob > chi2	=	0.0000
Log likelihood = -35326.096	Pseudo R2	=	0.0320

exhaust	Coefficient	Standard error	z	P>z	[95% Conf.	Interval]
educ	-.0212263	.0041174	-5.16	0.000	-.0292962	-.0131565
potential duration	-.0920423	.0031382	-29.33	0.000	-.0981931	-.0858916
work search	.0107519	.0417216	0.26	0.797	-.0710209	.0925247
nsuf	-.0181588	.1479111	-0.12	0.902	-.3080592	.2717416
rtowbo	.6055528	.038817	15.60	0.000	.529473	.6816327
emppchg	-.0033276	.0010766	-3.09	0.002	-.0054378	-.0012175
occ2	.3644747	.0487433	7.48	0.000	.2689395	.4600098
occ5	.2988011	.0837333	3.57	0.000	.134687	.4629153
occ9	.0698414	.0369221	1.89	0.059	-.0025246	.1422074
sda1	.0565677	.0485607	1.16	0.244	-.0386094	.1517448

sda2	.0779338	.0412961	1.89	0.059	-.003005	.1588726
sda3	-.3058025	.0423269	-7.22	0.000	-.3887616	-.2228434
sda4	-.0353287	.0423103	-0.83	0.404	-.1182553	.0475979
sda5	-.0170571	.0428851	-0.40	0.691	-.1011103	.0669961
sda6	-.0406492	.0432466	-0.94	0.347	-.125411	.0441126
sda7	.0376966	.0457744	0.82	0.410	-.0520195	.1274127
sda8	.1065415	.0442773	2.41	0.016	.0197596	.1933234
sda9	.0132839	.0422406	0.31	0.753	-.069506	.0960739
sda10	-.3189803	.0890418	-3.58	0.000	-.4934989	-.1444616
sda11	.0016771	.0512769	0.03	0.974	-.0988239	.102178
sic0	-.0461531	.0720149	-0.64	0.522	-.1872997	.0949935
sic1	.0779938	.0454945	1.71	0.086	-.0111738	.1671615
sic2	.4041304	.0440474	9.17	0.000	.3177991	.4904617
sic3	.2426572	.0415104	5.85	0.000	.1612983	.3240161
sic4	.2602227	.0518174	5.02	0.000	.1586624	.361783
sic5	.422752	.0404492	10.45	0.000	.343473	.5020309
sic6	.42824	.0682609	6.27	0.000	.294451	.5620289
sic7	.3177596	.0519647	6.11	0.000	.2159107	.4196084
sic8	.3742368	.0474426	7.89	0.000	.2812511	.4672225
sic9	.3776745	.0540652	6.99	0.000	.2717086	.4836403
benqtr2	.0077538	.025196	0.31	0.758	-.0416294	.0571369
benqtr3	.1041716	.0258734	4.03	0.000	.0534605	.1548826
benqtr4	-.0776761	.0249488	-3.11	0.002	-.1265748	-.0287775
xpod2	-.0014904	.0003606	-4.13	0.000	-.0021973	-.0007836
xrto2	-1.770277	.166254	-10.65	0.000	-2.096129	-1.444425
xep2	-.0001073	.0000576	-1.86	0.062	-.0002201	5.57e-06
xed	.0002508	.0002249	1.12	0.265	-.00019	.0006916
xepped	-.0001354	.0003201	-0.42	0.672	-.0007628	.000492
xrtoed	.0367328	.0160334	2.29	0.022	.0053079	.0681577
xrtoep	.0002115	.0030387	0.07	0.945	-.0057444	.0061673
xpoded	-.0034372	.0009657	-3.56	0.000	-.00533	-.0015444
xpodep	-.0002956	.0001596	-1.85	0.064	-.0006085	.0000173
xpodrto	.0158003	.0087969	1.80	0.072	-.0014414	.033042
_cons	1.911946	.1071802	17.84	0.000	1.701877	2.122015

Classification Table

	--------	True	--------	
Classified	D		~D	Total
+	13985		9983	23968
-	12311		16372	28683
Total	26296		26355	52651

Classified + if predicted Pr(D) >= .499
True D defined as exhaust != 0

Sensitivity		Pr(+ D)	53.18%	

Specificity		Pr(-~D)	62.12%	
Positive predictive value		Pr(D +)	58.35%	
Negative predictive value		Pr(~D -)	57.08%	
False + rate for true ~D		Pr(+~D)	37.88%	
False - rate for true D		Pr(- D)	46.82%	
False + rate for classified	+	Pr(~D +)	41.65%	
False - rate for classified	-	Pr(D -)	42.92%	
Correctly classified				57.66%

number of observations	=	52651
area under ROC curve	=	0.6106

The decile table for the revised model is as follows.

Decile	Mean	Standard Error (Mean)
1	.3260539	.0064604
2	.4138651	.0067884
3	.42594	.0068148
4	.4707447	.0068803
5	.4765699	.00688
6	.5033276	.0068953
7	.5348528	.0068747
8	.551567	.0068547
9	.6060779	.0067346
10	.6854701	.0063998
Total	.4994397	.0021791

Note that there is a significant improvement from the updated to the revised model in terms of log likelihood. The decile gradient, which ranged from a low of 0.38 to a high of 0.65 for the original model and from a low of 0.35 to a high of 0.69 for the updated model, has not improved. For the revised model the range is from a low of 0.33 to a high of 0.69. The updated and revised models are monotonically increasing across all deciles.

Tobit Analysis Using the Variables of the Revised Model

The Tobit model is similar to the logit model except that it uses information about non-exhaustees, assuming that non-exhaustees who are closer to exhaustion are more similar to exhaustees than those claimants who are farther from exhaustion. First, we created a new dependent variable, "/sigma."

/sigma = 100 X (maximum benefit amount – benefits paid)/ maximum benefit amount

This variable represents the percent of the allowed benefits left to claimants. Exhaustees have a value of 0. In the data, all negative values were recoded as 0.

Tobit regression		Number of observations	=	52651
		LR chi2(43)	=	2070.89
		Prob > chi2	=	0.0000
Log likelihood =	-163463.23	Pseudo R2	=	0.0063

tobit dependent var.	Coefficient	Standard error	t	P>t	[95% Conf.	Interval]
educ	.5456151	.1313553	4.15	0.000	.2881576	.8030726
potential duration	2.336738	.0824971	28.33	0.000	2.175043	2.498434
work search	-2.728984	1.337716	-2.04	0.041	-5.350919	-.1070497
nsuf	4.404507	4.694977	0.94	0.348	-4.79769	13.6067
rtowbo	-20.65493	1.233412	-16.75	0.000	-23.07243	-18.23743
emppchg	.1288951	.0343238	3.76	0.000	.06162	.1961701
occ2	-10.15191	1.587987	-6.39	0.000	-13.26438	-7.039441
occ5	-8.539526	2.717822	-3.14	0.002	-13.86648	-3.212569
occ9	-.199315	1.185997	-0.17	0.867	-2.523881	2.125251
sda1	-3.104566	1.567077	-1.98	0.048	-6.17605	-.0330815
sda2	-1.806825	1.331796	-1.36	0.175	-4.417157	.8035082
sda3	11.11162	1.342216	8.28	0.000	8.480863	13.74238
sda4	.9848292	1.359677	0.72	0.469	-1.680149	3.649808
sda5	2.552977	1.376696	1.85	0.064	-.14536	5.251315
sda6	3.295039	1.387493	2.37	0.018	.5755414	6.014537
sda7	.1812638	1.474548	0.12	0.902	-2.708864	3.071391
sda8	-1.954779	1.426505	-1.37	0.171	-4.750742	.841183
sda9	1.481406	1.358296	1.09	0.275	-1.180867	4.143679
sda10	7.08863	2.778236	2.55	0.011	1.643263	12.534
sda11	.572016	1.650337	0.35	0.729	-2.66266	3.806692
sic0	-1.963834	2.25609	-0.87	0.384	-6.38579	2.458122
sic1	-1.34057	1.441084	-0.93	0.352	-4.165107	1.483967
sic2	-8.138994	1.40067	-5.81	0.000	-10.88432	-5.393669
sic3	-3.608254	1.313514	-2.75	0.006	-6.182752	-1.033756

sic4	-5.220962	1.652062	-3.16	0.002	-8.459017	-1.982906
sic5	-10.74288	1.281997	-8.38	0.000	-13.25561	-8.230156
sic6	-11.84774	2.194708	-5.40	0.000	-16.14939	-7.546096
sic7	-8.433851	1.652226	-5.10	0.000	-11.67223	-5.195472
sic8	-9.134555	1.504156	-6.07	0.000	-12.08272	-6.186395
sic9	-9.897013	1.729158	-5.72	0.000	-13.28618	-6.507848
benqtr2	-.1454631	.8072819	-0.18	0.857	-1.727743	1.436817
benqtr3	-3.315498	.8316288	-3.99	0.000	-4.945498	-1.685498
benqtr4	1.635662	.7961139	2.05	0.040	.0752711	3.196052
xpod2	-.0852698	.0067215	-12.69	0.000	-.0984441	-.0720955
xrto2	47.4854	5.178073	9.17	0.000	37.33633	57.63447
xep2	.004745	.0018067	2.63	0.009	.0012039	.0082861
xed	-.0068492	.0068872	-0.99	0.320	-.0203482	.0066497
xepped	.0043679	.0101264	0.43	0.666	-.0154799	.0242157
xrtoed	-1.017589	.4989425	-2.04	0.041	-1.99552	-.0396569
xrtoep	.0586051	.0935677	0.63	0.531	-.1247883	.2419986
xpoded	.0932688	.0292655	3.19	0.001	.0359082	.1506294
xpodep	.0072085	.0048097	1.50	0.134	-.0022185	.0166355
xpodrto	.7708927	.2757427	2.80	0.005	.2304345	1.311351
_cons	-38.99819	3.103761	-12.56	0.000	-45.08159	-32.91479
/sigma	59.23466	.2914833			58.66335	59.80597

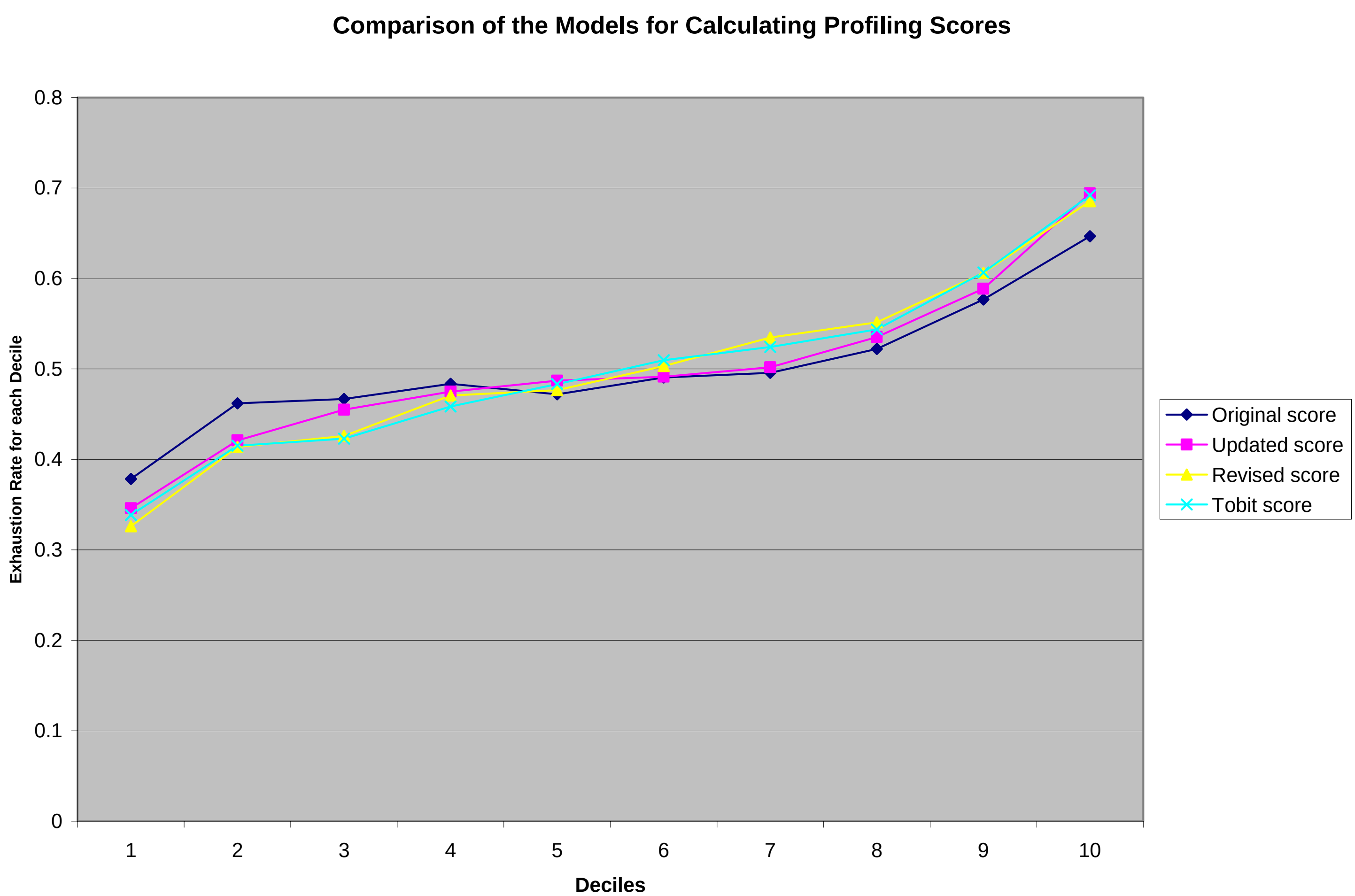
The decile table for the Tobit model is as follows.

Decile	Mean	Standard Error (Mean)
1	.3385872	.0065219
2	.4151947	.0067916
3	.422792	.0068088
4	.4584995	.0068677
5	.48321	.0068837
6	.5097927	.0068941
7	.5242165	.0068834
8	.5435897	.0068652
9	.6066477	.0067329
10	.6919278	.0063635
Total	.4994397	.0021791

Note that the Tobit model cannot be compared with the logistic regression models by log likelihood comparisons. However, from the decile tables, the model does not appear to be better than the revised model.

We created a summary table of the four decile tables to allow us to compare models. The Tobit model provides only marginal improvement over the revised model. The revised model appears to be as good as any of the other models.

Decile	Original score	Updated score	Revised score	Tobit score
1	.3785118	.3459716	.3260539	.3385872
2	.4620468	.4210428	.4138651	.4151947
3	.4667939	.4550377	.42594	.422792
4	.4835645	.474924	.4707447	.4584995
5	.4718697	.4869896	.4765699	.48321
6	.4905732	.4913907	.5033276	.5097927
7	.4956274	.5020019	.5348528	.5242165
8	.5221189	.5352327	.551567	.5435897
9	.5768281	.588604	.6060779	.6066477
10	.6467123	.6940171	.6854701	.6919278
Total	.4994397	.4994397	.4994397	.4994397



Correlations of the four profiling scores indicate that all model scores are highly correlated. The original score is highly positively correlated with the other three scores (updated, revised, Tobit). While these three scores are all highly correlated, they are not identical, which suggests that there is a significant difference between the models.

	original score	updated score	revised score	tobit score
original score	1.0000			
updated score	0.6773	1.0000		
revised score	0.5999	0.8139	1.0000	
tobit score	0.6128	0.7824	0.9753	1.0000

Note that the strongest correlation is between the revised and Tobit models with a correlation score of almost one. As expected, there is also a strong positive correlation between the updated, revised, and Tobit models. However, these correlations are not as strong as the relationship between the revised and the Tobit model.

We also tested the performance of each model using the metric below.

Percent exhausted of the top 49.9 percent of individuals in the score.

We used 49.9 percent because the exhaustion rate for benefit recipients in the Arkansas dataset was 49.9 percent. This metric will vary from about 49.9 percent, for a score that is a random draw, up to 100 percent for a score that is a perfect predictor of exhaustion. The scores for the four models are as follows:

Score	% exhausted of those with the top 49.9% of score	Standard error of the score
Original	54.64	0.30716
Updated	56.24	0.30606
Revised	57.62	0.30486
Tobit	57.51	0.30497

We note that the revised score performed better than the updated score. The original score performed worst, and the updated score performed worse than the revised and Tobit scores.

To compare models across SWAs, we developed a metric to gauge classification improvements between our models and the original model. In the metric below, *"Exhaustion"* is the percentage of all benefit recipients in our sample that exhaust benefits. Here we use 49.9 percent for "*Exhaustion"* because the exhaustion rate for all benefit recipients for Arkansas was 49.9 percent. In our metric, "Pr[*Exh*]" is determined by the model with the highest percentage of benefit exhaustees with profiling scores falling in the top X percent of the sample, where X percent is determined by the exhaustion rate for all benefit recipients in the sample. For Arkansas, "Pr[*Exh*]" is represented by the revised model with a score of 57.62% for benefit recipients that exhaust benefits with scores falling in the top 49.9 percent.

In addition to this metric, we also applied the equation below, derived by Silverman, Strange, and Lipscombe (2004), for calculating the variance (σ_z^2) of a quotient (p. 1069). This equation allowed us to calculate the variance for our metric, Z = X/Y, which is the quotient of two random variables X (100 - "Pr[*Exh*]") and Y (100 - "*Exhaustion*"). In the equation below, σ_X^2 is the variance of 100 - "Pr[*Exh*]," σ_Y^2 is the variance of 100 - "*Exhaustion,"* $E(X)$ is the mean for (100 - "Pr[*Exh*]"), and $E(Y)$ is the mean for (100- "*Exhaustion"*). By dividing the variance of the quotient of the two random variables (here 100 - "*Exhaustion*" and 100 - "Pr[*Exh*]") by the square root of our observations, we were able to determine the standard error of the metric.

Metric: 1 – (100 – Pr[*Exh*]) / (100 – *Exhaustion*)

Variance of Metric: $\sigma_z^2 \approx \frac{\sigma_X^2}{E(Y)^2} + \frac{E(X)^2 \sigma_Y^2}{E(Y)^4}$

Standard error of the metric: $\sqrt{\frac{\sigma_Z^2}{N}}$

For our metric, "Pr[*Exh*]" is 57.62 percent and "*Exhaustion*" is 49.9 percent. We used these to calculate a score of 0.153495, or roughly 15 percent, with a standard error of 0.00348661. For SWAs with hypothetically perfect models, this metric will have a value of 1, and for SWAs with models that predict no better than random, the metric will take a value of 0.

SWA	Profiling score	Control for endogeneity?	Exhaustion rate for the state	Number of individuals with the highest profiling score	Exhaustion rate for individuals with high profiling scores	Metric	Variance of the Metric	Standard Error of the metric
Arkansas	original score	N	49.9	26,273	54.6	0.095	1.804	0.008
Arkansas	revised score	N	49.9	26,273	57.6	0.154	1.686	0.008

Analysis of Type I Errors

For this analysis, Type I errors occur when individuals who are predicted to exhaust (reject the null hypothesis), do not exhaust (the null hypothesis is actually true). The analysis is restricted to the top 49.9 percent of individuals who are predicted to exhaust benefits using the revised model.

Variable	Mean for exhausted	Mean for non-exhausted	T statistic	P value
	N = 15,141	N = 11,133		
Potential Duration	20.0119	21.2843	19.0309	0.0000
Ratio of weekly allowance to maximum benefit amount	0.6136	0.6315	5.6053	0.0000
Service Delivery Area 4	0.1137	0.1069	-1.7291	0.0838
Service Delivery Area 5	0.0934	0.0917	-0.4639	0.6427
Service Delivery Area 7	0.0743	0.0817	2.2287	0.0258
Industry 1	0.0141	0.0138	-0.2052	0.8374
Industry 3	0.0828	0.0647	-5.4988	0.0000
Industry 4	0.2316	0.2491	3.2916	0.0010
Industry 7	0.1711	0.1715	0.0879	0.9299
Industry 9	0.2083	0.1983	-1.9834	0.0473

Percentage Change in Industry Employment	12.4168	12.0994	-2.1630	0.0305
Actual Change in Industry Employment	4642.7983	4502.7680	-1.9749	0.0483
Occupation 2	0.0665	0.0585	-2.6466	0.0081
Occupation 5	0.0205	0.0190	-0.8742	0.3820
Occupation 9	0.0821	0.0887	1.8855	0.0594
Low Education Level	0.0230	0.0312	4.0505	0.0001
Insufficient Job Preparation	0.0029	0.0035	0.8522	0.3941

For the above table, 15,141 individuals exhausted benefits and 11,133 did not. The total of these two types of individuals is 26,274, which is 49.9 percent of the 52,651 individuals in the sample. The Type I analysis shows that certain variables have more clarifying power than others for explaining the difference between Type I errors and correct predictions. For example, the variables for occupation 5 and industry 7 are not that important for explaining the difference between exhaustees and non-exhaustees. More important variables, with low p-values, are potential duration, ratio of weekly allowance to maximum benefit amount, occupation 2, and industries 3 and 4.

Expanded Analyses of the District of Columbia Profiling Data

Analysis of District of Columbia Data

Our first step was to replicate the given scores using the data and variable coefficients provided for the model. From the given data, we identified and replicated variables and categories for unemployment rate, education level, occupation, industry, base period wages, and job tenure. Our replicated score correlated with the provided score at .998.

We first developed a decile table for the original score. This table shows for each decile the actual exhaustion rate, with its standard error and allows us to demonstrate the effectiveness of each model. It is:

Original score deciles	mean	se(mean)
1	.4163223	.0158521
2	.5010438	.0161627
3	.5333333	.0161099
4	.5426516	.0159791
5	.5977249	.015777
6	.5405128	.0159684
7	.5820106	.0160532
8	.5964361	.0158925
9	.643595	.0154016
10	.6494192	.0155135
Total	.5600624	.0050625

We included a binary variable that indicated whether or not benefit recipients were referred to re-employment services. This binary variable will allow us to test for endogeneity within our data and will answer the question - does referral to re-employment services have an effect on the exhaustion of benefits? To test for endogeneity, we first calculated the logit model where only score (and a constant) is used to predict Pr[exh].

Logit Model with score only

Logistic regression	Number of obs	=	9615
	LR chi2(1)	=	164.02
	Prob > chi2	=	0.0000
Log likelihood = -6513.0601	Pseudo R2	=	0.0124

exhaust	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
score	.002008	.0001587	12.66	0.000	.001697	.0023189
_cons	-.81894	.0860793	-9.51	0.000	-.9876522	-.6502277

Adding the variable for referral tests for a uniform referral effect. The test would be a chi-squared test of difference in the (-2 X log likelihood) statistic for the nested models.

Logit Model with score and referral

Logistic regression	Number of obs	=	9615
	LR chi2(2)	=	164.92
	Prob > chi2	=	0.0000
Log likelihood = -6512.6093	Pseudo R2	=	0.0125

exhaust	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
score	.0019831	.0001607	12.34	0.000	.0016681	.0022981
refer	-.0667495	.0702656	-0.95	0.342	-.2044675	.0709686
_cons	-.7992317	.0884968	-9.03	0.000	-.9726822	-.6257812

The addition of the variable "ref" improved the log likelihood from -6513.0601 to -6512.6093. The difference in log likelihood was not significant at the .05 level. Our next step was to test for non-uniform effects. We added an interaction term (referral X score) to test for a non-uniform or unsigned effect.

Logit Model with score, referral and an interaction term

Logistic regression	Number of obs	=	9615
	LR chi2(3)	=	166.31
	Prob > chi2	=	0.0000
Log likelihood = -6511.9149	Pseudo R2	=	0.0126

exhaust	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
score	.0020351	.0001668	12.20	0.000	.0017081	.0023621
refer	.2792281	.3011024	0.93	0.354	-.3109217	.869378
scorref	-.0007392	.0006251	-1.18	0.237	-.0019644	.0004861
_cons	-.8269912	.0916506	-9.02	0.000	-1.006623	-.6473593

The addition of the interaction term changes the log likelihood from -6512.6093 to -6511.9149. The difference again was not significant. The analysis indicates that there is no need to control for endogeneity. No offset variable is needed for the further analyses:

Updated Model

The updated model for the District of Columbia uses the same variables from the original model to predict the profiling score, only the coefficients are generated using 2003 data. We include here diagnostic statistics to show how well the model works, including a classification table that looks at the top 56 percent of cases (because DC had approximately a 56 percent exhaustion rate for the sample).

Logistic regression	Number of obs	=	9615
	LR chi2(34)	=	410.28
	Prob > chi2	=	0.0000
Log likelihood = -6389.9293	Pseudo R2	=	0.0311

exhaust	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
tur	.0134483	.0020046	6.71	0.000	.0095194	.0173773
edmiss	-.1051131	.1687335	-0.62	0.533	-.4358247	.2255985
edlow	-.8541375	.1069163	-7.99	0.000	-1.06369	-.6445855
edhsdo	-.2015864	.0752988	-2.68	0.007	-.3491694	-.0540033
edcoldo	.1127764	.0673605	1.67	0.094	-.0192478	.2448005
edba	-.3957758	.0650832	-6.08	0.000	-.5233364	-.2682151
edgraddo	-.4033841	.1536708	-2.62	0.009	-.7045734	-.1021949
edmsphd	-.5266416	.1107432	-4.76	0.000	-.7436944	-.3095889
occler	.1190369	.0743408	1.60	0.109	-.0266683	.2647421
ocserv	-.2737408	.0646236	-4.24	0.000	-.4004008	-.1470808
ocaff	-.2312374	.3853623	-0.60	0.548	-.9865337	.5240589
ocprocs	-.1840963	.3571063	-0.52	0.606	-.8840119	.5158192
octools	-.0401533	.3228197	-0.12	0.901	-.6728683	.5925618
ocstruc	-.0296399	.1008083	-0.29	0.769	-.2272206	.1679407
ocmiss	.2971596	.63288	0.47	0.639	-.9432623	1.537582
ocmisc	.3569665	.2220074	1.61	0.108	-.0781601	.792093
indmiss	.0360645	.0689763	0.52	0.601	-.0991265	.1712556
oc99	-.3535066	.1117594	-3.16	0.002	-.572551	-.1344622
indcon	-.4180692	.1013574	-4.12	0.000	-.616726	-.2194124
indmfg	.3583904	.2153035	1.66	0.096	-.0635967	.7803776
indtrn	.4711927	.1400267	3.37	0.001	.1967453	.74564
indsal	-.2279706	.0713478	-3.20	0.001	-.3678096	-.0881316
indfir	.4147907	.1103634	3.76	0.000	.1984824	.631099
indgov	-.1533993	.0647095	-2.37	0.018	-.2802277	-.0265709
wg0to7	.3477517	.1087454	3.20	0.001	.1346148	.5608887
wg7to14	.1799942	.083284	2.16	0.031	.0167606	.3432278
wg14to21	.0184585	.0793355	0.23	0.816	-.1370362	.1739531
wg21to28	.0049154	.0823848	0.06	0.952	-.1565559	.1663867
wg35up	-.1487703	.0794859	-1.87	0.061	-.3045598	.0070192
jt0to90	-.0380514	.1136005	-0.33	0.738	-.2607042	.1846014
jt91to180	.0185196	.089363	0.21	0.836	-.1566287	.1936679
jt361to720	.1396888	.0661753	2.11	0.035	.0099875	.2693901
jt721to1800	.1504202	.064049	2.35	0.019	.0248865	.2759539
jt1800toup	-.103916	.0718191	-1.45	0.148	-.2446788	.0368467
_cons	-.4328918	.1465729	-2.95	0.003	-.7201695	-.1456142

	--------	True	--------	
Classified	D		~D	Total
+	3337		1885	5222
-	2048		2345	4393

Total	5385		4230	9615

Sensitivity		Pr(+ D)	61.97%	
Specificity		Pr(-~D)	55.44%	
Positive predictive value		Pr(D +)	63.90%	
Negative predictive value		Pr(~D -)	53.38%	
False + rate for true ~D		Pr(+~D)	44.56%	
False - rate for true D		Pr(- D)	38.03%	
False + rate for classified	+	Pr(~D +)	36.10%	
False - rate for classified	-	Pr(D -)	46.62%	
Correctly classified				59.10%

number of observations	=	9615
area under ROC curve	=	0.6157

The decile table for the updated model is as follows:

prupdec	mean	se(mean)
1	.3711019	.0155839
2	.4657676	.0160745
3	.4973931	.016154
4	.5098855	.0161343
5	.5316719	.0160883
6	.56639	.0159696
7	.6388309	.0155272
8	.635514	.0155173
9	.6690947	.0151866
10	.715625	.0145673
Total	.5600624	.0050625

From the original score to the updated model, there was a significant improvement. The decile gradient, which ranged from .41 to .64 for the original model improved to .37 to .71 for the updated model.

Revised Model

The revised model is similar to the updated model, but we incorporated more of the information in the variable set. We substituted continuous variables for job tenure, education and base period earnings instead of the categorical versions in the original model. We retained the variable for missing education, and set those observations to zero in the continuous variable. We also included second order and interaction terms for the continuous variables to capture nonlinear and discontinuous effects.

We created the second order variables by first centering the variables, by subtracting their mean, and squaring them. This gave us four variables to measure non-linear effects. We created the interaction variables by centering and multiplying the four variables, resulting in six additional variables. The means for the four continuous variables are shown below.

Variable	Obs	Mean	Std. Dev.	Min	Max
Unemployment rate	9615	59.75205	10.69554	21	73
Job tenure	9615	1247.651	1806.014	5	36805
Base period wages	9615	26419.81	23894.42	2031	806357
Education	9461	12.82909	2.678957	1	18

The logit model results for the revised model are as follows.

Logistic regression	Number of obs	=	9615
	LR chi2(31)	=	449.70
	Prob > chi2	=	0.0000
Log likelihood = -6370.2206	Pseudo R2	=	0.0341

Exhaust	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
tur	.0142967	.0025944	5.51	0.000	.0092118	.0193816
edmiss	-.2664462	.2222356	-1.20	0.231	-.70202	.1691276
edcon	-.0249457	.0098782	-2.53	0.012	-.0443067	-.0055847
occler	.1263922	.0742144	1.70	0.089	-.0190653	.2718497
ocserv	-.2898645	.0646227	-4.49	0.000	-.4165226	-.1632064
ocaff	-.2022851	.3834741	-0.53	0.598	-.9538805	.5493102
ocprocs	-.2245927	.3573905	-0.63	0.530	-.9250652	.4758797
octools	-.0906157	.3225454	-0.28	0.779	-.7227931	.5415617
ocstruc	-.0555857	.1012038	-0.55	0.583	-.2539415	.1427701
ocmiss	.35076	.6361202	0.55	0.581	-.8960128	1.597533
ocmisc	.3759411	.2246645	1.67	0.094	-.0643932	.8162755
indmiss	-.0184154	.0680369	-0.27	0.787	-.1517653	.1149345
oc99	-.3676257	.1119282	-3.28	0.001	-.587001	-.1482504
indcon	-.4527752	.1023355	-4.42	0.000	-.6533491	-.2522012
indmfg	.3852669	.2166544	1.78	0.075	-.0393679	.8099017
indtrn	.4424017	.1405375	3.15	0.002	.1669533	.7178501
indsal	-.229847	.0712111	-3.23	0.001	-.3694181	-.0902758
indfir	.3983932	.1103069	3.61	0.000	.1821955	.6145908
indgov	-.1932919	.0645884	-2.99	0.003	-.3198829	-.066701
bpw	-7.37e-06	1.56e-06	-4.73	0.000	-.0000104	-4.32e-06
tenure	-.0000581	.0000187	-3.10	0.002	-.0000948	-.0000214
xtur2	.000062	.0001562	0.40	0.692	-.0002442	.0003681
xten2	4.56e-09	1.89e-09	2.42	0.016	8.62e-10	8.26e-09
xbpw2	-1.36e-12	9.71e-12	-0.14	0.889	-2.04e-11	1.77e-11

xedu2	-.0163381	.0018357	-8.90	0.000	-.019936	-.0127403
xtute	-5.33e-07	1.13e-06	-0.47	0.636	-2.74e-06	1.67e-06
xtubp	5.51e-08	9.75e-08	0.57	0.572	-1.36e-07	2.46e-07
xtued	-.0030395	.0008308	-3.66	0.000	-.0046678	-.0014111
xtebp	1.64e-09	5.85e-10	2.81	0.005	4.96e-10	2.79e-09
xteed	.0000276	5.66e-06	4.88	0.000	.0000165	.0000387
xbped	6.77e-07	4.74e-07	1.43	0.153	-2.52e-07	1.61e-06
_cons	.1419783	.214745	0.66	0.509	-.2789142	.5628709

Classification Table

	--------	True	--------	
Classified	D		~D	Total
+	3318		1856	5174
-	2067		2374	4441
Total	5385		4230	9615

Sensitivity		Pr(+ D)	61.62%	
Specificity		Pr(-~D)	56.12%	
Positive predictive value		Pr(D +)	64.13%	
Negative predictive value		Pr(~D -)	53.46%	
False + rate for true ~D		Pr(+~D)	43.88%	
False - rate for true D		Pr(- D)	38.38%	
False + rate for classified	+	Pr(~D +)	35.87%	
False - rate for classified	-	Pr(D -)	46.54%	
Correctly classified				59.20%

number of observations	=	9615
area under ROC curve	=	0.6204

The decile table for the revised model is as follows.

prrevdec	mean	se(mean)
1	.3409563	.0152913
2	.4693028	.016107
3	.491684	.0161268
4	.5109261	.0161336
5	.5602911	.0160113
6	.6024974	.0157947
7	.6070686	.0157549
8	.628512	.0155953
9	.6580042	.0153025
10	.7315297	.014303
Total	.5600624	.0050625

This model appears to be an improvement over the updated model. For the updated model, the exhaustion rate for the deciles ranged from .37 to .71. For the revised model, the deciles range from .34 to .73.

Tobit analysis using the variables of the revised model

The following is the procedure we used to generate a Tobit model to predict exhaustion. The Tobit model is similar to the logit model except that it uses information about non-exhaustees, assuming that non-exhaustees who are closer to exhaustion are more similar to exhaustees than those who are further from exhaustion. First, we created a new dependent variable. It is:

100 X (balance of unused UI benefits)/ maximum benefit amount

This variable represents the percent of the allowed benefits left to individuals. Exhaustees have a value of 0.

Second, we tested for endogeneity using the same procedure as for the logit analyses. Replication is necessary because of the difference in functional form for the Tobit model. The first model uses only the score as independent variable.

Tobit regression		Number of obs	=	9615
		LR chi2(1)	=	191.27
		Prob > chi2	=	0.0000
Log likelihood =	-7553.2451	Pseudo R2	=	0.0125

tobdep	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
score	-.000758	.000055	-13.78	0.000	-.0008659	-.0006502
_cons	.3398938	.0295554	11.50	0.000	.2819589	.3978286
/sigma	.633128	.0078806			.6176804	.6485756

The second model uses only score and a binary variable for referred status as independent variables.

Tobit regression		Number of obs	=	9615
		LR chi2(2)	=	193.26
		Prob > chi2	=	0.0000
Log likelihood =	-7552.2527	Pseudo R2	=	0.0126

tobdep	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
score	-.0007458	.0000557	-13.40	0.000	-.0008549	-.0006366
refer	.0345363	.0244905	1.41	0.159	-.0134703	.082543
_cons	.3300588	.0303724	10.87	0.000	.2705226	.3895951

/sigma	.6330238	.0078792			.617579	.6484686

The addition of the variable "refer" improved the log likelihood from -7553.2451 to -7552.2527. This is not a significant difference at the 5 percent level. Our next step was to test for non-uniform effects. We added an interaction term (referral X score) to test for a non-uniform or unsigned effect.

Tobit Model with score, referral and an interaction term

Tobit regression		Number of obs	=	9615
		LR chi2(3)	=	193.79
		Prob > chi2	=	0.0000
Log likelihood =	-7551.9868	Pseudo R2	=	0.0127

tobdep	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
score	-.0007566	.0000576	-13.13	0.000	-.0008696	-.0006436
refer	-.0403752	.1055647	-0.38	0.702	-.2473043	.1665539
scorref	.000161	.0002206	0.73	0.466	-.0002714	.0005934
_cons	.3358105	.0313733	10.70	0.000	.2743123	.3973088
/sigma	.6330194	.0078791			.6175747	.6484641

Here the addition of the interaction term significantly changed the log likelihood from -7552.2527 to -7551.9868. This difference is again not significant, indicating that there is no significant referral effect. There is not need to control for endogeneity.

The Tobit model uses the same independent variables as the revised model. The results are as follows.

Tobit regression		Number of obs	=	9615
		LR chi2(31)	=	428.81
		Prob > chi2	=	0.0000
Log likelihood =	-7434.4767	Pseudo R2	=	0.0280

tobdep	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
tur	-.0046333	.000895	-5.18	0.000	-.0063877	-.0028789
edmiss	.1098075	.0755469	1.45	0.146	-.0382804	.2578954
edcon	.0080515	.0033138	2.43	0.015	.0015558	.0145472
occler	-.0529211	.0258876	-2.04	0.041	-.1036664	-.0021759
ocserv	.1099427	.0221418	4.97	0.000	.0665401	.1533453
ocaff	.1094962	.1317675	0.83	0.406	-.1487959	.3677883
ocprocs	.1191342	.1216745	0.98	0.328	-.1193735	.357642
octools	-.0109415	.1114489	-0.10	0.922	-.2294049	.2075218
ocstruc	.0000987	.0345264	0.00	0.998	-.0675804	.0677778
ocmiss	-.0869477	.2199987	-0.40	0.693	-.5181917	.3442964

ocmisc	-.125542	.0767279	-1.64	0.102	-.2759448	.0248608
indmiss	-.0196092	.0236153	-0.83	0.406	-.0659001	.0266818
oc99	.1070987	.0372113	2.88	0.004	.0341566	.1800407
indcon	.1381525	.034195	4.04	0.000	.071123	.2051821
indmfg	-.1108362	.0749104	-1.48	0.139	-.2576764	.0360039
indtrn	-.1850227	.0488638	-3.79	0.000	-.2808061	-.0892392
indsal	.0642923	.0243826	2.64	0.008	.0164972	.1120875
indfir	-.1519587	.0383993	-3.96	0.000	-.2272295	-.0766879
indgov	.0804123	.022207	3.62	0.000	.0368819	.1239428
bpw	2.85e-06	4.75e-07	6.00	0.000	1.92e-06	3.78e-06
tenure	.0000239	6.43e-06	3.72	0.000	.0000113	.0000365
xtur2	-.0000197	.0000517	-0.38	0.703	-.0001211	.0000817
xten2	-1.68e-09	6.76e-10	-2.48	0.013	-3.00e-09	-3.53e-10
xbpw2	-1.76e-12	1.46e-12	-1.21	0.227	-4.63e-12	1.10e-12
xedu2	.004419	.0005604	7.89	0.000	.0033205	.0055175
xtute	2.86e-07	3.66e-07	0.78	0.435	-4.31e-07	1.00e-06
xtubp	1.70e-08	3.07e-08	0.55	0.581	-4.32e-08	7.72e-08
xtued	.0004772	.0002488	1.92	0.055	-.0000106	.0009649
xtebp	-4.67e-10	1.78e-10	-2.62	0.009	-8.16e-10	-1.17e-10
xteed	-7.74e-06	1.64e-06	-4.73	0.000	-.0000109	-4.53e-06
xbped	-2.74e-07	1.47e-07	-1.87	0.062	-5.62e-07	1.36e-08
_cons	-.0325818	.0737347	-0.44	0.659	-.1771173	.1119538
/sigma	.624028	.0077549			.6088268	.6392291

The decile table for the Tobit model is as follows.

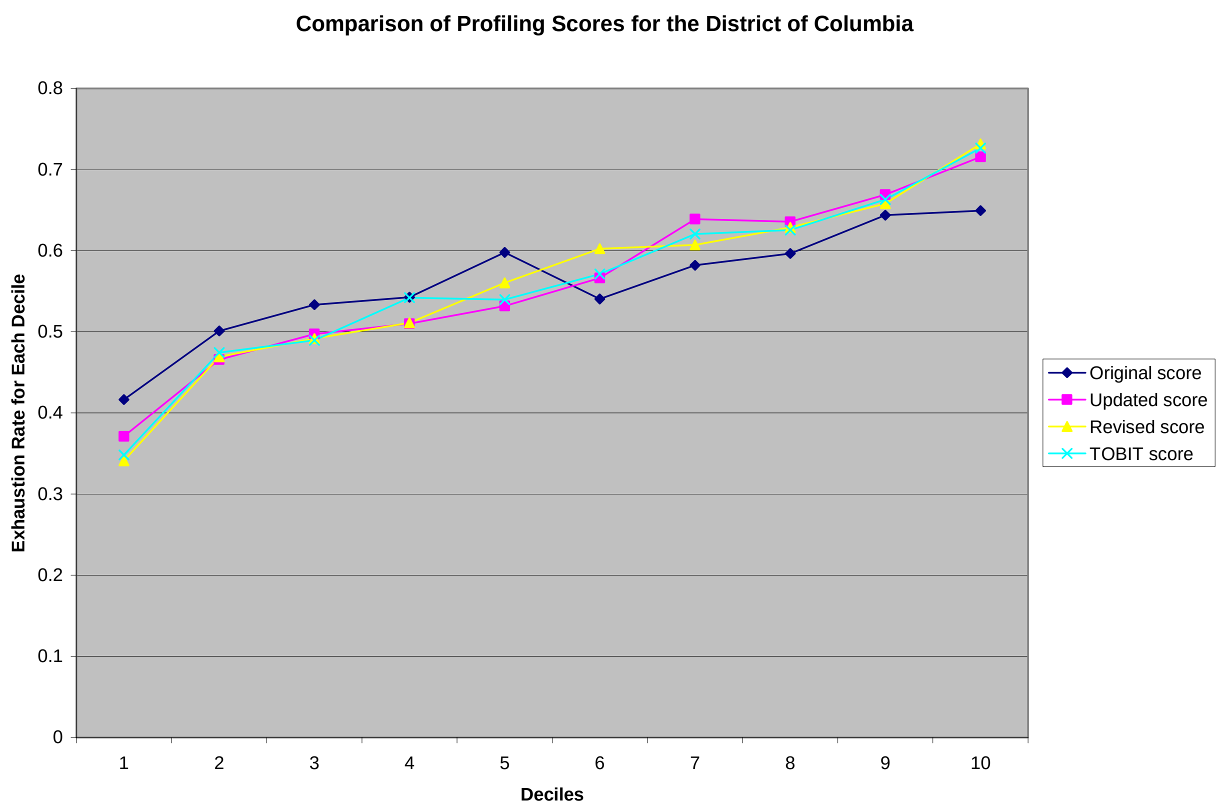
prtobdec	mean	se(mean)
1	.3482328	.0153681
2	.4745057	.0161164
3	.489605	.0161255
4	.5421436	.01608
5	.539501	.0160786
6	.5712799	.0159726
7	.6205821	.015653
8	.6253902	.0156217
9	.6632017	.0152457
10	.7263267	.0143895
Total	.5600624	.0050625

Note that the Tobit model cannot be compared with the logit models by log likelihood comparisons. However, from the decile tables, the model did not perform substantially better than either the revised model.

Summary Tables

We created a summary table of the four decile tables that allows us to compare models. The revised score appears to be the best model for the data available.

Decile	Original score	Updated score	Revised score	TOBIT score
1	.4163223	.3711019	.3409563	.3482328
2	.5010438	.4657676	.4693028	.4745057
3	.5333333	.4973931	.491684	.489605
4	.5426516	.5098855	.5109261	.5421436
5	.5977249	.5316719	.5602911	.539501
6	.5405128	.56639	.6024974	.5712799
7	.5820106	.6388309	.6070686	.6205821
8	.5964361	.635514	.628512	.6253902
9	.643595	.6690947	.6580042	.6632017
10	.6494192	.715625	.7315297	.7263267
Total	.5600624	.5600624	.5600624	.5600624



Correlations of the four profiling scores indicate that all model scores are positively correlated, as is to be expected. While the scores are positively correlated, they are not identical, which suggests that there are differences between the models.

	score	prup	prrev	protobn
score	1.0000			
prup	0.6465	1.0000		
prrev	0.5365	0.8392	1.0000	
protobn	0.5606	0.8343	0.9776	1.0000

We also tested the performance of each model using the following metric.

Percent exhausted of the top 56 percent of individuals in the score.

We used 56 percent because that is the exhaustion rate for benefit recipients in the data set provided by DC. This metric will vary from about 56 percent, for a score that is a random draw, to 100 percent for a score that is a perfect predictor of exhaustion. The scores for the four models are as follows:

Score	% exhausted of those with the top 56% of score	Standard error of the score
Original	60.25213	.66639
Updated	63.55366	.65585
Revised	63.76973	.65507
TOBIT	62.93408	.65823

The revised model performs the best, but it is insignificantly better than the updated model.

To compare models across SWAs, we developed a metric to gauge classification improvements between our models and the original model. In the metric below, *"Exhaustion"* is the percentage of all benefit recipients in our sample that exhaust benefits. Here we use 56 percent for "*Exhaustion"* because the exhaustion rate for all benefit recipients for the District of Columbia was 56 percent. In our metric, "Pr[*Exh*]" is determined by the model with the highest percentage of benefit exhaustees with profiling scores falling in the top X percent of the sample where X percent is determined by the exhaustion rate for all benefit recipients in the sample. For the District of Columbia, "Pr[*Exh*]" is represented by the revised model with a score of 63.77 percent for benefit recipients that exhaust benefits with scores falling in the top 56 percent.

In addition to this metric, we also applied the equation below, derived by Silverman, Strange, and Lipscombe (2004), for calculating the variance (σ_z^2) of a quotient (p. 1069)[i]. This equation allowed us to calculate the variance for our metric, Z, which is the quotient of two random variables X and Y where X

= 100 - Pr[*Exh*] and Y = 100 - "*Exhaustion*." In the equation below, σ_X^2 is the variance of 100 - Pr[*Exh*], σ_Y^2 is the variance of 100 - "*Exhaustion,*" $E(X)$ is the mean for 100 - Pr[*Exh*], and $E(Y)$ is the mean for 100 - "*Exhaustion.*" By dividing the variance of the quotient of the two random variables (here 100 - "*Exhaustion*" and 100 - "Pr[*Exh*]") by the square root of our observations we were able to determine the standard error of the metric.

$$\text{Metric: } 1-\left(\frac{100-\Pr[Exh]}{100-Exhaustion} \right)$$

$$\text{Variance of Metric: } \sigma_z^2 \approx \frac{\sigma_X^2}{E(Y)^2}+\frac{E(X)^2\sigma_Y^2}{E(Y)^4}$$

$$\text{Standard error of the metric: } \sqrt{\frac{\sigma_Z^2}{N}}$$

For our metric, we use 63.77 percent for "Pr[*Exh*]" for the revised model and 60.25 pecent for "Pr[*Exh*]" for the original model. "*Exhaustion*" for both was 56 percent. The model metrics are shown below. For other SWAs, the statistic is recalculated using the exhaustion rate of that SWA from the given sample and the score from the model with the highest percentage of exhaustion. For SWAs with hypothetically perfect models, this metric will have a value of 1, and for SWAs with models that predict no better than random, the metric will take a value of 0.

SWA	Profiling score	Control for endogeneity?	Exhaustion rate for the state	Number of individuals with the highest profiling score	Exhaustion rate for individuals with high profiling scores	Metric	Variance of the Metric	Standard Error of the metric
District of Columbia	original score	N**	56.0	5,385	60.3	0.097	2.277	0.021
District of Columbia	revised score	N**	56.0	5,385	63.8	0.176	2.057	0.020

Analysis of Type I errors

Type I errors are individuals who are predicted to exhaust (reject the null hypothesis) and do not exhaust (the null hypothesis is actually true). Our analysis will be restricted to the top 56 percent of individuals who are predicted to exhaust benefits using the updated model. We use the variables included in the updated model.

Variable	Mean for exhausted	Mean for non-exhausted	T statistic	P value
	N=3,434	N= 1,951		
Unemployment rate	63.5300	62.8273	-3.0404	0.0024
Education through 8th grade	0.0116	0.0159	1.3114	0.1898
Education, some high school	0.1040	0.1102	0.7142	0.4751
Education, high school grad	0.5961	0.5664	-2.1284	0.0333
Education, some college	0.1712	0.1589	-1.1672	0.2432
Education, college graduate	0.0612	0.0907	4.0438	0.0001
Education, some graduate school	0.0041	0.0051	0.5552	0.5788
Education, masters or doctorate	0.0058	0.0072	0.6018	0.5473
Education, missing data	0.0154	0.0190	0.9714	0.3314
Occupation, professional and technical	0.2892	0.2932	0.3119	0.7551
Occupation, clerical	0.1514	0.1440	-0.7332	0.4634
Occupation, service	0.1025	0.1005	-0.2383	0.8116
Occupation, agriculture, fish, forest	0.0017	0.0015	-0.1809	0.8564
Occupation, processing	0.0044	0.0031	-0.7315	0.4645
Occupation, machine trades	0.0035	0.0051	0.9019	0.3672
Occupation, benchwork	0.0020	0.0015	-0.4102	0.6817
Occupation, structural	0.0504	0.0436	-1.1248	0.2607
Occupation, miscellaneous	0.0160	0.0118	-1.2480	0.2121
Occupation, missing	0.3789	0.3957	1.2204	0.2224
Industry, construction	0.0160	0.0103	-1.7354	0.0827
Industry, manufacturing	0.0178	0.0149	-0.7977	0.4251
Industry, transportation	0.0475	0.0379	-1.6401	0.1010
Industry, wholesale and retail	0.0964	0.0984	0.2408	0.8097
Industry, finance, insurance and real estate	0.0754	0.0615	-1.9192	0.0550
Industry, government	0.0958	0.1292	3.7969	0.0001
Industry, missing data	0.1570	0.1497	-0.7120	0.4765
Base period wages, $0 to $7,000	0.1174	0.1030	-1.6020	0.1092
Base period wages, $7,000 to $14,000	0.2871	0.2896	0.1921	0.8477
Base period wages, $14,000 to $21,000	0.2504	0.2742	1.9149	0.0556
Base period wages, $21,000 to $28,000	0.1605	0.1486	-1.1477	0.2512
Base period wages, $28,000 to $35,000	0.0874	0.0759	-1.4692	0.1418
Base period wages, $35,000 and above	0.0973	0.1087	1.3321	0.1829
Job tenure, 0 to 90 days	0.0440	0.0528	1.4677	0.1422
Job tenure, 91 to 180 days	0.0981	0.0938	-0.5180	0.6045
Job tenure, 181 to 360 days	0.2545	0.2711	1.3363	0.1815
Job tenure, 361 to 720 days	0.2356	0.2071	-2.4082	0.0161
Job tenure, 721 to 1800 days	0.2598	0.2542	-0.4456	0.6559
Job tenure, more than 1800 days	0.1080	0.1210	1.4417	0.1494

For the table above, note that it includes 3,434 individuals who exhausted benefits and 1,951 who did not. The total of these two types of individuals is 5,385, which is 56 percent of the 9,615 individuals in the sample. The Type I analysis shows that certain variables have more explanatory power than others for explaining the difference between Type I errors and correct predictions. For example, the variables for unemployment rate and education, college graduate are important for explaining the difference between exhaustees and non-exhaustees. Less important variables, with low p-values, are occupation, professional and technical and job tenure, 721 to 1800 days.

Expanded Analyses of Georgia Profiling Data

ANALYSIS OF GEORGIA PROFILING DATA

At the time the Georgia survey was completed, the SWA was in the process of programming and implementing a new linear probability profiling model estimated by ordinary least squares. The new model is being developed by the W.E. Upjohn Institute. The discussion that follows describes the model being replaced.

Reported Profiling Model

Currently, Georgia uses a logistical regression model to determine a claimant's Worker Profiling and Reemployment Services (WPRS) eligibility. The original model was estimated in 1995 with a sample size of 10,000. Georgia estimated the existing model in 1998 with a sample size of 77,000 and revised the model at that time.

Georgia provided their model structure and a dataset for data analysis and possible model revision. From the given data, we derived variables and categories for education, job tenure, county of residence unemployment rate, occupation code, and industry code. Further, we successfully replicated the provided profiling scores. We ranked these profiling scores in ascending order, divided them into deciles, and produced the decile table shown below. The decile means are calculated by dividing the percentage of recipients that exhaust benefits for a given decile by 100. For example, in the first decile, our mean is 0.2840939, which indicates that approximately 28 percent of benefit recipients in this decile exhausted benefits.

Decile	Mean	Standard Error (Mean)
1	.2840939	.0029731
2	.3311886	.0032492
3	.3382839	.0033743
4	.3436295	.003126
5	.3475689	.0033578
6	.3665276	.0035024
7	.3879867	.0037862
8	.394546	.0039152
9	.405396	.0034609
10	.403749	.0037612
Total	.35681	.0010847

For purposes of the analysis, we employed a logistic regression model to ensure that we were able to properly estimate exhaustibility of benefits using the binary response variables in the original model and provided in our sample. (Note: we eliminated observations with a value of “0” for maximum benefit allowance because it is possible that these individuals were erroneously included in the dataset provided.) Included with the dataset was a binary variable indicating whether or not benefit recipients were referred to reemployment services. This variable allowed us to test for endogeneity within the data and answer the question - does referral to reemployment services have an effect on the exhaustion of benefits?

For the analysis, we calculated the logistic regression model where only score (along with a constant) is used to predict the probability of exhaustion (Pr[exh]).

Logistic Regression Model with Score Only

Logistic regression	Number of observations	=	195073
	LR chi2(1)	=	1133.27
	Prob > chi2	=	0.0000
Log likelihood = -126535.26	Pseudo R2	=	0.0045

exh	Coefficient	Standard error	Z	P>z	[95% Conf.	Interval]
score	.022607	.0006742	33.53	0.000	.0212857	.0239283
_cons	-1.42629	.0255125	-55.91	0.000	-1.476294	-1.376286

Adding the variable for “referral” tests for a uniform referral effect. The test is a chi-squared test of difference in the (-2 X log likelihood) statistic for the nested models.

Logistic Regression Model with Score and Referral

Logistic regression		Number of observations	=	195073
		LR chi2(2)	=	5773.78
		Prob > chi2	=	0.0000
Log likelihood =	-124215	Pseudo R2	=	0.0227

exh	Coefficient	Standard error	z	P>z	[95% Conf.	Interval]
score	.013059	.0006959	18.77	0.000	.011695	.0144229
referred individuals	.7287322	.0106794	68.24	0.000	.707801	.7496633
_cons	-1.281733	.0258481	-49.59	0.000	-1.332394	-1.231072

The addition of the variable "referred individuals" improves the log likelihood from -126,535.26 to -124,215. This represents a significant difference, showing signed or uniform effect. We add an interaction term (referral X score) to test for a non-uniform or unsigned effect.

Logistic Regression Model with Score, Referral and an Interaction Term

Logistic regression	Number of observations	=	195073
	LR chi2(3)	=	5831.32
	Prob > chi2	=	0.0000
Log likelihood = -124186.24	Pseudo R2	=	0.0229

exh	Coefficient	Standard error	z	P>z	[95% Conf.	Interval]
score	.0097581	.0008208	11.89	0.000	.0081493	.0113668
referred individuals	.276535	.0606683	4.56	0.000	.1576273	.3954427
referred individuals X score	.0117644	.0015536	7.57	0.000	.0087194	.0148095
_cons	-1.162289	.0302252	-38.45	0.000	-1.221529	-1.103048

Again, the addition of the interaction term changes the log likelihood from -124215 to -124186.24. This represents a significant difference, showing an unsigned or non-uniform effect.

The offset variable is calculated from the referral and interaction variables times their coefficients as:

offset = .276535*referred individuals+ .0117644*cross of referred individuals times score

This value represents the difference between the Pr[exh] for referred and non-referred individuals. Adding this variable to the logistic regression as a fixed coefficient variable should adjust referred and exempted individuals to the Pr[exh] that they would have had if they were not referred.

By adjusting the original scores with this control for endogeneity, we can estimate the true exhaustion rate for the original score. The logistic regression has exhaustion as a dependent variable, score as the independent variable and the offset, named endogeneity control, to control for endogeneity.

Logistic regression	Number of observations	=	195073
	Wald chi2(1)	=	204.78
Log likelihood = -124186.24	Prob > chi2	=	0.0000

exh	Coefficient	Standard error	z	P>z	[95% Conf.	Interval]
score	.0097581	.0006819	14.31	0.000	.0084216	.0110946
_cons	-1.162289	.0257541	-45.13	0.000	-1.212767	-1.111812
endogeneity control	(offset)					

By taking the predictions of the model, ordering and dividing them into deciles, and then for each decile showing the actual exhaustion rate, with its standard error, we obtain the following table that demonstrates the effectiveness of each model.

Decile	Mean	Standard Error (Mean)
1	.269121	.0031115
2	.3191817	.0033981
3	.3127325	.0029322
4	.2944923	.0036021
5	.2855699	.0033847
6	.3357326	.0032498
7	.3364993	.0034811
8	.4043413	.0036018
9	.4866126	.0035034
10	.5259009	.0036566
Total	.35681	.0010847

By adjusting for endogeneity, our decile gradient improved from a range of a low of 0.28 to a high of 0.40 for the original scores to a low of 0.26 to a high of 0.52.

Updated Profiling Model

The updated model has the same form as the original model used to predict score, only the coefficients are generated using 2003 data. Additionally, the updated model includes the offset to control for endogeneity. We also include diagnostic statistics to show how well the model works, including a classification table that looks at the top 36 percent of cases because that is Georgia’s exhaustion rate.

For this model, we are not using a separate model for each geographic (sub-state) area (SSA). Rather, we are including a binary variable to estimate the variation in exhaustion for each SSA. Unlike in the original model, this approach does not capture the uniqueness of each region. We are assuming that the effects for education, tenure, unemployment rate, occupational titles, Standard Industrial Classification code, and industry change, as measured by their coefficients, will be similar across regions.

The model run showed collinearity between the SSA variables and the industry growth rate, which took on different values only for each SSA. To correct for this, we used binary variables for only nine of the eleven SSAs. We dropped the binary variables for SSAs 1 and 2. Similarly, we dropped variables for edu2 (high school diploma), dot1 (the first type of job title), and sic1 (the first industry classification).

Updated Model Results

Logistic regression	Number of observations	=	195073
	Wald chi2(31)	=	3549.15
Log likelihood = -122442.98	Prob > chi2	=	0.0000

exh	Coefficient	Standard error	Z	P>z	[95% Conf.	Interval]
ed1	-.1160946	.0149378	-7.77	0.000	-.1453721	-.086817
ed3	.0771709	.0128641	6.00	0.000	.0519578	.1023841
ed4	.1059333	.0147215	7.20	0.000	.0770797	.1347869
tenure	.0324916	.0017111	18.99	0.000	.0291379	.0358453
unemployment rate	.0061226	.0036944	1.66	0.097	-.0011182	.0133634
dot2	.046577	.0132009	3.53	0.000	.0207038	.0724503
dot3	-.1976218	.0187164	-10.56	0.000	-.2343053	-.1609383
dot4	-.1199376	.0599173	-2.00	0.045	-.2373733	-.0025019
dot5	-.2027409	.0447526	-4.53	0.000	-.2904544	-.1150274
dot6	-.1741834	.0244379	-7.13	0.000	-.2220808	-.1262861
dot7	.0625821	.0314	1.99	0.046	.0010392	.1241251
dot8	-.0314562	.0203683	-1.54	0.122	-.0713772	.0084649
dot9	-.0937155	.0177125	-5.29	0.000	-.1284313	-.0589996
sic2	.1716698	.0290238	5.91	0.000	.1147842	.2285555
sic3	.2769711	.032676	8.48	0.000	.2129273	.3410149
sic4	.0746161	.0359445	2.08	0.038	.0041661	.1450661
sic5	.0010642	.0190012	0.06	0.955	-.0361774	.0383057
sic6	.1965589	.0462413	4.25	0.000	.1059277	.2871901
sic7	.3089762	.0214788	14.39	0.000	.2668785	.3510739
sic8	.1053133	.0239066	4.41	0.000	.0584573	.1521694
sic9	.1463108	.0391431	3.74	0.000	.0695917	.2230299
ssa3	.3687098	.0333179	11.07	0.000	.3034079	.4340116
ssa4	-.123113	.0379413	-3.24	0.001	-.1974765	-.0487495
ssa5	.2389732	.0349329	6.84	0.000	.1705059	.3074405
ssa6	-.2439554	.0278371	-8.76	0.000	-.2985151	-.1893956
ssa7	-.2223315	.0306923	-7.24	0.000	-.2824873	-.1621756
ssa8	-.1177148	.0483199	-2.44	0.015	-.2124201	-.0230095
ssa9	-.025174	.0465988	-0.54	0.589	-.116506	.066158
ssa10	-.4014942	.0450889	-8.90	0.000	-.4898669	-.3131216
ssa11	.102602	.035924	2.86	0.004	.0321922	.1730117
industry change	5.656012	3.490768	1.62	0.105	-1.185769	12.49779

_cons	-1.101941	.0396315	-27.80	0.000	-1.179618	-1.024265
endogeneity control	(offset)					

Classified	D	~D	Total
+	37681	44525	82206
-	31923	80944	112867
Total	69604	125469	195073

Classified + if predicted Pr(D)	>=	.36
True D defined as exhaust	!=	0

Sensitivity		Pr(+ D)	54.14%	
Specificity		Pr(-~D)	64.51%	
Positive predictive value		Pr(D +)	45.84%	
Negative predictive value		Pr(~D -)	71.72%	
False + rate for true ~D		Pr(+~D)	35.49%	
False - rate for true D		Pr(- D)	45.86%	
False + rate for classified	+	Pr(~D +)	54.16%	
False - rate for classified	-	Pr(D -)	28.28%	
Correctly classified				60.81%

number of observations	=	195073
area under ROC curve	=	0.6326

The decile table for the updated model is as follows:

Decile	Mean	Standard Error (Mean)
1	.1763198	.0027284
2	.2317355	.0030213
3	.2759027	.0031988
4	.3171106	.0033273
5	.3411982	.0033956
6	.3764332	.0034433
7	.3982042	.003537
8	.4366638	.0035512
9	.49713	.0035795
10	.5180494	.0035781
Total	.35681	.0010847

From the change in the log-likelihood, the updated model performed significantly better than the original model. There is also an improvement in the decile gradient, from a low of 0.27 to a high of 0.53 for the original model, to a low of 0.18 to a high of 0.52 for the updated model. Also, the updated model shows a monotonic increase in ability to predict exhaustion.

Revised Model

The revised model is the same as the updated model except that we added 14 more variables to account for some nonlinear and second-order interaction effects. Two of the variables were second-order versions of job tenure and unemployment rate. These variables were created by first centering the variables, by subtracting their mean, and squaring them. A third continuous variable, industry growth rate, was not included in the second-order effects due to collinearity with the SSA variables. Three interaction terms were created by centering and multiplying the three second-order combinations (industry growth X job tenure, industry growth X unemployment rate, and job tenure X unemployment rate). In addition, we created nine more interaction terms by centering and multiplying job tenure, unemployment rate, and industrial growth by the three education level binary variables. The means for the variables job tenure, unemployment rate, and industrial growth are shown below.

Variable	Job tenure	Unemployment rate	Industry growth
Mean	4.742332	4.58945	-.0146383

The logistic regression model results for the revised model are as follows.

Logistic regression	Number of observations	=	195073
	Wald chi2(45)	=	3707.13
Log likelihood = -122353.66	Prob > chi2	=	0.0000

exh	Coefficient	Standard error	z	P>z	[95% Conf.	Interval]
ed1	-.1062255	.0156577	-6.78	0.000	-.1369139	-.075537
ed3	.0773488	.0130138	5.94	0.000	.0518422	.1028554
ed4	.1030417	.0157385	6.55	0.000	.0721948	.1338886
tenure	.0356726	.002629	13.57	0.000	.0305198	.0408254
unemployment rate	.0295643	.0058729	5.03	0.000	.0180536	.0410751
dot2	.0426767	.0132192	3.23	0.001	.0167676	.0685858
dot3	-.2065151	.018763	-11.01	0.000	-.2432898	-.1697404
dot4	-.1223833	.0599755	-2.04	0.041	-.239933	-.0048336
dot5	-.1961001	.0448341	-4.37	0.000	-.2839733	-.1082269
dot6	-.1746693	.0244739	-7.14	0.000	-.2226372	-.1267014
dot7	.060952	.0314543	1.94	0.053	-.0006973	.1226013

dot8	-.0394995	.020429	-1.93	0.053	-.0795397	.0005406
dot9	-.1013158	.0177572	-5.71	0.000	-.1361192	-.0665123
sic2	.170476	.0290952	5.86	0.000	.1134505	.2275016
sic3	.2762831	.0327473	8.44	0.000	.2120997	.3404665
sic4	.0658167	.0359907	1.83	0.067	-.0047236	.1363571
sic5	-.0031969	.0190607	-0.17	0.867	-.0405553	.0341614
sic6	.1841531	.0462899	3.98	0.000	.0934266	.2748796
sic7	.2999858	.0215617	13.91	0.000	.2577256	.342246
sic8	.0987422	.0239771	4.12	0.000	.0517478	.1457365
sic9	.1427686	.0391897	3.64	0.000	.0659581	.219579
ssa3	.3829197	.0336799	11.37	0.000	.3169082	.4489311
ssa4	-.044004	.0397864	-1.11	0.269	-.1219839	.0339759
ssa5	.1833339	.0359658	5.10	0.000	.1128423	.2538255
ssa6	-.2079831	.0283208	-7.34	0.000	-.2634908	-.1524753
ssa7	-.178459	.0312668	-5.71	0.000	-.2397408	-.1171772
ssa8	-.1984627	.0494136	-4.02	0.000	-.2953115	-.1016138
ssa9	-.0608354	.0470337	-1.29	0.196	-.1530198	.0313491
ssa10	-.4111007	.0452167	-9.09	0.000	-.4997239	-.3224775
ssa11	.1734597	.0376932	4.60	0.000	.0995823	.2473371
industry change	-1.328503	3.712532	-0.36	0.720	-8.604931	5.947925
xt2	.0015943	.0008573	1.86	0.063	-.0000859	.0032745
xu2	-.002237	.000691	-3.24	0.001	-.0035914	-.0008826
xit	-.0196541	.3080067	-0.06	0.949	-.6233361	.5840279
xiu	-6.78295	.8196579	-8.28	0.000	-8.38945	-5.17645
xtu	.0019267	.0009712	1.98	0.047	.0000232	.0038302
xie1	4.17389	2.518685	1.66	0.097	-.7626423	9.110422
xie3	.2940127	2.421071	0.12	0.903	-4.4512	5.039225
xie4	17.17809	2.857317	6.01	0.000	11.57785	22.77832
xte1	.0117554	.0048798	2.41	0.016	.0021911	.0213196
xte3	-.010396	.0043241	-2.40	0.016	-.0188711	-.0019209
xte4	-.0103147	.0048018	-2.15	0.032	-.0197261	-.0009032
xue1	-.0097391	.0077524	-1.26	0.209	-.0249336	.0054553
xue3	-.0081767	.0077511	-1.05	0.291	-.0233686	.0070153
xue4	-.0663594	.0099582	-6.66	0.000	-.0858771	-.0468418
_cons	-1.330325	.0491236	-27.08	0.000	-1.426605	-1.234044
endogeneity control	(offset)					

Classification Table

	--------	True	--------	
Classified	D		~D	Total
+	38391		45387	83778
-	31213		80082	111295
Total	69604		125469	195073

Classified + if predicted Pr(D) >= .36
True D defined as exhaust != 0

Sensitivity		Pr(+ D)	55.16%	
Specificity		Pr(-~D)	63.83%	
Positive predictive value		Pr(D +)	45.82%	
Negative predictive value		Pr(~D -)	71.95%	
False + rate for true ~D		Pr(+~D)	36.17%	
False - rate for true D		Pr(- D)	44.84%	
False + rate for classified	+	Pr(~D +)	54.18%	
False - rate for classified	-	Pr(D -)	28.05%	
Correctly classified				60.73%

number of observations	=	195073
number of covariate patterns	=	43883
Pearson chi2(43837)	=	43766.92
Prob > chi2	=	0.5927

number of observations	=	195073
area under ROC curve	=	0.6339

The decile table for the revised model is as follows.

Decile	Mean	Standard Error (Mean)
1	.1748513	.0027196
2	.232582	.003024
3	.2757719	.0032006
4	.3093566	.0033097
5	.3449972	.0034026
6	.3744304	.0034439
7	.4017281	.0034952
8	.4381681	.0035917
9	.4991541	.00358
10	.5182755	.0035776
Total	.35681	.0010847

Note that there is a significant improvement from the updated to the revised model in terms of log likelihood. However, the decile gradient is not much different than the updated model.

Tobit Analysis Using the Variables of the Revised Model

Next we analyzed the Georgia data using a Tobit model to predict exhaustion. The Tobit model is similar to the logistic model except that the Tobit model uses information about non-exhaustees, assuming that non-exhaustees who are closer to exhaustion are more similar to exhaustees than those claimants who are further from exhaustion. First, we created a new dependent variable, "/sigma."

/sigma = 100 X (allowed benefits – benefits paid)/ allowed benefits

This variable represents the percent of the allowed benefits left to individuals. Exhaustees have a value of 0. In the data, all negative values were recoded as 0.

Second, we tested for endogeneity using the same procedure as for the logistic analyses. Replication is necessary because of the difference in functional form for the Tobit model. The first model uses only the score as the independent variable.

Tobit regression		Number of observations	=	195073
		LR chi2(1)	=	840.16
		Prob > chi2	=	0.0000
Log likelihood =	-764544.46	Pseudo R2	=	0.0005

Tobit dependent var.	Coefficient	Standard error	t	P>t	[95% Conf.	Interval]
Score	-.6311914	.0217849	-28.97	0.000	-.6738892	-.5884935
_cons	59.22275	.8151841	72.65	0.000	57.62501	60.82049
/sigma	64.72412	.1429358			64.44397	65.00427

The second model uses only score and a binary variable for referred status as independent variables.

Tobit regression		Number of observations	=	195073
		LR chi2(2)	=	11287.60
		Prob > chi2	=	0.0000
Log likelihood =	-759320.74	Pseudo R2	=	0.0074

tobit dependent var.	Coefficient	Standard error	t	P>t	[95% Conf.	Interval]
score	-.1732102	.0215123	-8.05	0.000	-.2153737	-.1310467

referred individuals	-36.16161	.352659	-102.54	0.000	-36.85282	-35.47041
_cons	52.22412	.7921652	65.93	0.000	50.67149	53.77674
/sigma	62.54957	.1378871			62.27931	62.81982

The change in log likelihood shows uniform endogeneity. Next is the inclusion of interaction effects.

Tobit regression		Number of observations	=	195073
		LR chi2(3)	=	11454.67
		Prob > chi2	=	0.0000
Log likelihood =	-759237.2	Pseudo R2	=	0.0075

Tobit dependent var.	Coefficient	Standard error	t	P>t	[95% Conf.	Interval]
Score	-.0197728	.0245542	-0.81	0.421	-.0678984	.0283528
Referred individuals	-10.91369	1.983569	-5.50	0.000	-14.80143	-7.02594
referred individuals X score	-.6570979	.0508443	-12.92	0.000	-.7567515	-.5574444
_cons	46.71614	.8995094	51.94	0.000	44.95312	48.47915
/sigma	62.52118	.1378168			62.25106	62.79129

The change in log likelihood again demonstrates endogeneity. The offset variable to control for endogeneity is:

offset = -10.91369*refbin-0.6570979*cross of referred individuals times score

The Tobit model uses the same independent variables as the revised model and includes the control for endogeneity. The results are as follows.

Tobit regression		Number of observations	=	195073
		LR chi2(45)	=	6618.71
		Prob > chi2	=	0.0000
Log likelihood =	-755928.28	Pseudo R2	=	0.0044

tobit dependent var.	Coefficient	Standard error	t	P>t	[95% Conf.	Interval]
ed1	5.069987	.4604692	11.01	0.000	4.167478	5.972495

ed3	-3.435752	.3952771	-8.69	0.000	-4.210485	-2.661018
ed4	-8.036164	.4813009	-16.70	0.000	-8.979502	-7.092826
tenure	-1.373171	.078728	-17.44	0.000	-1.527476	-1.218866
unemployment rate	-.1843556	.1750566	-1.05	0.292	-.5274624	.1587512
dot2	1.005231	.4092656	2.46	0.014	.2030798	1.807381
dot3	9.884773	.5498551	17.98	0.000	8.807071	10.96248
dot4	6.001274	1.720541	3.49	0.000	2.629054	9.373494
dot5	7.965155	1.266836	6.29	0.000	5.482186	10.44812
dot6	5.950474	.7148331	8.32	0.000	4.549418	7.35153
dot7	-.5867457	.9640386	-0.61	0.543	-2.476238	1.302747
dot8	.0647052	.6091886	0.11	0.915	-1.12929	1.2587
dot9	4.567563	.5292177	8.63	0.000	3.530309	5.604817
sic2	-4.492342	.8568635	-5.24	0.000	-6.171774	-2.81291
sic3	-10.95953	.9934645	-11.03	0.000	-12.9067	-9.012362
sic4	-1.202585	1.069351	-1.12	0.261	-3.298487	.8933164
sic5	1.33033	.5540288	2.40	0.016	.2444472	2.416214
sic6	-5.71412	1.433949	-3.98	0.000	-8.524626	-2.903614
sic7	-10.44492	.6591466	-15.85	0.000	-11.73683	-9.153011
sic8	-2.022165	.7118249	-2.84	0.005	-3.417325	-.6270055
sic9	-3.798288	1.167174	-3.25	0.001	-6.085921	-1.510655
ssa3	-9.767501	.9767781	-10.00	0.000	-11.68196	-7.853039
ssa4	.1852328	1.146887	0.16	0.872	-2.062639	2.433105
ssa5	-5.721148	1.054643	-5.42	0.000	-7.788222	-3.654073
ssa6	8.380592	.8053247	10.41	0.000	6.802175	9.959009
ssa7	5.123843	.8812741	5.81	0.000	3.396567	6.851119
ssa8	8.225395	1.412202	5.82	0.000	5.457513	10.99328
ssa9	4.342947	1.353898	3.21	0.001	1.68934	6.996555
ssa10	15.06619	1.260142	11.96	0.000	12.59634	17.53604
ssa11	-6.950502	1.101365	-6.31	0.000	-9.10915	-4.791854
industry change	133.6846	107.1862	1.25	0.212	-76.3979	343.7671
xt2	-.0601968	.0255331	-2.36	0.018	-.110241	-.0101527
xu2	.0113155	.0209131	0.54	0.588	-.0296737	.0523047
xit	22.9023	9.113746	2.51	0.012	5.039579	40.76503
xiu	233.9308	23.91956	9.78	0.000	187.049	280.8126
xtu	.0060012	.0290333	0.21	0.836	-.0509033	.0629057
xie1	-84.06095	72.23	-1.16	0.245	-225.63	57.50813
xie3	37.50738	72.17031	0.52	0.603	-103.9447	178.9595
xie4	-398.8507	87.59991	-4.55	0.000	-570.5444	-227.1569
xte1	-.1988438	.1415403	-1.40	0.160	-.4762594	.0785718
xte3	.2876966	.1313591	2.19	0.029	.0302359	.5451572
xte4	.2370301	.1477318	1.60	0.109	-.0525206	.5265809
xue1	.1671875	.2259057	0.74	0.459	-.2755823	.6099572
xue3	.563227	.2358587	2.39	0.017	.1009495	1.025505
xue4	2.996777	.2981889	10.05	0.000	2.412334	3.58122
_cons	60.20863	1.435741	41.94	0.000	57.39461	63.02265
endogeneity control	(offset)					

/sigma	61.20241	.1342908			60.93921	61.46562

The decile table for the Tobit model is as follows.

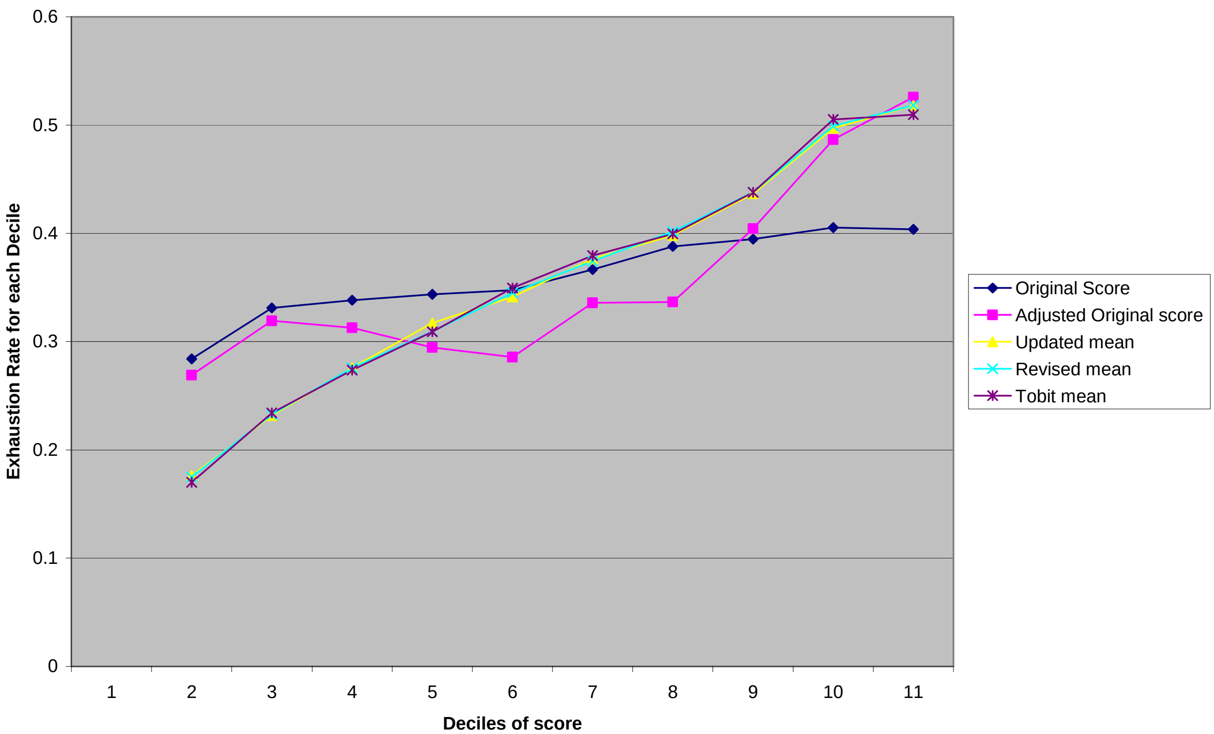
Decile	Mean	Standard Error (Mean)
1	.1701005	.0026898
2	.2341178	.0030322
3	.2737851	.0031926
4	.3091216	.0033064
5	.3494533	.0034163
6	.3794323	.0034736
7	.3994262	.0035059
8	.4378592	.003554
9	.5052783	.0035792
10	.5096672	.0035801
Total	.35681	.0010847

Note that the Tobit model cannot be compared with the logistic regression models by log likelihood comparisons. However, from the decile tables, the model does not appear to be significantly better than the revised model.

We created a summary table of the four decile tables that allows us to compare models. The Tobit model allows only marginal improvement over the revised model. The revised model appears better at predicting benefit exhaustion than other models.

Decile	Original Score	Adjusted Original score	Updated score	Revised score	Tobit score
1	.2840939	.269121	.1763198	.1748513	.1701005
2	.3311886	.3191817	.2317355	.232582	.2341178
3	.3382839	.3127325	.2759027	.2757719	.2737851
4	.3436295	.2944923	.3171106	.3093566	.3091216
5	.3475689	.2855699	.3411982	.3449972	.3494533
6	.3665276	.3357326	.3764332	.3744304	.3794323
7	.3879867	.3364993	.3982042	.4017281	.3994262
8	.394546	.4043413	.4366638	.4381681	.4378592
9	.405396	.4866126	.49713	.4991541	.5052783
10	.403749	.5259009	.5180494	.5182755	.5096672
Total	.35681	.35681	.35681	.35681	.35681

Comparison of the Models for Calculating Profiling Scores



Correlations of the four profiling scores indicate that the updated, revised, and Tobit scores are highly correlated. As expected, the original score is positively correlated with the other three scores, though not at the same magnitude. While the latter three scores are highly correlated, they are not identical, which suggests that there is a significant difference between the models.

	original score	updated score	revised score	tobit score
original score	1.0000			
updated score	0.3624	1.0000		
revised score	0.3827	0.9856	1.0000	
tobit score	0.2800	0.9690	0.9754	1.0000

We also tested the performance of each model using the metric below:

Percent exhausted of the top 35.7 percent of individuals in the score.

We used 35.7 percent because the exhaustion rate for benefit recipients in the Georgia dataset was 35.7 percent. This metric will vary from about 35.7 percent, for a score that is a random draw, up to 100 percent for a score that is a perfect predictor of exhaustion. The scores for the four models are as follows:

Score	% exhausted of those with the top 35.7% of score	Standard error of the score
Original	39.83	0.18598
Updated	47.12	0.18926
Revised	47.32	0.18919
Tobit	47.14	0.18925

To compare models across SWAs, we developed a metric to gauge classification improvements between our models and the original model. In the below metric, *"Exhaustion"* is the percentage of all benefit recipients in our sample that exhaust benefits. Here we use 35.7 percent for "*Exhaustion"* because the exhaustion rate for all benefit recipients for Georgia was 35.7 percent. In our metric, "Pr[*Exh*]" is determined by the model with the highest percentage of benefit exhaustees with profiling scores falling in the top X percent of the sample, where X percent is determined by the exhaustion rate for all benefit recipients in the sample. For Georgia, "Pr[*Exh*]" is represented by the revised model with a score of 47.32 percent for benefit recipients that exhaust benefits with scores falling in the top 35.7 percent.

In addition to this metric, we also applied the equation below, derived by Silverman, Strange, and Lipscombe (2004), for calculating the variance (σ_z^2) of a quotient (p. 1069). This equation allowed us to calculate the variance for our metric, Z = X/Y, which is the quotient of two random variables X (100 - "Pr[*Exh*]") and Y (100 - "*Exhaustion*"). In the equation below, σ_X^2 is the variance of 100 - "Pr[*Exh*]," σ_Y^2 is the variance of 100 - "*Exhaustion,"* $E(X)$ is the mean for (100 - "Pr[*Exh*]"), and $E(Y)$ is the mean for (100- "*Exhaustion"*). By dividing the variance of the quotient of the two random variables (here 100 - "*Exhaustion*" and 100 - "Pr[*Exh*]") by the square root of our observations we were able to determine the standard error of the metric.

Metric = 1 – (100 - Pr[*Exh*])/(100 – *Exhaustion*)

Variance of Metric: $\sigma_z^2 \approx \frac{\sigma_X^2}{E(Y)^2} + \frac{E(X)^2 \sigma_Y^2}{E(Y)^4}$ where X = $(100 - \Pr[Exh])$, (Y = $100 - Exhaustion$)

Standard error of the metric: $\sqrt{\frac{\sigma_Z^2}{N}}$

For our metric, "Pr[*Exh*]" is 47.32 percent and *"Exhaustion"* is 35.7 percent. We used these to calculate a score of 0.19412879, or roughly 19.4 percent, with a standard error of 0.003648754. For SWAs with hypothetically perfect models, this metric will have a value of 1, and for SWAs with models that predict no better than random, the metric will take a value of 0.

SWA	Profiling score	Control for endogeneity?	Exhaustion rate for the state	Number of individuals with the highest profiling score	Exhaustion rate for individuals with high profiling scores	Metric	Variance of the Metric	Standard Error of the metric
Georgia	original score	Y	35.7	75,994	44.0	0.129	1.017	0.004
Georgia	revised score	Y	35.7	75,994	47.3	0.181	0.976	0.004

Analysis of Type I Errors

For this analysis, Type I errors occur when individuals who are predicted to exhaust (reject the null hypothesis) do not exhaust (the null hypothesis is actually true). The analysis is restricted to the top 35.7 percent of individuals who are predicted to exhaust benefits using the revised model.

Variable	Mean for exhausted	Mean for non-exhausted	T statistic	P value
	N=32,953	N=36,692		
Education < HS diploma	0.0835	0.0899	-3.0051	0.0027
Education = HS diploma	0.3152	0.3418	-7.4620	0.0000
Education=some college	0.2828	0.2910	-2.4072	0.0161
Education=college grad+	0.3185	0.2772	11.8840	0.0000
Job tenure	6.0272	5.9909	1.7969	0.0724
Local unemployment rate	4.3973	4.4445	-3.7872	0.0002
Occupation type 1	0.4521	0.4253	7.1061	0.0000
Occupation type 2	0.3136	0.3394	-7.2346	0.0000
Occupation type 3	0.0476	0.0571	-5.6671	0.0000
Occupation type 4	0.0042	0.0036	1.3132	0.1891
Occupation type 5	0.0064	0.0076	-1.7814	0.0748
Occupation type 6	0.0279	0.0252	2.1327	0.0330
Occupation type 7	0.0325	0.0345	-1.4783	0.1393
Occupation type 8	0.0540	0.0469	4.2548	0.0000
Occupation type 9	0.0618	0.0604	0.7489	0.4539
Industry class 0	0.7202	0.7096	3.1101	0.0019
Industry class 1	0.0137	0.0132	0.4840	0.6284
Industry class 2	0.0267	0.0294	-2.1991	0.0279
Industry class 3	0.0283	0.0273	0.8050	0.4208
Industry class 4	0.0152	0.0168	-1.5945	0.1108
Industry class 5	0.0425	0.0507	-5.1513	0.0000
Industry class 6	0.0161	0.0171	-1.0117	0.3117
Industry class 7	0.0782	0.0770	0.5624	0.5738
Industry class 8	0.0438	0.0435	0.1809	0.8565
Industry class 9	0.0153	0.0153	-0.0347	0.9723
Area 1	0.0350	0.0391	-2.8612	0.0042
Area 2	0.0588	0.0596	-0.4558	0.6485

Area 3	0.7188	0.7155	0.9458	0.3442
Area 4	0.0248	0.0228	1.7366	0.0825
Area 5	0.0313	0.0317	-0.2995	0.7645
Area 6	0.0316	0.0334	-1.2929	0.1960
Area 7	0.0196	0.0171	2.4352	0.0149
Area 8	0.0163	0.0173	-1.0847	0.2781
Area 9	0.0311	0.0308	0.2477	0.8043
Area 10	0.0050	0.0049	0.0829	0.9339
Area 11	0.0277	0.0277	0.0089	0.9929
Industry growth rate	-0.0161	-0.0162	0.3443	0.7306

For the above table, 32,953 individuals exhausted benefits and 36,692 did not. The total of these two types of individuals is 69,645, which is 35.7 percent of the 195,073 individuals in the sample. The Type I analysis shows that certain variables have more explanatory power than others for explaining the difference between Type I errors and correct predictions. For example, the area variables are not that important for explaining the difference between exhaustees and non-exhaustees. More important variables, with low p-values, are education = High School diploma, education = college grad+, local unemployment rate and occupation types 1, 2, and 3.

Expanded Analyses of Hawaii Profiling Data

Analysis of Hawaii Data

For our analysis, we employed a logit model to predict exhaustibility similar to the logit model used by Hawaii to calculate the original profiling scores. We did this to ensure that we were able to properly estimate exhaustibility of benefits using the binary response variables used in the original model and provided in our sample.

Our first step was to replicate the given scores using the data and variable coefficients provided for the model. From the given data, we identified and replicated variables and categories for county total unemployment rate, education level, industry code, occupation code, job tenure, and weekly benefit amount. We noticed that there were four cases that were outliers, one with no profiling score and three with scores that were at least ten times that of the other scores. The correlation of our replicated score with the original profiling score was only .42. The elimination of the four outlier cases reduced the sample from 8976 to 8972, and we were able to develop a score that correlated with the original score at a level of .86. Our analysis proceeded with the revised sample.

Another problem with the data is that there was little variation in occupation. Of the 8,972 cases, 8,969 were occupation 1 - professional, technical, managerial. One was occupation 4 - agricultural, fishery, forestry, and two were occupation 8 - structural work. We suspect that the data are incomplete for the occupation variable, but the high correlation shows that this omission is not serious. In our analyses below, we will not include occupation variables.

We first developed a decile table for the original score. This table shows for each decile the actual exhaustion rate, with its standard error and allows us to demonstrate the effectiveness of each model. It is:

Original score deciles	mean	se(mean)
1	.320356	.0155711
2	.359375	.0160385
3	.3489409	.0159233
4	.3534002	.0159697
5	.4087432	.0162607
6	.3886364	.016441
7	.4197121	.0164321
8	.4480088	.0165488
9	.4366516	.0166907
10	.4548495	.0166356
Total	.3938921	.0051587

Also included was a binary variable that indicated whether or not benefit recipients were referred to re-employment services. This binary variable will allow us to test for endogeneity within our data and will answer the question - does referral to re-employment services have an effect on the exhaustion of benefits? To test for endogeneity, we first calculated the logit model where only score (and a constant) is used to predict Pr[exh].

Logit Model with score only

Logistic regression	Number of obs	=	8972
	LR chi2(1)	=	69.82
	Prob > chi2	=	0.0000
Log likelihood = -5980.4347	Pseudo R2	=	0.0058

exhaust	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
scorereal	2.241093	.269989	8.30	0.000	1.711924	2.770261
_cons	-1.456022	.1258169	-11.57	0.000	-1.702618	-1.209425

Adding the variable for referral tests for a uniform referral effect. The test would be a chi-squared test of difference in the (-2 X log likelihood) statistic for the nested models.

Logit Model with score and referral

Logistic regression	Number of obs	=	8972
	LR chi2(2)	=	73.72
	Prob > chi2	=	0.0000
Log likelihood = - 5978.484	Pseudo R2	=	0.0061

exhaust	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
scorereal	2.607491	.3284657	7.94	0.000	1.96371	3.251272
refer	-.1039734	.0526927	-1.97	0.048	-.2072491	-.0006977
_cons	-1.572106	.1392873	-11.29	0.000	-1.845105	-1.299108

The addition of the variable "refer" improved the log likelihood from -5980.4347 to -5978.484. The difference in log likelihood was 1.95, which is significant at the .05 level. Our next step was to test for non-uniform effects. We added an interaction term (referral X score) to test for a non-uniform or unsigned effect.

Logit Model with score, referral and an interaction term

Logistic regression	Number of obs	=	8972
	LR chi2(3)	=	73.87
	Prob > chi2	=	0.0000
Log likelihood = -5978.4087	Pseudo R2	=	0.0061

exhaust	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
scorereal	2.474107	.4751427	5.21	0.000	1.542844	3.405369
refer	-.2206746	.3053479	-0.72	0.470	-.8191454	.3777963
xrefscore	.2553012	.6578512	0.39	0.698	-1.034064	1.544666
_cons	-1.516941	.1988522	-7.63	0.000	-1.906685	-1.127198

The addition of the interaction term changes the log likelihood from -5978.484 to -5978.4087. The difference was not significant. The analysis indicates that there is only a need to control for uniform endogeneity. The offset variable is as follows:

-.1039734*refer

After correcting for endogeneity, we obtain the following decile table.

prorigdec	mean	se(mean)
1	.3273942	.0156682
2	.3143813	.0155101
3	.3756968	.0161794
4	.3756968	.0161794
5	.4046823	.0163975
6	.3886414	.0162752
7	.406015	.0161034
8	.4229432	.0168266
9	.4570792	.0166422
10	.4671126	.0166677
Total	.3938921	.0051587

Updated Model

The updated model for Hawaii uses the same variables as used in the original model to predict the profiling score, only the coefficients are generated using 2003 data. We also included diagnostic statistics to show how well the model works, including a classification table that looks at the top 39.3 percent of cases (because Hawaii has approximately a 39.3 percent exhaustion rate for the 8,972 cases in our analysis). As noted above, we did not use the occupation variable because of the lack of variation.

Logistic regression	Number of obs	=	8972
	Wald chi2(8)	=	102.90
Log likelihood = -5973.5191	Prob > chi2	=	0.0000
Logistic regression	Number of obs	=	8972

exhaust	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
tur	-.0391454	.0146026	-2.68	0.007	-.0677659	-.0105249
edu1	-.0011308	.0817388	-0.01	0.989	-.1613359	.1590743
edu3	.0196977	.0574813	0.34	0.732	-.0929636	.132359
edu4	-.1030133	.0678498	-1.52	0.129	-.2359965	.0299699
edu5	-.5466895	.1615675	-3.38	0.001	-.863356	-.230023
indchg	.0081247	.0041752	1.95	0.052	-.0000585	.0163078
tenure	.0132191	.0037979	3.48	0.001	.0057754	.0206629
wba	.0012269	.0001768	6.94	0.000	.0008804	.0015734
_cons	-.5474571	.0814076	-6.72	0.000	-.7070131	-.3879011
offset	(offset)					

	--------	True	--------	
Classified	D		~D	Total
+	1793		2344	4137
-	1741		3094	4835
Total	3534		5438	8972

Classified + if predicted	Pr(D)	>=	.393
True D defined as exhaust	!= 0		

Sensitivity		Pr(+ D)	50.74%	
Specificity		Pr(-~D)	56.90%	
Positive predictive value		Pr(D +)	43.34%	
Negative predictive value		Pr(~D -)	63.99%	
False + rate for true ~D		Pr(+~D)	43.10%	
False - rate for true D		Pr(- D)	49.26%	
False + rate for classified	+	Pr(~D +)	56.66%	
False - rate for classified	-	Pr(D -)	36.01%	
Correctly classified				54.47%

number of observations	=	8972
area under ROC curve	=	0.5569

The decile table for the updated model is as follows:

prupdec	mean	se(mean)
1	.2817372	.0150199
2	.3322185	.0157353
3	.3730512	.0161475
4	.4129464	.0164579
5	.386845	.0162705
6	.4153675	.0164536
7	.4292085	.0165356
8	.3908686	.016292
9	.4424779	.0165285
10	.4746907	.0167574
Total	.3938921	.0051587

From the original score to the updated model, there was a significant improvement. The decile gradient, which ranged from .327 to .467 for the original model (corrected for endogeneity) improved to .282 to .474 for the updated model.

Revised Model

The revised model is similar to the updated model, but we incorporated more of the information in the variable set. We included second order terms to capture nonlinear and discontinuous effects, which differs from the original model. The original model used a series of categories to account for these effects. The revised model consists of the following variables.

- Categorical variables for industry and local office
- Continuous variables for job tenure, weekly benefit amount (wba), education, total county unemployment rate, and industry employment percentage change (indchg)
- Second order variables for tenure, wba, educ, and indchg
- And interaction variables for tenure X wba, tenure X educ, tenure X indchg, wba X educ, wba X indchg, and educ X indchg

The revised model basically replaces the categorical variable for education with a continuous variable, adds variables for office and industry, and includes second order and interaction effects.

We created the second order variable by first centering the variables, by subtracting their mean, and squaring them. We created the interaction variables by centering and multiplying the three second order combinations. The means for the three continuous variables are shown below.

stats	tenure	wba	educ	indchg
mean	3.743873	240.2494	12.93405	3.694286

The logit model results for the revised model are as follows.

Logistic regression	Number of obs	=	8972
	Wald chi2(24)	=	131.33
Log likelihood = -5956.7856	Prob > chi2	=	0.0000
Logistic regression	Number of obs	=	8972

exhaust	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
tur	.0289942	.0266588	1.09	0.277	-.0232562	.0812445
educ	-.0171485	.0085116	-2.01	0.044	-.0338309	-.0004661
indchg	-.0053149	.0065375	-0.81	0.416	-.0181282	.0074984
tenure	.0151414	.0073575	2.06	0.040	.000721	.0295617
wba	.0014189	.0001978	7.17	0.000	.0010312	.0018066
off1	.2655104	.0870633	3.05	0.002	.0948695	.4361514
off4	-.0910092	.1111705	-0.82	0.413	-.3088993	.126881
sic0	.0426573	.1454797	0.29	0.769	-.2424777	.3277923
sic2	-.0769933	.1341431	-0.57	0.566	-.339909	.1859224
sic3	.1208014	.0776097	1.56	0.120	-.0313108	.2729136
sic4	.0658229	.1219436	0.54	0.589	-.1731822	.304828
sic5	.0838578	.070134	1.20	0.232	-.0536024	.221318
sic9	-.1751695	.0779081	-2.25	0.025	-.3278665	-.0224725
sic10	-.0796735	.0890464	-0.89	0.371	-.2542013	.0948543
xten2	-.0005519	.0003647	-1.51	0.130	-.0012666	.0001629
xwba2	-3.32e-06	2.05e-06	-1.62	0.106	-7.34e-06	7.06e-07
xedu2	-.0017244	.000973	-1.77	0.076	-.0036315	.0001828
xind2	.0005858	.0004086	1.43	0.152	-.0002151	.0013867
xtenwba	.0000119	.0000351	0.34	0.735	-.0000568	.0000806
xtenedu	-.000592	.0014018	-0.42	0.673	-.0033395	.0021556
xtenind	-.0011375	.0010682	-1.06	0.287	-.0032311	.0009562
xwbaedu	.0000651	.0000631	1.03	0.302	-.0000586	.0001887
xwbaind	.0000344	.0000372	0.92	0.355	-.0000385	.0001072
xeduind	-.0049737	.0018046	-2.76	0.006	-.0085107	-.0014366
_cons	-.7876039	.2256337	-3.49	0.000	-1.229838	-.3453699
offset	(offset)					

Classification Table

	--------	True	--------	
Classified	D		~D	Total
+	1939		2446	4385

-	1595		2992	4587
Total	3534		5438	8972

Classified + if predicted	Pr(D)	>=	.393
True D defined as exhaust	!= 0		

Sensitivity		Pr(+ D)	54.87%	
Specificity		Pr(-~D)	55.02%	
Positive predictive value		Pr(D +)	44.22%	
Negative predictive value		Pr(~D -)	65.23%	
False + rate for true ~D		Pr(+~D)	44.98%	
False - rate for true D		Pr(- D)	45.13%	
False + rate for classified	+	Pr(~D +)	55.78%	
False - rate for classified	-	Pr(D -)	34.77%	
Correctly classified				54.96%

number of observations	=	8972
area under ROC curve	=	0.5682

The decile table for the revised model is as follows.

prrevdec	mean	se(mean)
1	.3084633	.015421
2	.3188406	.0155689
3	.3377926	.0158004
4	.3846154	.016253
5	.3734671	.0161601
6	.422049	.0164904
7	.4225195	.0165021
8	.4180602	.016478
9	.4537347	.0166322
10	.4994426	.0167038
Total	.3938921	.0051587

This model appears to be similar to the updated model.

Tobit analysis using the variables of the revised model

The following is the procedure we used to generate a Tobit model to predict exhaustion. The Tobit model is similar to the logit model except that it uses information about non-exhaustees, assuming that non-exhaustees who are closer to exhaustion are more similar to exhaustees than those who are further from exhaustion. First, we created a new dependent variable. It is:

100 X (maximum benefit amount – benefits paid)/ maximum benefit amount

This variable represents the percent of the allowed benefits left to individuals. Exhaustees have a value of 0. In the data, all negative values were recoded as 0.

Second, we tested for endogeneity using the same procedure as for the logit analyses. Replication is necessary because of the difference in functional form for the Tobit model. The first model uses only the score as independent variable.

Tobit regression		Number of obs	=	8957
		LR chi2(1)	=	96.17
		Prob > chi2	=	0.0000
Log likelihood =	-32337.664	Pseudo R2	=	0.0015

tobdep	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
scorereal	-73.305	7.471521	-9.81	0.000	-87.95089	-58.65911
_cons	53.03798	3.442452	15.41	0.000	46.28998	59.78597
/sigma	54.00479	.5716541			52.88421	55.12536

The second model uses only score and a binary variable for referred status as independent variables.

Tobit regression		Number of obs	=	8957
		LR chi2(2)	=	100.39
		Prob > chi2	=	0.0000
Log likelihood =	-32335.558	Pseudo R2	=	0.0015

tobdep	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
scorereal	-83.59934	9.000689	-9.29	0.000	-101.2427	-65.95593
refer	3.002482	1.462918	2.05	0.040	.1348274	5.870137
_cons	56.25198	3.780041	14.88	0.000	48.84223	63.66172
/sigma	53.99114	.5714957			52.87088	55.1114

The addition of the variable “refer” improved the log likelihood from -32,337.664 to -32,335.558. This is a significant difference. Our next step was to test for non-uniform effects. We added an interaction term (referral X score) to test for a non-uniform or unsigned effect.

Tobit Model with score, referral and an interaction term

Tobit regression		Number of obs	=	8957
		LR chi2(3)	=	100.82
		Prob > chi2	=	0.0000
Log likelihood =	-32335.339	Pseudo R2	=	0.0016

tobdep	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
scorereal	-77.37716	13.01251	-5.95	0.000	-102.8847	-51.86966
refer	8.399741	8.285013	1.01	0.311	-7.840782	24.64026
xrefscore	-11.91289	17.99937	-0.66	0.508	-47.19578	23.37001
_cons	53.70331	5.396295	9.95	0.000	43.12533	64.28128
/sigma	53.98965	.571478			52.86943	55.10988

Here the addition of the interaction term significantly changed the log likelihood from -32,335.558 to -32,335.339. This difference is not significant, indicating only a uniform endogeneity. The offset variable to control for endogeneity is:

3.002482*refer

The Tobit model uses the same independent variables as the revised model, and includes the Tobit control for endogeneity. The results are as follows.

Tobit regression		Number of obs	=	8957
		LR chi2(24)	=	192.19
		Prob > chi2	=	0.0000
Log likelihood =	-32301.934	Pseudo R2	=	0.0030

tobdep	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
tur	-.3451683	.7293353	-0.47	0.636	-1.774833	1.084496
educ	.2863111	.2033531	1.41	0.159	-.1123075	.6849298
indchg	.1332884	.181889	0.73	0.464	-.2232558	.4898326
tenure	-.4894389	.2069076	-2.37	0.018	-.8950253	-.0838526
wba	-.0476838	.0054322	-8.78	0.000	-.0583322	-.0370355
off1	-7.545566	2.377297	-3.17	0.002	-12.20561	-2.885519
off4	1.632075	3.019966	0.54	0.589	-4.287751	7.551901
sic0	-3.712503	4.026695	-0.92	0.357	-11.60575	4.180743
sic2	3.638701	3.677433	0.99	0.322	-3.569911	10.84731

sic3	-6.391724	2.205565	-2.90	0.004	-10.71514	-2.068311
sic4	.8271065	3.439165	0.24	0.810	-5.914446	7.568659
sic5	-1.940512	1.959434	-0.99	0.322	-5.781453	1.900428
sic9	7.05395	2.100153	3.36	0.001	2.937167	11.17073
sic10	2.953944	2.450827	1.21	0.228	-1.85024	7.758127
xten2	.0166888	.010239	1.63	0.103	-.003382	.0367595
xwba2	.0001105	.0000554	2.00	0.046	1.95e-06	.0002191
xedu2	.0118038	.0071749	1.65	0.100	-.0022606	.0258682
xind2	-.0148024	.0113823	-1.30	0.193	-.0371144	.0075096
xtenwba	-.000074	.0009701	-0.08	0.939	-.0019755	.0018276
xtenedu	.0456322	.039288	1.16	0.245	-.0313813	.1226458
xtenind	.0217588	.0303875	0.72	0.474	-.0378077	.0813253
xwbaedu	-.0006531	.001685	-0.39	0.698	-.003956	.0026498
xwbaind	-.0012345	.0010308	-1.20	0.231	-.0032552	.0007862
xeduind	.1096415	.0480574	2.28	0.023	.0154378	.2038451
_cons	31.7311	5.910246	5.37	0.000	20.14566	43.31654
tobend	(offset)					

The decile table for the Tobit model is as follows.

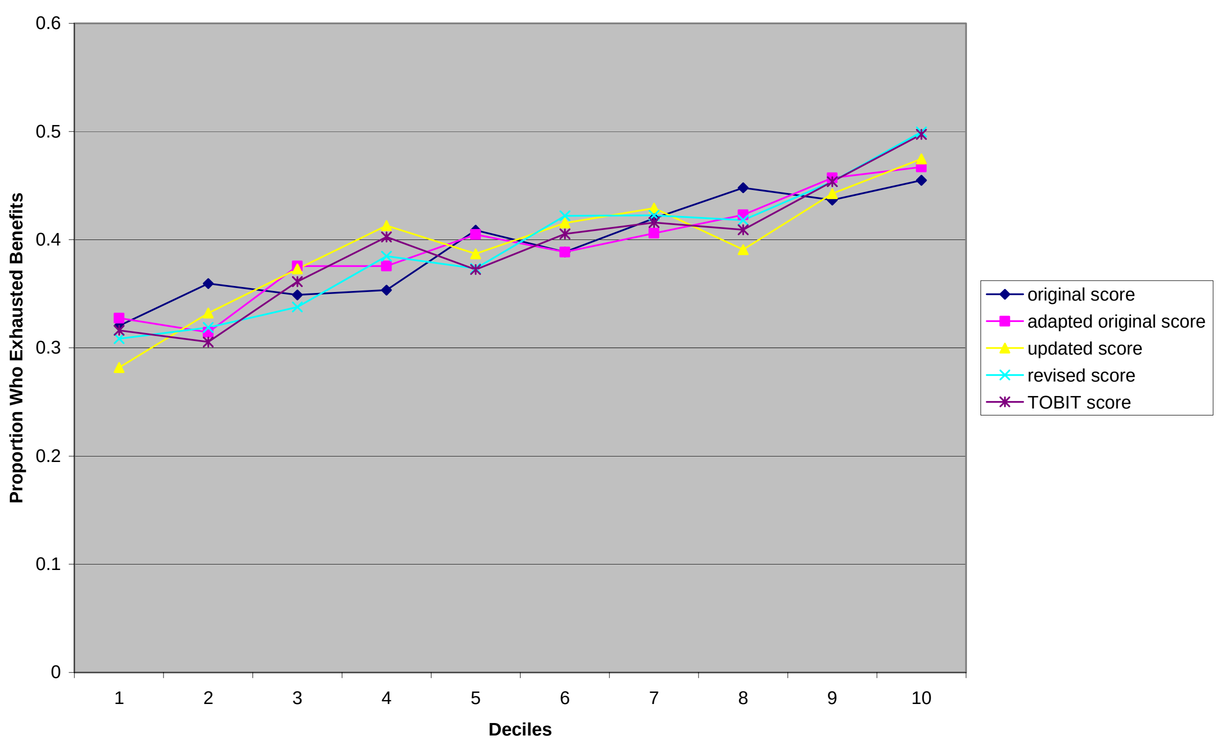
prtobdec	mean	se(mean)
1	.3162584	.0155264
2	.3054627	.0153877
3	.361204	.0160474
4	.4024526	.0163829
5	.3723523	.0161503
6	.4053452	.0163926
7	.4158305	.0164655
8	.4091416	.0164257
9	.4537347	.0166322
10	.4972129	.0167036
Total	.3938921	.0051587

Note that the Tobit model cannot be compared with the logit models by log likelihood comparisons. However, from the decile tables, the model did not perform substantially better than either the updated or revised models.

We created a summary table of the four decile tables that allows us to compare models. While there was considerable improvement between the updated and revised models, there was no improvement with the Tobit model. The updated model appears to be the best model for the data available.

Decile	Original score	Original score adapted for endogeneity	Updated mean	Revised mean	Tobit mean
1	.320356	.3273942	.2817372	.3084633	.3162584
2	.359375	.3143813	.3322185	.3188406	.3054627
3	.3489409	.3756968	.3730512	.3377926	.361204
4	.3534002	.3756968	.4129464	.3846154	.4024526
5	.4087432	.4046823	.386845	.3734671	.3723523
6	.3886364	.3886414	.4153675	.422049	.4053452
7	.4197121	.406015	.4292085	.4225195	.4158305
8	.4480088	.4229432	.3908686	.4180602	.4091416
9	.4366516	.4570792	.4424779	.4537347	.4537347
10	.4548495	.4671126	.4746907	.4994426	.4972129
Total	.3938921	.3938921	.3938921	.3938921	.3938921

Comparison of Profiling Scores for Hawaii



Correlations of the five profiling scores indicate that all model scores are positively correlated, as is to be expected. While the scores are positively correlated, they are not identical, which suggests that there are differences between the models. Note, the strongest correlation is between the revised and Tobit models with a correlation of 0.96.

	scorereal	prorig	prup	prrev	protobn
scorereal	1.0000				
prorig	0.9742	1.0000			
prup	0.7231	0.6816	1.0000		
prrev	0.6830	0.6780	0.7227	1.0000	
protobn	0.6813	0.6715	0.7274	0.9616	1.0000

We also tested the performance of each model using the following metric.

Percent exhausted of the top 39.3 percent of individuals in the score.

We used 39.3 percent because the exhaustion rate for benefit recipients in the data set provided by Hawaii was 39.3 percent. This metric will vary from about 39.3 percent, for a score that is a random draw, to 100 percent for a score that is a perfect predictor of exhaustion. The scores for the four models are as follows:

Score	% exhausted of those with the top 39.3% of score	Standard error of the score
Original	43.87408	.83581
Adapted	43.87408	.83581
Updated	43.2785	.83451
Revised	44.81293	.83737
TOBIT	44.36281	.83524

To compare models across SWAs, we developed a metric to gauge classification improvements between our models and the original model. In the below metric, "*Exhaustion*" is the percentage of all benefit recipients in our sample that exhaust benefits. Here we use 39.3 percent for "*Exhaustion*" because the exhaustion rate for all benefit recipients for Hawaii was 39.3 percent. In our metric, "Pr[*Exh*]" is determined by the model with the highest percentage of benefit exhaustees with profiling scores falling in the top X percent of the sample where X percent is determined by the exhaustion rate for all benefit recipients in the sample. For Hawaii, "Pr[*Exh*]" is represented by the revised model with a score of 44.38 percent for benefit recipients that exhaust benefits with scores falling in the top 39.3 percent.

In addition to this metric we also applied the equation below, derived by Silverman, Strange, and Lipscombe (2004), for calculating the variance (σ_z^2) of a quotient (p. 1069)[ii]. This equation allowed us to calculate the variance for our metric, Z, which is the quotient of two random variables X and Y where X = 100 - Pr[*Exh*] and Y = 100 - "*Exhaustion.*" In the equation below, σ_X^2 is the variance of 100 - Pr[*Exh*], σ_Y^2 is the variance of 100 - "*Exhaustion,*" $E(X)$ is the mean for 100 - Pr[*Exh*], and $E(Y)$ is the mean for 100 - "*Exhaustion.*" By dividing the variance of the quotient of the two random variables (here 100 - "*Exhaustion*" and 100 - "Pr[*Exh*]") by the square root of our observations we were able to determine the standard error of the metric.

$$\text{Metric: } 1-\left(\frac{100-\Pr[Exh]}{100-Exhaustion} \right)$$

$$\text{Variance of Metric: } \sigma_z^2 \approx \frac{\sigma_X^2}{E(Y)^2}+\frac{E(X)^2\sigma_Y^2}{E(Y)^4}$$

$$\text{Standard error of the metric: } \sqrt{\frac{\sigma_Z^2}{N}}$$

For our metric, we use 44.81 percent for "Pr[*Exh*]" and 37.9 percent for *"Exhaustion"* and arrive at a score of 0.082398031, or roughly 8.2 percent, with a standard error of 0.018592762. For other SWAs, the statistic is recalculated using the exhaustion rate of that SWA from the given sample and the score from the model with the highest percentage of exhaustion. For SWAs with hypothetically perfect models, this metric will have a value of 1, and for SWAs with models that predict no better than random, the metric will take a value of 0.

SWA	Profiling score	Control for endogeneity?	Exhaustion rate for the state	Number of individuals with the highest profiling score	Exhaustion rate for individuals with high profiling scores	Metric	Variance of the Metric	Standard Error of the metric
Hawaii	original score	Y	39.7	3,526	43.9	0.069	1.248	0.019
Hawaii	revised score	Y	39.7	3,526	44.8	0.085	1.232	0.019

Analysis of Type I Errors

Type I errors are individuals who are predicted to exhaust (reject the null hypothesis) and do not exhaust (the null hypothesis is actually true). Our analysis will be restricted to the top 39.3 percent of individuals who are predicted to exhaust benefits using the revised model.

Variable	Mean for exhausted	Mean for non-exhausted	T statistic	P value
	N=1,566	N=1,961		
Education	12.5281	12.5984	0.6029	0.5466
Weekly Benefit Amount	326.4700	320.0785	-1.7440	0.0813
Tenure	6.9138	6.2513	-2.5333	0.0113
Total County Unemployment Rate	4.5465	4.4888	-1.2523	0.2105
County Industry Employment Percentage Change	4.3902	4.1807	-0.9086	0.3636
Oahu Local Office	0.7848	0.7992	1.0471	0.2951
Kauai Local Office	0.0166	0.0143	-0.5603	0.5753
SIC Code 0	0.0217	0.0219	0.0414	0.9670

SIC Code 2	0.0211	0.0234	0.4731	0.6362
SIC Code 3	0.2018	0.1850	-1.2555	0.2094
SIC Code 4	0.0536	0.0632	1.1978	0.2311
SIC Code 5	0.1782	0.1860	0.6014	0.5476
SIC Code 9	0.0096	0.0076	-0.6212	0.5345
SIC Code 10	0.0383	0.0612	3.0675	0.0022
Centered and Squared Tenure	73.7313	62.5058	-1.9328	0.0533
Centered and Squared WBA	1.9e+04	1.8e+04	-1.5970	0.1104
Centered and Squared Education	10.8138	12.8790	0.5179	0.6045
Centered and Squared Industry Change	49.1252	44.5841	-1.1491	0.2506
Tenure and WBA Cross Variable	360.3548	270.4654	-2.2497	0.0245
Tenure and Education Cross Variable	0.1073	0.2307	0.1666	0.8677
Tenure and Industry Change Cross Variable	-13.7246	-11.1366	2.1007	0.0357
WBA and Education Cross Variable	-41.3053	-45.6545	-0.3061	0.7595
WBA and Industry Change Cross Variable	170.5243	139.0871	-0.9917	0.3214
Education and Industry Change Cross Variable	-4.1042	-3.5695	0.9447	0.3449

For the table above, note that it includes 1,566 individuals who exhausted benefits and 1,961 who did not. The total of these two types of individuals is 3,527, which is 39.3 percent of the 8,972 individuals in the sample. The Type I analysis shows that certain variables have more explanatory power than others for explaining the difference between Type I errors and correct predictions. For example, the variables for education, total county unemployment rate, and SIC code 9 are not important for explaining the difference between exhaustees and non-exhaustees. More important variables, with low p-values, are SIC code 10, Tenure and WBA cross variable, and Tenure and Industry Change cross variable.

Expanded Analyses of Idaho Profiling Data

ANALYSIS OF IDAHO PROFILING DATA

Reported Profiling Model

Idaho used a model called a "decision tree." In it, various expressions were used to define groups of individuals for selection and referral to WPRS services. The variables used were:

- Duration of Benefit Receipt
- Principal Industry
- County of Residence
- Local Office
- Marital Status
- Job Tenure
- Weekly Benefit Amount (WBA)
- Ratio of Total Wage to High Quarter Wage
- Number of Employers
- Education (years completed)
- Month of Filing

The model used various combinations of these variables to define 31 groups of individuals to be selected. For example, the first group was defined as individuals having a duration of benefit receipt greater than 16 weeks, a principal industry of 1 (an NAICS of 0, or no reported industry), a county of residence of FIPS code 1, 19, 27, 35, 69, 75, or 79, and a ratio of total wage to high quarter wage between 2.34 and 2.68. Individuals who belonged to any one of these 31 groups were selected for referral to reemployment services. In the sample given, 73 percent of the individuals were selected.

This approach has both strengths and weaknesses. The model can be tailored to various subsets of applicants. That is, individuals with a principal industry of 2 are selected very differently from individuals with a principal industry of 7. However, the model also probably leaves out many individuals who are likely to exhaust and/or selects individuals who are not likely to exhaust. For example, individuals with a principal industry of 1 are not selected on the basis of any variable except duration and county of residence. Inclusion of other variables in the selection process for individuals with a principal industry of 1 would probably improve the model.

To analyze the Idaho model, we calculated a new selection variable that takes a value of zero or one. We used the same variables in the decision tree to calculate a continuous selection variable where the higher values correspond to the "ones" of the original selection variable and lower values correspond to the "zeros" of the original selection variable.

Our method is to run a logistic regression model with the variables listed above as the independent variables and the original selection variable as the dependent variable. Because of collinearity problems, we eliminated principal industry 1, FIPS 1 (county 1), month 1, Duration (correlated at 0.9789 with RATIO), WBA (correlated at 0.8572 with Total Benefit Amount). The results of this analysis are as follows:

Logistic regression	Number of observations	=	33997
	LR chi2(77)	=	38496.70
	Prob > chi2	=	0.0000
Log likelihood = -570.56032	Pseudo R2	=	0.9712

select	Coefficient	Standard error	z	P>z	[95% Conf.	Interval]
prin2	.2913942	.3247748	0.90	0.370	-.3451528	.9279412
prin3	.6703753	1.05716	0.63	0.526	-1.401621	2.742372
prin4	.008526	.2530625	0.03	0.973	-.4874673	.5045193
prin5	.0095383	.3921887	0.02	0.981	-.7591374	.7782139
prin6	.2669864	.543831	0.49	0.623	-.7989028	1.332876
prin7	.7556037	.5856881	1.29	0.197	-.3923239	1.903531
prin8	-.0294108	.3622316	-0.08	0.935	-.7393717	.6805501
prin9	.4101936	.3569138	1.15	0.250	-.2893445	1.109732
prin10	.382265	.381861	1.00	0.317	-.3661688	1.130699
prin11	.5724482	.2857807	2.00	0.045	.0123283	1.132568
prin12	.1848765	.5667552	0.33	0.744	-.9259433	1.295696
prin13	.5420419	.4738942	1.14	0.253	-.3867738	1.470857
prin14	.3823535	.2646348	1.44	0.149	-.1363211	.9010281
prin15	.4381956	.3099639	1.41	0.157	-.1693226	1.045714
prin16	.3082899	.2855907	1.08	0.280	-.2514577	.8680375
prin17	.3824933	.4665144	0.82	0.412	-.531858	1.296845
prin18	.228857	.3557414	0.64	0.520	-.4683835	.9260974
fips3	-.5634919	.974501	-0.58	0.563	-2.473479	1.346495
fips5	.212756	.2640425	0.81	0.420	-.3047577	.7302697
fips7	-.1193664	1.441468	-0.08	0.934	-2.944592	2.70586
fips9	-.6021774	.5835209	-1.03	0.302	-1.745857	.5415024
fips11	.2084714	.4548852	0.46	0.647	-.6830873	1.10003
fips13	-.2117326	.4506146	-0.47	0.638	-1.094921	.6714558
fips15	.056985	.6996689	0.08	0.935	-1.314341	1.428311
fips17	-.2071971	.391165	-0.53	0.596	-.9738664	.5594722
fips19	-.1408596	.296682	-0.47	0.635	-.7223456	.4406264
fips21	-.0897109	.5351269	-0.17	0.867	-1.13854	.9591185

fips23	-3.677538	3.645309	-1.01	0.313	-10.82221	3.467137
fips25	-2.316362	3.72914	-0.62	0.534	-9.625343	4.992619
fips27	-.0071411	.2109037	-0.03	0.973	-.4205048	.4062226
fips29	.2380863	.6734649	0.35	0.724	-1.081881	1.558053
fips31	.5686645	.5102885	1.11	0.265	-.4314825	1.568812
fips33	.9575203	17.75946	0.05	0.957	-33.85039	35.76543
fips35	-.5672088	.7229776	-0.78	0.433	-1.984219	.8498013
fips37	.7254465	1.352988	0.54	0.592	-1.926362	3.377255
fips39	-.0699751	.5161653	-0.14	0.892	-1.08164	.9416903
fips41	-.2674027	1.779345	-0.15	0.881	-3.754855	3.22005
fips43	.5199543	.8763534	0.59	0.553	-1.197667	2.237575
fips45	-.2143707	.5629663	-0.38	0.703	-1.317764	.8890229
fips47	.5881011	.7253775	0.81	0.418	-.8336128	2.009815
fips49	-.1439457	.4975444	-0.29	0.772	-1.119115	.8312234
fips51	.1395146	.6251594	0.22	0.823	-1.085775	1.364804
fips53	.1351564	.5237916	0.26	0.796	-.8914563	1.161769
fips55	.0689287	.2219554	0.31	0.756	-.3660959	.5039532
fips57	-.4803646	.6060628	-0.79	0.428	-1.668226	.7074966
fips59	.2953489	.7271588	0.41	0.685	-1.129856	1.720554
fips61	.4032533	2.935851	0.14	0.891	-5.350908	6.157415
fips63	-.6081272	.9346697	-0.65	0.515	-2.440046	1.223792
fips65	.0291386	.7456408	0.04	0.969	-1.432291	1.490568
fips67	.3035178	.4427224	0.69	0.493	-.5642021	1.171238
fips69	-.1543227	.41364	-0.37	0.709	-.9650423	.6563969
fips71	.0164959	1.632236	0.01	0.992	-3.182628	3.21562
fips73	.8712118	1.158895	0.75	0.452	-1.400181	3.142605
fips75	-.3168052	.5482625	-0.58	0.563	-1.39138	.7577695
fips77	.2464611	.7081019	0.35	0.728	-1.141393	1.634315
fips79	-.1823396	.3913379	-0.47	0.641	-.9493479	.5846686
fips81	.1608988	2.044031	0.08	0.937	-3.845328	4.167125
fips83	-.0202751	.3174891	-0.06	0.949	-.6425424	.6019922
fips85	.3338513	.7152708	0.47	0.641	-1.068054	1.735756
fips87	-.3484457	.7467012	-0.47	0.641	-1.811953	1.115062
RATIO	35.41223	1.155051	30.66	0.000	33.14837	37.67608
TBA	.0001895	.0000493	3.84	0.000	.0000928	.0002862
TENURE	-.0005884	.0012374	-0.48	0.634	-.0030137	.0018368
NO_EMPL	.0556614	.0483355	1.15	0.250	-.0390745	.1503973
married	.1873134	.125946	1.49	0.137	-.0595363	.434163
month2	-.1039907	.2596084	-0.40	0.689	-.6128139	.4048325
month3	-.0981913	.2725418	-0.36	0.719	-.6323634	.4359809
month4	-.1958204	.255366	-0.77	0.443	-.6963285	.3046877
month5	-.3959846	.3140154	-1.26	0.207	-1.011443	.2194742
month6	-.4067201	.2936349	-1.39	0.166	-.9822339	.1687938
month7	.1284308	.3037512	0.42	0.672	-.4669106	.7237722
month8	-.5123652	.3415608	-1.50	0.134	-1.181812	.1570817
month9	-.420318	.3350149	-1.25	0.210	-1.076935	.2362991
month10	-.4439906	.2645802	-1.68	0.093	-.9625583	.0745771
month11	-.3314632	.2113724	-1.57	0.117	-.7457455	.0828191
month12	-.3703046	.2437445	-1.52	0.129	-.8480352	.1074259

EDUC	-.0166222	.0257221	-0.65	0.518	-.0670366	.0337923
_cons	-80.16034	2.634111	-30.43	0.000	-85.32311	-74.99758

The following diagnostics demonstrate how well the model corresponds to the original selection variable. The diagnostic below indicates that the model performs quite well, with 99.79 percent of the cases correctly classified.

	--------	True	--------	
Classified	D		~D	Total
+	24812		54	24866
-	16		9115	9131
Total	24828		9169	33997

Sensitivity		Pr(+ D)	99.94%
Specificity		Pr(-~D)	99.41%
Positive predictive value		Pr(D +)	99.78%
Negative predictive value		Pr(~D -)	99.82%

False + rate for true ~D		Pr(+~D)	0.59%	
False - rate for true D		Pr(- D)	0.06%	
False + rate for classified	+	Pr(~D +)	0.22%	
False - rate for classified	-	Pr(D -)	0.18%	
Correctly classified				99.79%

area	under	ROC	Curve	=	0.9997

We saved the linear fitted values from this model as variable “xb.” (Saving the predicted value resulted in about 60 percent of the cases having a value of 1.) The variable “xb” is simply the sum of the coefficients times the variables from the logistic regression model. It increases monotonically with the predicted value. Next, we tested for endogeneity, or referral effect, based on whether the selected individuals had different exhaustion rates depending on whether or not they were selected and referred. The models with exhaustion as dependent variable are as follows:

Logistic Regression Model with XB Only

Logistic regression	Number of observations	=	33997
	LR chi2(1)	=	1605.35
	Prob > chi2	=	0.0000
Log likelihood = -22648.376	Pseudo R2	=	0.0342

EXHAUST	Coefficient	Standard error	z	P>z	[95% Conf.	Interval]
xb	-.016323	.000416	-39.24	0.000	-.0171383	-.0155076
_cons	.164632	.0138976	11.85	0.000	.1373932	.1918708

Adding the variable for selection, tests for a uniform selection effect. The test is a chi-squared test of difference in the (-2 X log likelihood) statistic for the nested models.

Logistic Regression Model with XB and Selection.

Logistic regression	Number of observations	=	33997	Logistic regression
	LR chi2(2)	=	1921.78	
	Prob > chi2	=	0.0000	
Log likelihood = -22490.162	Pseudo R2	=	0.0410	Log likelihood = -22490.162

EXHAUST	Coefficient	Standard error	Z	P>z	[95% Conf.	Interval]
xb	-.0058518	.0007197	-8.13	0.000	-.0072624	-.0044412
select	-.7793237	.0440501	-17.69	0.000	-.8656603	-.6929871
_cons	.5242321	.0248178	21.12	0.000	.4755902	.572874

The addition of the variable “select” improves the log likelihood from -22648.376 to -22490.162. This represents a significant difference, showing signed or uniform effect. Next we add an interaction term (select X xb) to test for a non-uniform or unsigned effect.

Logistic Regression Model with XB, Select and an Interaction Term

Logistic regression	Number of observations	=	33997
	LR chi2(3)	=	2003.22
	Prob > chi2	=	0.0000
Log likelihood = -22449.442	Pseudo R2	=	0.0427

EXHAUST	Coefficient	Standard error	z	P>z	[95% Conf.	Interval]
xb	-.0249757	.002258	-11.06	0.000	-.0294012	-.0205501

select	-.5499427	.0506408	-10.86	0.000	-.6491968	-.4506886
xscse	.0213465	.0023828	8.96	0.000	.0166764	.0260166
_cons	.2197822	.0416125	5.28	0.000	.1382231	.3013413

The addition of the interaction term changes the log likelihood from -22490.162 to -22449.442. This is a significant difference, showing an unsigned or non-uniform effect.

The offset variable is calculated from the selection variable times its coefficient and the interaction term times its coefficient, and is:

Offset = -.5499427*select + .0213465*xscse

This value represents the difference between the Pr[exh] for selected and non-selected individuals. Adding this variable to the logit as a fixed coefficient variable should adjust selected individuals to the Pr[exh] that they would have had if they were not selected.

By adjusting the original scores with this control for endogeneity, we can estimate the true exhaustion rate for the original score. The logit regression has exhaustion as a dependent variable, with xb as the independent variable and the offset, named endogeneity control, to control for endogeneity.

Logistic regression	Number of observations	=	33997
	Wald chi2(1)	=	3528.01
Log likelihood = -22449.442	Prob > chi2	=	0.0000

EXHAUST	Coefficient	Standard error	z	P>z	[95% Conf.	Interval]
xb	-.0249757	.0004205	-59.40	0.000	-.0257998	-.0241515
_cons	.219782	.0142846	15.39	0.000	.1917847	.2477793
endogeneity control	(offset)					

By taking the predictions of the model, ordering and dividing them into deciles, and then for each decile showing the actual exhaustion rate, with its standard error, we obtain the following table to demonstrate the effectiveness of each model.

Decile	Mean	Standard Error (Mean)
1	.4117647	.0084416
2	.3935294	.0083795
3	.365	.0082577
4	.3598117	.0082334
5	.35	.0081812
6	.3620588	.0082434
7	.4389526	.0085133
8	.5502941	.0085327
9	.65	.0081812
10	.7096205	.0077873
Total	.4590993	.0027027

Updated Profiling Model

The updated model has the same form as the model used to predict score, only the coefficients are generated using 2003 data, and the model includes the offset to control for endogeneity. We also include diagnostic statistics to show how well the model works, including a classification table that looks at the top 45.9 percent of cases because Idaho has 45.9 percent exhaustion rate. We used the same variables in the model that we used to replicate the selection variable. This required elimination of some variables as described above.

Updated Model Results

Logistic regression	Number of observations	=	33997
	Wald chi2(77)	=	4271.67
Log likelihood = -21917.387	Prob > chi2	=	0.0000

EXHAUST	Coefficient	Standard error	z	P>z	[95% Conf.	Interval]
prin2	-.0871584	.0733022	-1.19	0.234	-.2308282	.0565113
prin3	-.5217122	.1910295	-2.73	0.006	-.8961232	-.1473012
prin4	-.4532681	.0558793	-8.11	0.000	-.5627895	-.3437467
prin5	.1351207	.0711427	1.90	0.058	-.0043164	.2745578
prin6	-.3264507	.0954781	-3.42	0.001	-.5135843	-.139317
prin7	.4919833	.0770492	6.39	0.000	.3409696	.6429969
prin8	-.1575311	.0666686	-2.36	0.018	-.2881991	-.0268631
prin9	-.1869441	.0784125	-2.38	0.017	-.3406297	-.0332585
prin10	-.0060437	.0715314	-0.08	0.933	-.1462426	.1341552
prin11	-.0562389	.0573267	-0.98	0.327	-.1685971	.0561193
prin12	.3269122	.0949186	3.44	0.001	.1408752	.5129493
prin13	.1267461	.0799936	1.58	0.113	-.0300386	.2835308

prin14	.0525259	.0550288	0.95	0.340	-.0553287	.1603804
prin15	.1426362	.0613677	2.32	0.020	.0223577	.2629146
prin16	-.1951369	.062692	-3.11	0.002	-.3180109	-.0722628
prin17	.0055793	.0837694	0.07	0.947	-.1586057	.1697643
prin18	.1978626	.0831633	2.38	0.017	.0348656	.3608596
fips3	.3913784	.1961292	2.00	0.046	.0069723	.7757846
fips5	-.0335511	.0531296	-0.63	0.528	-.1376831	.070581
fips7	.5105693	.2109314	2.42	0.015	.0971514	.9239872
fips9	-.0220604	.1331248	-0.17	0.868	-.2829802	.2388595
fips11	-.4372962	.0856771	-5.10	0.000	-.6052201	-.2693723
fips13	-.0826895	.0984362	-0.84	0.401	-.275621	.110242
fips15	-.0908697	.1895642	-0.48	0.632	-.4624088	.2806693
fips17	.0447752	.0754199	0.59	0.553	-.1030451	.1925955
fips19	-.3475418	.059212	-5.87	0.000	-.4635951	-.2314885
fips21	.0456084	.1129391	0.40	0.686	-.1757482	.2669649
fips23	.3415776	.2741134	1.25	0.213	-.1956747	.8788299
fips25	-.1272077	.4439599	-0.29	0.774	-.9973532	.7429378
fips27	-.0457996	.0378215	-1.21	0.226	-.1199284	.0283292
fips29	.092796	.1484633	0.63	0.532	-.1981867	.3837787
fips31	.1739642	.0950456	1.83	0.067	-.0123217	.3602501
fips33	.0162309	.5105912	0.03	0.975	-.9845095	1.016971
fips35	-.230618	.1594553	-1.45	0.148	-.5431446	.0819086
fips37	-.1764331	.2533327	-0.70	0.486	-.6729561	.3200898
fips39	-.2828643	.0992408	-2.85	0.004	-.4773727	-.0883559
fips41	-.0897314	.2582951	-0.35	0.728	-.5959805	.4165177
fips43	-.3874357	.1424014	-2.72	0.007	-.6665374	-.108334
fips45	-.2367318	.1133249	-2.09	0.037	-.4588445	-.014619
fips47	-.0381672	.1354021	-0.28	0.778	-.3035505	.2272161
fips49	.0664578	.1168516	0.57	0.570	-.1625671	.2954827
fips51	-.5841914	.1278529	-4.57	0.000	-.8347786	-.3336043
fips53	-.0982958	.1055115	-0.93	0.352	-.3050944	.1085029
fips55	-.0292256	.0417948	-0.70	0.484	-.1111419	.0526907
fips57	-.646518	.1126278	-5.74	0.000	-.8672645	-.4257715
fips59	.2572824	.1739542	1.48	0.139	-.0836616	.5982264
fips61	-.0915619	.4350345	-0.21	0.833	-.9442138	.76109
fips63	-.1699145	.20577	-0.83	0.409	-.5732162	.2333873
fips65	-.9153673	.1667867	-5.49	0.000	-1.242263	-.5884714
fips67	.1146146	.0838778	1.37	0.172	-.0497828	.279012
fips69	.0526658	.0814107	0.65	0.518	-.1068962	.2122277
fips71	-.2868195	.3648958	-0.79	0.432	-1.002002	.4283632
fips73	-.1290711	.321426	-0.40	0.688	-.7590545	.5009123
fips75	-.1280111	.1005455	-1.27	0.203	-.3250767	.0690545
fips77	-.2321563	.1425533	-1.63	0.103	-.5115555	.0472429
fips79	.0369871	.0856664	0.43	0.666	-.130916	.2048902
fips81	-.2710463	.2561771	-1.06	0.290	-.7731442	.2310517
fips83	-.0477285	.0590475	-0.81	0.419	-.1634594	.0680025
fips85	-.5933654	.1540087	-3.85	0.000	-.8952169	-.2915139
fips87	.0041403	.1300233	0.03	0.975	-.2507006	.2589812
RATIO	-1.074505	.02289	-46.94	0.000	-1.119368	-1.029641

TBA	.000023	7.87e-06	2.92	0.003	7.59e-06	.0000385
TENURE	.001679	.0002203	7.62	0.000	.0012473	.0021107
NO_EMPL	-.0984897	.0113894	-8.65	0.000	-.1208124	-.0761669
married	.0855108	.0235353	3.63	0.000	.0393825	.1316391
month2	-.0917402	.048229	-1.90	0.057	-.1862673	.0027868
month3	-.0386801	.0497359	-0.78	0.437	-.1361607	.0588004
month4	.2610093	.0503856	5.18	0.000	.1622554	.3597632
month5	.1017784	.0575914	1.77	0.077	-.0110987	.2146555
month6	.144582	.0534232	2.71	0.007	.0398745	.2492895
month7	.1041154	.0562348	1.85	0.064	-.0061028	.2143337
month8	.1151279	.0568191	2.03	0.043	.0037646	.2264913
month9	.2486323	.0589906	4.21	0.000	.1330128	.3642519
month10	.2529396	.0530013	4.77	0.000	.149059	.3568203
month11	-.0063013	.0440969	-0.14	0.886	-.0927296	.0801269
month12	-.3864046	.0503919	-7.67	0.000	-.4851709	-.2876382
EDUC	-.0133187	.005286	-2.52	0.012	-.023679	-.0029584
_cons	2.94567	.1053423	27.96	0.000	2.739203	3.152137
endogeneity control	(offset)					

Classification Table

	--------	True	--------	
Classified	D		~D	Total
+	8338		5321	13659
-	7270		13068	20338
Total	15608		18389	33997

Classified + if predicted Pr(D)	>=	.36
True D defined as exhaust	!=	0

Sensitivity		Pr(+ D)	53.42%	
Specificity		Pr(-~D)	71.06%	
Positive predictive value		Pr(D +)	61.04%	
Negative predictive value		Pr(~D -)	64.25%	
False + rate for true ~D		Pr(+~D)	28.94%	
False - rate for true D		Pr(- D)	46.58%	
False + rate for classified	+	Pr(~D +)	38.96%	
False - rate for classified	-	Pr(D -)	35.75%	
Correctly classified				62.96%

number of observations	=	33997
area under ROC curve	=	0.6706

The decile table for the updated model is as follows:

Decile	Mean	Standard Error (Mean)
1	.2194118	.0070985
2	.3047059	.0078949
3	.3535294	.0082
4	.3895263	.0083655
5	.4355882	.0085047
6	.4444118	.008523
7	.504266	.0085771
8	.5664706	.0085001
9	.6438235	.0082137
10	.7293322	.007622
Total	.4590993	.0027027

From the change in the log-likelihood, the updated model performed significantly better than the original model. There is also an improvement in the decile gradient, from a low of 0.41 to a high of 0.71 for the original model, to a low of 0.22 to a high of 0.73 for the updated model. Also, the updated model shows a monotonic increase in ability to predict exhaustion.

Revised Model

The revised model is the same as the updated model except that 15 additional variables were added to account for several nonlinear and second-order interaction effects. Five of the variables were second-order versions of ratio, TBA, job tenure, number of employers, and years of education. These variables were created by first centering the variables, then subtracting their mean, and finally squaring them. Ten other variables were created by centering and multiplying all combinations of these five variables. The means for the variables ratio, TBA, job tenure, number of employers, and years of education are shown below.

stats	Ratio	TBA	Job Tenure	number of employers	years of education
mean	2.815652	4749.994	34.96476	1.809571	12.52578

The logit model results for the revised model are as follows.

Logistic regression	Number of observations	=	33997
	Wald chi2(92)	=	4382.77
Log likelihood = -21848.248	Prob > chi2	=	0.0000

EXHAUST	Coefficient	Standard error	Z	P>z	[95% Conf.	Interval]
prin2	-.1319523	.0751189	-1.76	0.079	-.2791826	.0152781
prin3	-.5246818	.1912165	-2.74	0.006	-.8994592	-.1499043
prin4	-.4642926	.0567095	-8.19	0.000	-.5754413	-.353144
prin5	.1484992	.0722479	2.06	0.040	.006896	.2901025
prin6	-.3137458	.0961478	-3.26	0.001	-.502192	-.1252997
prin7	.4780318	.0782299	6.11	0.000	.3247039	.6313596
prin8	-.1545026	.0673761	-2.29	0.022	-.2865573	-.0224479
prin9	-.1898338	.0790758	-2.40	0.016	-.3448195	-.0348481
prin10	-.0099477	.072339	-0.14	0.891	-.1517295	.1318342
prin11	-.0570958	.0580283	-0.98	0.325	-.1708291	.0566376
prin12	.333755	.095452	3.50	0.000	.1466725	.5208374
prin13	.129068	.0805213	1.60	0.109	-.0287508	.2868868
prin14	.052258	.0557884	0.94	0.349	-.0570851	.1616012
prin15	.1420995	.0620214	2.29	0.022	.0205398	.2636592
prin16	-.1630687	.0636532	-2.56	0.010	-.2878267	-.0383107
prin17	.0176947	.0842967	0.21	0.834	-.1475237	.1829132
prin18	.1947689	.0837779	2.32	0.020	.0305672	.3589706
fips3	.3642846	.1964383	1.85	0.064	-.0207274	.7492965
fips5	-.037045	.053229	-0.70	0.486	-.1413718	.0672819
fips7	.5336973	.2117378	2.52	0.012	.1186989	.9486958
fips9	-.0319252	.1332446	-0.24	0.811	-.2930798	.2292294
fips11	-.4466864	.0858286	-5.20	0.000	-.6149074	-.2784654
fips13	-.0975668	.0988779	-0.99	0.324	-.2913638	.0962303
fips15	-.1017581	.1901382	-0.54	0.593	-.4744222	.270906
fips17	.0445668	.0753232	0.59	0.554	-.1030639	.1921976
fips19	-.3638411	.0593636	-6.13	0.000	-.4801917	-.2474904
fips21	.0294917	.1135715	0.26	0.795	-.1931043	.2520877
fips23	.2969607	.2747248	1.08	0.280	-.2414899	.8354114
fips25	-.1329286	.4426453	-0.30	0.764	-1.000497	.7346403
fips27	-.0514044	.0379607	-1.35	0.176	-.125806	.0229972
fips29	.1113481	.1486131	0.75	0.454	-.1799281	.4026244
fips31	.1861565	.0954505	1.95	0.051	-.000923	.373236
fips33	.039217	.5136435	0.08	0.939	-.9675058	1.04594
fips35	-.2354611	.1593378	-1.48	0.139	-.5477574	.0768352
fips37	-.1898904	.2520208	-0.75	0.451	-.683842	.3040613
fips39	-.2719764	.0993631	-2.74	0.006	-.4667246	-.0772283
fips41	-.0923711	.259122	-0.36	0.721	-.6002409	.4154986
fips43	-.4046357	.142707	-2.84	0.005	-.6843364	-.1249351
fips45	-.2268153	.1137129	-1.99	0.046	-.4496885	-.0039421
fips47	-.0384464	.1362681	-0.28	0.778	-.3055271	.2286342
fips49	.0542295	.1171346	0.46	0.643	-.1753501	.2838091
fips51	-.5973561	.1284012	-4.65	0.000	-.8490179	-.3456944
fips53	-.0836938	.1058643	-0.79	0.429	-.291184	.1237965
fips55	-.0358489	.0419237	-0.86	0.392	-.1180178	.0463201
fips57	-.6384637	.1123122	-5.68	0.000	-.8585916	-.4183357

fips59	.2413275	.1740444	1.39	0.166	-.0997933	.5824483
fips61	-.1043326	.4343525	-0.24	0.810	-.9556479	.7469826
fips63	-.1600048	.2066185	-0.77	0.439	-.5649697	.2449601
fips65	-.9385446	.1671733	-5.61	0.000	-1.266198	-.6108909
fips67	.1140345	.0840987	1.36	0.175	-.0507959	.2788648
fips69	.0502197	.0813377	0.62	0.537	-.1091994	.2096387
fips71	-.2656294	.3660836	-0.73	0.468	-.9831401	.4518813
fips73	-.1533663	.3227679	-0.48	0.635	-.7859798	.4792471
fips75	-.1250243	.1008272	-1.24	0.215	-.322642	.0725935
fips77	-.2507046	.143249	-1.75	0.080	-.5314676	.0300583
fips79	.04042	.0858016	0.47	0.638	-.1277479	.208588
fips81	-.2987142	.25664	-1.16	0.244	-.8017193	.204291
fips83	-.0555661	.0593387	-0.94	0.349	-.1718678	.0607356
fips85	-.5982615	.1538111	-3.89	0.000	-.8997257	-.2967974
fips87	-.0011682	.1303057	-0.01	0.993	-.2565628	.2542263
RATIO	-1.125281	.0264617	-42.52	0.000	-1.177145	-1.073417
TBA	.0000305	8.64e-06	3.53	0.000	.0000136	.0000475
TENURE	.0017405	.0004435	3.92	0.000	.0008712	.0026098
NO_EMPL	-.1520831	.0172768	-8.80	0.000	-.1859449	-.1182212
married	.0941312	.0236844	3.97	0.000	.0477107	.1405517
month2	-.0913985	.0483269	-1.89	0.059	-.1861175	.0033205
month3	-.0386195	.0498445	-0.77	0.438	-.136313	.0590739
month4	.258235	.0504709	5.12	0.000	.1593138	.3571562
month5	.1008163	.057694	1.75	0.081	-.0122619	.2138946
month6	.1438849	.0535189	2.69	0.007	.0389897	.2487801
month7	.1158304	.056299	2.06	0.040	.0054864	.2261744
month8	.1184386	.0569567	2.08	0.038	.0068056	.2300717
month9	.2641728	.0591415	4.47	0.000	.1482576	.380088
month10	.2568752	.0531231	4.84	0.000	.1527558	.3609945
month11	-.0091682	.0442126	-0.21	0.836	-.0958233	.0774868
month12	-.3863208	.0505361	-7.64	0.000	-.4853697	-.2872718
EDUC	-.0098242	.0059999	-1.64	0.102	-.0215838	.0019353
xr2	-.0269528	.0347159	-0.78	0.438	-.0949946	.0410891
xtba2	-1.64e-08	4.46e-09	-3.67	0.000	-2.51e-08	-7.62e-09
xten2	-7.79e-07	1.33e-06	-0.59	0.557	-3.38e-06	1.82e-06
xn2	.0168776	.0058154	2.90	0.004	.0054796	.0282757
xe2	-.0002936	.0008855	-0.33	0.740	-.0020291	.0014419
xrtba	-.0000107	.0000183	-0.58	0.559	-.0000467	.0000252
xrten	.0022318	.0004326	5.16	0.000	.001384	.0030797
xrn	-.0893601	.0218943	-4.08	0.000	-.1322721	-.0464481
xre	.0170489	.0098359	1.73	0.083	-.0022291	.036327
xtbaten	-4.15e-07	1.44e-07	-2.88	0.004	-6.98e-07	-1.32e-07
xtban	9.55e-06	7.59e-06	1.26	0.208	-5.33e-06	.0000244
xtbae	7.37e-06	3.32e-06	2.22	0.026	8.71e-07	.0000139
xtenn	-.0000822	.0003137	-0.26	0.793	-.0006969	.0005326
xtene	.0000485	.0000893	0.54	0.587	-.0001266	.0002236
xne	-.002605	.0045384	-0.57	0.566	-.0115001	.00629
_cons	3.160844	.1238216	25.53	0.000	2.918158	3.40353
endogeneity	(offset)					

control							

Classification Table

	--------	True	--------	
Classified	D		~D	Total
+	8689		5706	14395
-	6919		12683	19602
Total	15608		18389	33997

Classified + if predicted Pr(D) >= .459
True D defined as EXHAUST != 0

Sensitivity		Pr(+ D)	55.67%	
Specificity		Pr(-~D)	68.97%	
Positive predictive value		Pr(D +)	60.36%	
Negative predictive value		Pr(~D -)	64.70%	
False + rate for true ~D		Pr(+~D)	31.03%	
False - rate for true D		Pr(- D)	44.33%	
False + rate for classified	+	Pr(~D +)	39.64%	
False - rate for classified	-	Pr(D -)	35.30%	
Correctly classified				62.86%

number of observations	=	33997
area under ROC curve	=	0.6730

The decile table for the revised model is as follows.

Decile	Mean	Standard Error (Mean)
1	.2164706	.007064
2	.2970588	.007838
3	.3591176	.0082287
4	.39188	.0083745
5	.4247059	.0084784
6	.4594118	.0085479
7	.5001471	.0085775
8	.5658824	.0085014
9	.6423529	.0082213
10	.7340394	.0075798
Total	.4590993	.0027027

Note that there is a significant improvement from the updated to the revised model in terms of log likelihood, from -21917.387 to -21848.248. The decile gradient also shows some improvement over the updated model.

Tobit Analysis Using the Variables of the Revised Model

We next analyzed the Idaho data using a Tobit model to predict exhaustion. The Tobit model is similar to the logit model except that the Tobit model uses information about non-exhaustees, assuming that non-exhaustees who are closer to exhaustion are more similar to exhaustees than those claimants who are further from exhaustion. First, we created a new dependent variable, "/sigma."

/sigma = 100 X (total benefit amount (TBA) – benefits paid)/ TBA

This variable represents the percent of the allowed benefits left to individuals. Exhaustees have a value of 0. In the data, all negative values were recoded as 0.

Second, we tested for endogeneity using the same procedure as for the logit analyses. Replication is necessary because of the difference in functional form for the Tobit model. The first model uses only the variable "xb" as independent variable.

Tobit regression		Number of observations	=	33997
		LR chi2(1)	=	1977.99
		Prob > chi2	=	0.0000
Log likelihood =	-113681.86	Pseudo R2	=	0.0086

exhvrpct	Coefficient	Standard error	t	P>t	[95% Conf.	Interval]
xb	.5485168	.0124254	44.14	0.000	.5241625	.572871
_cons	.5361734	.4594576	1.17	0.243	-.3643791	1.436726
/sigma	55.28924	.316945			54.66802	55.91046

The second model uses only xb and the binary variable ("select") for selected status as independent variables.

Tobit regression		Number of observations	=	33997
		LR chi2(2)	=	2230.69
		Prob > chi2	=	0.0000
Log likelihood =	-113555.51	Pseudo R2	=	0.0097

exhvrpct	Coefficient	Standard error	t	P>t	[95% Conf.	Interval]

xb	.2802509	.0208233	13.46	0.000	.2394366	.3210652
select	20.63633	1.300402	15.87	0.000	18.0875	23.18516
_cons	-9.151436	.7794142	-11.74	0.000	-10.67911	-7.623757
/sigma	55.14232	.3159478			54.52305	55.76158

The change in log likelihood shows uniform endogeneity. Next is the inclusion of interaction effects.

Tobit regression		Number of observations	=	33997
		LR chi2(3)	=	2288.67
		Prob > chi2	=	0.0000
Log likelihood =	-113526.52	Pseudo R2	=	0.0100

exhvrpct	Coefficient	Standard error	t	P>t	[95% Conf.	Interval]
xb	.7738104	.0682986	11.33	0.000	.6399429	.907678
select	14.55291	1.520236	9.57	0.000	11.5732	17.53262
xscse	-.5445413	.0716964	-7.60	0.000	-.6850686	-.404014
_cons	-1.316179	1.280303	-1.03	0.304	-3.825617	1.193259
/sigma	55.12647	.315834			54.50742	55.74551

The change in log likelihood again demonstrates endogeneity. The offset variable to control for endogeneity is:

offset = 14.55291*select-0.5445413*xscse

The Tobit model uses the same independent variables as the revised model and includes the control for endogeneity. The results are as follows.

Tobit regression		Number of observations	=	33997
		LR chi2(92)	=	5072.11
		Prob > chi2	=	0.0000
Log likelihood =	-112881.55	Pseudo R2	=	0.0220

exhvrpct	Coefficient	Standard error	t	P>t	[95% Conf.	Interval]
prin2	1.838698	2.126205	0.86	0.387	-2.328737	6.006132
prin3	14.96192	5.087759	2.94	0.003	4.989742	24.9341
prin4	13.02302	1.572731	8.28	0.000	9.940414	16.10562
prin5	-.5483434	2.041257	-0.27	0.788	-4.549276	3.45259
prin6	15.80152	2.617141	6.04	0.000	10.67184	20.93121
prin7	-11.92104	2.25045	-5.30	0.000	-16.332	-7.510083
prin8	7.4315	1.871636	3.97	0.000	3.763029	11.09997

prin9	5.991955	2.199872	2.72	0.006	1.680132	10.30378
prin10	1.670911	2.031375	0.82	0.411	-2.310653	5.652474
prin11	4.056979	1.626724	2.49	0.013	.8685436	7.245414
prin12	-9.432082	2.752904	-3.43	0.001	-14.82787	-4.036296
prin13	-.614821	2.268693	-0.27	0.786	-5.061536	3.831894
prin14	-.7627646	1.572735	-0.48	0.628	-3.845379	2.31985
prin15	-2.226503	1.754647	-1.27	0.204	-5.665671	1.212664
prin16	6.157917	1.776727	3.47	0.001	2.675472	9.640361
prin17	-1.093589	2.371452	-0.46	0.645	-5.741715	3.554538
prin18	-6.744379	2.405572	-2.80	0.005	-11.45938	-2.029377
fips3	-16.70747	5.73351	-2.91	0.004	-27.94534	-5.469597
fips5	-.7101899	1.493209	-0.48	0.634	-3.63693	2.216551
fips7	-22.73577	6.20903	-3.66	0.000	-34.90568	-10.56586
fips9	-1.385227	3.789074	-0.37	0.715	-8.81194	6.041486
fips11	11.35483	2.304849	4.93	0.000	6.837246	15.87241
fips13	1.740066	2.736735	0.64	0.525	-3.624027	7.10416
fips15	-5.22281	5.430832	-0.96	0.336	-15.86742	5.421805
fips17	-5.904855	2.144049	-2.75	0.006	-10.10726	-1.702446
fips19	8.616267	1.601658	5.38	0.000	5.476963	11.75557
fips21	-8.026541	3.246022	-2.47	0.013	-14.38885	-1.664227
fips23	-7.619202	7.871628	-0.97	0.333	-23.04786	7.809455
fips25	-.2753287	11.97021	-0.02	0.982	-23.73734	23.18668
fips27	1.184743	1.059837	1.12	0.264	-.8925729	3.26206
fips29	-4.164783	4.175929	-1.00	0.319	-12.34975	4.020179
fips31	-5.647749	2.722144	-2.07	0.038	-10.98324	-.3122539
fips33	3.414728	14.76718	0.23	0.817	-25.52944	32.3589
fips35	4.177591	4.456411	0.94	0.349	-4.557127	12.91231
fips37	1.502191	7.086265	0.21	0.832	-12.38713	15.39151
fips39	5.548351	2.731608	2.03	0.042	.1943064	10.9024
fips41	-1.679934	7.075816	-0.24	0.812	-15.54877	12.18891
fips43	6.784629	3.853078	1.76	0.078	-.7675335	14.33679
fips45	2.561862	3.102882	0.83	0.409	-3.519892	8.643616
fips47	2.514067	3.806229	0.66	0.509	-4.946272	9.974406
fips49	-1.072155	3.311681	-0.32	0.746	-7.563163	5.418853
fips51	12.24576	3.28113	3.73	0.000	5.814633	18.67689
fips53	.3558983	2.933066	0.12	0.903	-5.39301	6.104807
fips55	-.8534077	1.17486	-0.73	0.468	-3.156173	1.449357
fips57	15.28134	2.93444	5.21	0.000	9.529737	21.03294
fips59	-15.05113	5.029979	-2.99	0.003	-24.91005	-5.192196
fips61	2.835334	12.37553	0.23	0.819	-21.42112	27.09178
fips63	-1.068317	5.516325	-0.19	0.846	-11.8805	9.743866
fips65	21.58394	3.98348	5.42	0.000	13.77618	29.39169
fips67	-4.28882	2.392833	-1.79	0.073	-8.978854	.4012129
fips69	-2.038007	2.304379	-0.88	0.376	-6.554668	2.478654
fips71	-1.881871	10.00034	-0.19	0.851	-21.48287	17.71913
fips73	9.37145	9.091829	1.03	0.303	-8.448844	27.19174
fips75	.0108188	2.823978	0.00	0.997	-5.524273	5.545911
fips77	6.208158	3.995961	1.55	0.120	-1.624062	14.04038
fips79	-4.222469	2.440605	-1.73	0.084	-9.006139	.5612

fips81	10.80122	7.024927	1.54	0.124	-2.967872	24.57032
fips83	1.530257	1.653753	0.93	0.355	-1.711154	4.771669
fips85	13.79814	4.099532	3.37	0.001	5.762916	21.83336
fips87	-6.601427	3.726771	-1.77	0.077	-13.90602	.7031717
RATIO	33.81319	.7347498	46.02	0.000	32.37306	35.25333
TBA	-.0012807	.0002424	-5.28	0.000	-.0017558	-.0008056
TENURE	-.0450733	.0126318	-3.57	0.000	-.069832	-.0203145
NO_EMPL	5.097326	.4743556	10.75	0.000	4.167573	6.027079
married	-1.954712	.6620932	-2.95	0.003	-3.252437	-.656987
month2	2.758672	1.339939	2.06	0.040	.1323469	5.384998
month3	2.527765	1.380766	1.83	0.067	-.1785822	5.234113
month4	-5.489959	1.429653	-3.84	0.000	-8.292127	-2.68779
month5	-1.306657	1.616511	-0.81	0.419	-4.475073	1.861758
month6	-3.098541	1.503365	-2.06	0.039	-6.045188	-.1518935
month7	.2671022	1.57762	0.17	0.866	-2.825087	3.359291
month8	-2.764899	1.597651	-1.73	0.084	-5.89635	.3665514
month9	-9.924481	1.680614	-5.91	0.000	-13.21854	-6.630421
month10	-6.997265	1.507473	-4.64	0.000	-9.951963	-4.042567
month11	-4.625766	1.23931	-3.73	0.000	-7.054856	-2.196676
month12	8.087613	1.353109	5.98	0.000	5.435473	10.73975
EDUC	.1354143	.1689292	0.80	0.423	-.1956927	.4665213
xr2	-.2246871	.9630963	-0.23	0.816	-2.112388	1.663014
xtba2	5.45e-07	1.22e-07	4.47	0.000	3.06e-07	7.83e-07
xten2	-1.28e-06	.0000385	-0.03	0.974	-.0000767	.0000742
xn2	-.4558682	.1577174	-2.89	0.004	-.7649997	-.1467367
xe2	-.0582135	.0249294	-2.34	0.020	-.1070759	-.0093511
xrtba	.0005156	.0005048	1.02	0.307	-.0004738	.001505
xrten	-.0653217	.0126287	-5.17	0.000	-.0900743	-.0405691
xrn	1.532081	.5851719	2.62	0.009	.3851248	2.679038
xre	-.8305795	.2763587	-3.01	0.003	-1.372252	-.2889071
xtbaten	.0000157	4.16e-06	3.77	0.000	7.52e-06	.0000238
xtban	-.0001006	.000203	-0.50	0.620	-.0004985	.0002973
xtbae	-.0000808	.0000918	-0.88	0.379	-.0002608	.0000993
xtenn	.0096361	.0092262	1.04	0.296	-.0084476	.0277198
xtene	-.0023736	.0025907	-0.92	0.360	-.0074515	.0027044
xne	.1603107	.1271347	1.26	0.207	-.0888777	.4094991
_cons	-86.66414	3.474893	-24.94	0.000	-93.47505	-79.85324
endogeneity control	(offset)					
/sigma	54.00209	.3084014			53.39761	54.60657

The decile table for the Tobit model is as follows.

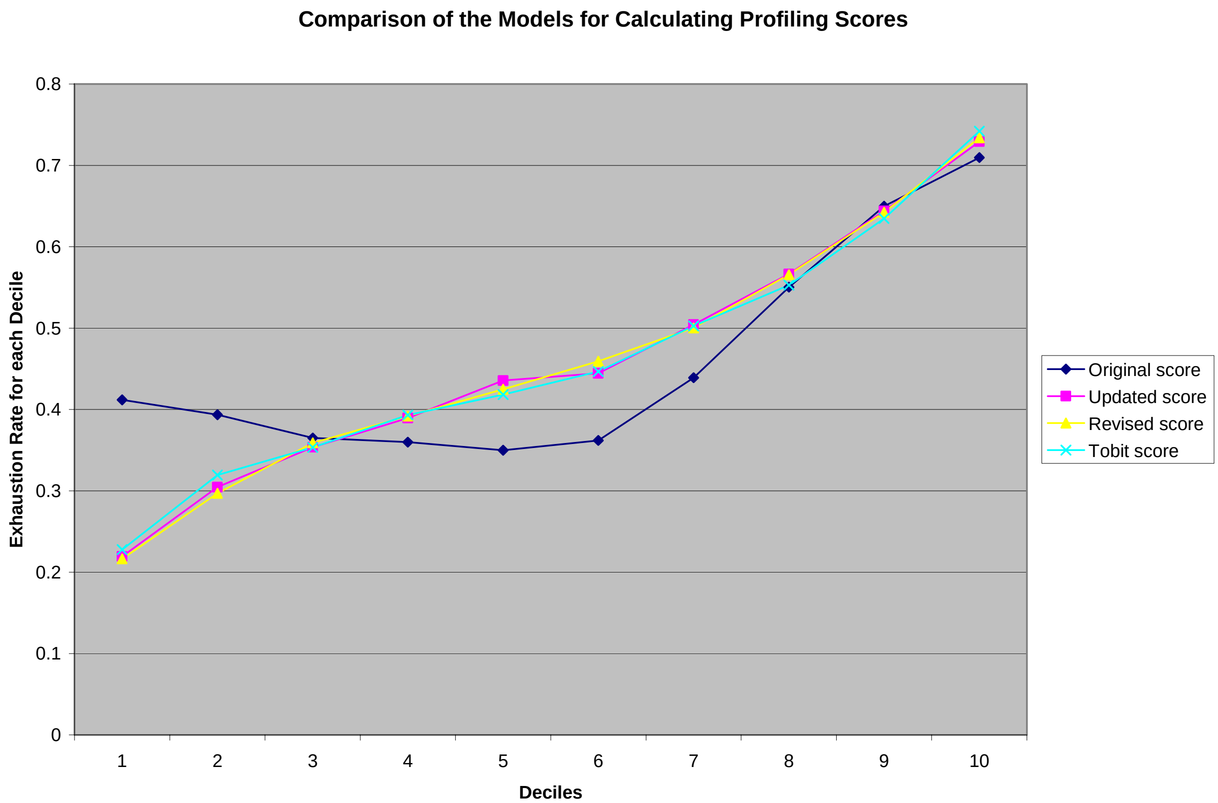
Decile	Mean	Standard Error (Mean)
1	.2276471	.0071922
2	.3194118	.0079973
3	.3532353	.0081984

4	.393351	.0083801
5	.4182353	.0084607
6	.4467647	.0085274
7	.5027949	.0085773
8	.5529412	.008528
9	.6347059	.0082591
10	.7419829	.007506
Total	.4590993	.0027027

Note that the Tobit model cannot be compared with the logit models by log likelihood comparisons. However, from the decile tables, the model appears to perform approximately as well as the revised model.

We created a summary table of the four decile tables that allows us to compare models. The Tobit model shows only marginal improvement over the revised model. The revised model appears to be the best appropriate model to use to predict between exhaustion.

Decile	Original Score	Updated score	Revised score	Tobit score
1	.4117647	.2194118	.2164706	.2276471
2	.3935294	.3047059	.2970588	.3194118
3	.365	.3535294	.3591176	.3532353
4	.3598117	.3895263	.39188	.393351
5	.35	.4355882	.4247059	.4182353
6	.3620588	.4444118	.4594118	.4467647
7	.4389526	.504266	.5001471	.5027949
8	.5502941	.5664706	.5658824	.5529412
9	.65	.6438235	.6423529	.6347059
10	.7096205	.7293322	.7340394	.7419829
Total	.4590993	.4590993	.4590993	.4590993



Correlations of the four profiling scores indicate that the updated, revised, and Tobit scores are highly correlated. The original score is also highly positively correlated with the other four scores. While the latter four scores are highly correlated, they are not identical, which suggests that there is a significant difference between the models. The strongest correlation exists between the updated and revised models with a correlation of 0.9775.

	original score	updated score	revised score	tobit score
original score	1.0000			
updated score	0.5916	1.0000		
revised score	0.5957	0.9775	1.0000	
tobit score	0.6662	0.9416	0.9682	1.0000

We also tested the performance of each model using the metric below:

Percent exhausted of the top 45.9 percent of individuals in the score.

We used 45.9 percent because the exhaustion rate for benefit recipients in the Idaho dataset was 45.9 percent. This metric will vary from about 45.9 percent, for a score that is a random draw, up to 100 percent for a score that is a perfect predictor of exhaustion. The scores for the four models are as follows:

Score	% exhausted of those with the top 45.9% of score	Standard error of the score
Original	56.1	0.39729
Updated	59.03	0.39367
Revised	59.26	0.39335
Tobit	58.82	0.39399

We note that the revised score performed better than the updated and Tobit scores. The original score performed worst, and the Tobit score performed slightly worse than the updated score.

To compare models across SWAs, we developed a metric to gauge classification improvements between our models and the original model. In the metric below, *"Exhaustion"* is the percentage of all benefit recipients in our sample that exhaust benefits. Here we use 45.9 percent for "*Exhaustion*" because the exhaustion rate for all benefit recipients for Idaho was 45.9 percent. In our metric, "Pr[*Exh*]" is determined by the model with the highest percentage of benefit exhaustees with profiling scores falling in the top X percent of the sample, where X percent is determined by the exhaustion rate for all benefit recipients in the sample. For Idaho, "Pr[*Exh*]" is represented by the revised model with a score of 59.26 percent for benefit recipients that exhaust benefits with scores falling in the top 45.9 percent.

In addition to this metric, we also applied the equation below, derived by Silverman, Strange, and Lipscombe (2004), for calculating the variance (σ_z^2) of a quotient (p. 1069). This equation allowed us to calculate the variance for our metric, Z = X/Y, which is the quotient of two random variables X (100 - "Pr[*Exh*]") and Y (100 - "*Exhaustion*"). In the equation below, σ_X^2 is the variance of 100 - "Pr[*Exh*]," σ_Y^2 is the variance of 100 - "*Exhaustion,*" $E(X)$ is the mean for (100 - "Pr[*Exh*]"), and $E(Y)$ is the mean for (100- *"Exhaustion"*). By dividing the variance of the quotient of the two random variables (here 100 - "*Exhaustion*" and 100 - "Pr[*Exh*]") by the square root of our observations, we were able to determine the standard error of the metric.

Metric = 1 – (100 – Pr[*Exh*])/(100 – *Exhaustion*)

Variance of Metric: $\sigma_z^2 \approx \frac{\sigma_X^2}{E(Y)^2} + \frac{E(X)^2 \sigma_Y^2}{E(Y)^4}$ where X = $(100 - \Pr[Exh])$, (Y = $100 - Exhaustion$)

Standard error of the metric: $\sqrt{\frac{\sigma_Z^2}{N}}$

For our metric, "Pr[*Exh*]" is 59.26 percent and *"Exhaustion"* is 45.9 percent. We used these to calculate a score of 0.246749912, or roughly 24.67 percent, with a standard error of 0.009151244. For SWAs with hypothetically perfect models, this metric will have a value of 1, and for SWAs with models that predict no better than random, the metric will take a value of 0.

SWA	Profiling score	Control for endogeneity?	Exhaustion rate for the state	Number of individuals with the highest profiling score	Exhaustion rate for individuals with high profiling scores	Metric	Variance of the Metric	Standard Error of the metric
Idaho	estimated score*	Y	45.9	15,605	56.1	0.189	1.400	0.009
Idaho	revised score	Y	45.9	15,605	59.3	0.247	1.306	0.009

Analysis of Type I Errors

For this analysis, Type I errors occur when individuals who are predicted to exhaust (reject the null hypothesis) and do not exhaust (the null hypothesis is actually true). Our analysis is restricted to the top 45.9 percent of individuals who are predicted to exhaust benefits using the revised model.

Variable	Mean for non-exhausted	Mean for exhausted	T statistic	P value
	N=6,358	N=9,247		
Principle industry 1	0.0716	0.0879	-3.6759	0.0002
Principle industry 2	0.0429	0.0643	-5.7387	0.0000
Principle industry 3	0.0020	0.0027	-0.8206	0.4119
Principle industry 4	0.0750	0.0906	-3.4482	0.0006
Principle industry 5	0.0694	0.0616	1.9251	0.0542
Principle industry 6	0.0105	0.0102	0.2262	0.8210
Principle industry 7	0.0837	0.0720	2.6866	0.0072
Principle industry 8	0.0395	0.0348	1.5195	0.1287
Principle industry 9	0.0266	0.0263	0.1156	0.9080
Principle industry 10	0.0433	0.0377	1.7264	0.0843
Principle industry 11	0.0941	0.0863	1.6682	0.0953
Principle industry 12	0.0322	0.0307	0.5391	0.5899
Principle industry 13	0.0370	0.0314	1.9064	0.0566
Principle industry 14	0.1472	0.1439	0.5709	0.5681
Principle industry 15	0.1013	0.0949	1.3117	0.1897
Principle industry 16	0.0554	0.0599	-1.1937	0.2326
Principle industry 17	0.0264	0.0221	1.7553	0.0792

Principle industry 18	0.0417	0.0423	-0.1848	0.8534
County 1	0.2888	0.2571	4.3872	0.0000
County 3	0.0060	0.0062	-0.1479	0.8824
County 5	0.0554	0.0587	-0.8865	0.3753
County 7	0.0044	0.0072	-2.2426	0.0249
County 9	0.0077	0.0103	-1.6477	0.0994
County 11	0.0134	0.0109	1.3837	0.1665
County 13	0.0131	0.0125	0.2789	0.7803
County 15	0.0038	0.0037	0.0987	0.9213
County 17	0.0302	0.0316	-0.4884	0.6252
County 19	0.0278	0.0248	1.1853	0.2359
County 21	0.0112	0.0151	-2.1117	0.0347
County 23	0.0028	0.0022	0.8321	0.4053
County 25	0.0005	0.0006	-0.4525	0.6509
County 27	0.1522	0.1506	0.2750	0.7833
County 29	0.0063	0.0064	-0.0689	0.9451
County 31	0.0236	0.0215	0.8600	0.3898
County 33	0.0005	0.0006	-0.4525	0.6509
County 35	0.0041	0.0052	-0.9842	0.3251
County 37	0.0020	0.0023	-0.2979	0.7658
County 39	0.0107	0.0107	-0.0066	0.9948
County 41	0.0013	0.0012	0.1209	0.9038
County 43	0.0047	0.0053	-0.5021	0.6156
County 45	0.0083	0.0084	-0.0667	0.9468
County 47	0.0069	0.0080	-0.7667	0.4432
County 49	0.0126	0.0119	0.3844	0.7007
County 51	0.0038	0.0037	0.0987	0.9213
County 53	0.0099	0.0101	-0.0916	0.9270
County 55	0.0942	0.1012	-1.4448	0.1485
County 57	0.0066	0.0062	0.3414	0.7328
County 59	0.0049	0.0066	-1.3798	0.1677
County 61	0.0008	0.0008	0.0651	0.9481
County 63	0.0014	0.0024	-1.3283	0.1841
County 65	0.0017	0.0015	0.3316	0.7402
County 67	0.0260	0.0293	-1.2497	0.2114
County 69	0.0266	0.0249	0.6641	0.5067
County 71	0.0006	0.0009	-0.5226	0.6013
County 73	0.0013	0.0014	-0.2471	0.8048
County 75	0.0142	0.0156	-0.7157	0.4742
County 77	0.0050	0.0075	-1.8592	0.0630
County 79	0.0190	0.0262	-2.9079	0.0036
County 81	0.0019	0.0017	0.2278	0.8198
County 83	0.0406	0.0430	-0.7531	0.4514
County 85	0.0052	0.0042	0.8810	0.3783
County 87	0.0107	0.0099	0.4545	0.6495
RATIO	2.5162	2.2665	19.7311	0.0000
Total benefit amount	4273.8606	3771.4340	13.8354	0.0000
Job tenure	44.1269	38.4212	4.9044	0.0000
Number of employers	1.7364	1.7698	-1.9374	0.0527

Marital status	0.5340	0.5371	-0.3907	0.6961
January filing	0.1316	0.1466	-2.6491	0.0081
February filing	0.1000	0.0864	2.8947	0.0038
March filing	0.0700	0.0700	0.0053	0.9958
April filing	0.1175	0.1208	-0.6257	0.5315
May filing	0.0595	0.0517	2.0921	0.0364
June filing	0.0827	0.0682	3.3961	0.0007
July filing	0.0643	0.0635	0.2130	0.8313
August filing	0.0590	0.0547	1.1330	0.2572
September filing	0.0728	0.0621	2.6490	0.0081
October filing	0.0931	0.0971	-0.8357	0.4033
November filing	0.1118	0.1351	-4.3073	0.0000
December filing	0.0376	0.0438	-1.9156	0.0554
Number of years of education	12.6711	12.3802	6.6890	0.0000

For the above table, 9,247 individuals exhausted benefits and 6,358 did not. The total of these two types of individuals is 15,605, which is 45.9 percent of the 33,997 individuals in the sample. The Type I analysis shows that certain variables have more explanatory power than others for explaining the difference between Type I errors and correct predictions. For example, industry 1, county 1, ratio, total benefit amount, job tenure, and number of years of education have different means for exhaustees and non-exhaustees.

Expanded Analyses of New Jersey Profiling Data

Analysis of New Jersey Profiling Data

Reported Profiling Model

New Jersey uses a logistical regression model to determine claimant's Worker Profiling and Reemployment Services (WPRS) eligibility. The model was last revised effective January 1, 2004.

Our first step in analyzing both the model used by and the data provided by New Jersey was to use the profiling scores provided to produce a decile table as shown below. The decile means in this table are calculated by dividing the percentage of recipients that exhaust benefits for a given decile by 100. For example, in the first decile our mean is 0.4994117, or approximately 49.9 percent, which indicates that approximately 50 percent of benefit recipients in this decile exhausted benefits.

Decile	Mean	Standard Error (Mean)
1	.4994117	.0037426
2	.5670739	.0037091
3	.5924552	.0036845
4	.6079857	.0036509
5	.6290051	.0036219
6	.6438648	.0035828
7	.6527864	.0035666
8	.6694806	.003529
9	.6911517	.0034598
10	.6901045	.0034657
Total	.6242945	.0011471

After creating this decile table, we attempted to replicate these scores using the provided data and coefficients for the variables given. From the given data, we were able to derive variables and categories for college graduate, job tenure, recall status, weekly benefit rate, benefit year earnings, county unemployment rate, and binary variables for occupation categories, and a variable indicating missing data for occupation. We were able to generate a profiling score that correlated with the given score at .956.

New Jersey did include a binary variable indicating whether or not benefit recipients were selected for reemployment services. This variable will allow us to test for endogeneity within our data and answer the question - does referral to re-employment services have an effect on the exhaustion of benefits? To test for endogeneity, we first calculated the logistic regression model where only score (and a constant) is used to predict exhaustion.

To test for endogeneity, we first calculated the logistic regression model where only score (and a constant) is used to predict the probability of benefit exhaustion, Pr[exh].

Logistic Regression Model with score only

Logistic regression	Number of obs	=	178246
	LR chi2(1)	=	2353.13
	Prob > chi2	=	0.0000
Log likelihood = -116808.48	Pseudo R2	=	0.0100

exhaust	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
score	3.084558	.064866	47.55	0.000	2.957423	3.211693
_cons	-1.153446	.0351185	-32.84	0.000	-1.222277	-1.084615

Adding the variable for selection tests for a uniform referral effect.

Logistic Regression Model with score and referral

Logistic regression	Number of obs	=	178246
	LR chi2(2)	=	2381.96
	Prob > chi2	=	0.0000
Log likelihood = -116794.07	Pseudo R2	=	0.0101

exhaust	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
score	3.260315	.0727566	44.81	0.000	3.117715	3.402916
select	-.0752425	.0139987	-5.37	0.000	-.1026794	-.0478055
_cons	-1.233274	.0381789	-32.30	0.000	-1.308103	-1.158444

The addition of the variable "select" improves the log likelihood from -116,808.48to -116,794.07. The difference in log likelihood is about 14, which is significant. We next add an interaction term (referral X score) to test for a non-uniform or unsigned effect.

Logistic Regression Model with score, selection and an interaction term

Logistic regression	Number of obs	=	178246
	LR chi2(3)	=	2462.44
	Prob > chi2	=	0.0000
Log likelihood = -116753.83	Pseudo R2	=	0.0104

exhaust	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
score	3.618609	.0833604	43.41	0.000	3.455225	3.781992
select	.8298088	.1014635	8.18	0.000	.630944	1.028674
xrefscore	-1.541696	.1710449	-9.01	0.000	-1.876938	-1.206454
_cons	-1.419276	.0436068	-32.55	0.000	-1.504744	-1.333808

Again, the addition of the interaction term changes the log likelihood from -116,794.07to -116,753.83. The difference in log likelihood is about 40, which is also significant. This analysis shows an unsigned or non-uniform effect.

The offset variable is calculated from the referral and interaction variables times their coefficients as:

.8298088*select - 1.541696*xrefscore

This value represents the difference between the Pr[exh] for referred and non-referred individuals. Adding this variable to the logistic regression model as a fixed coefficient variable should adjust referred and exempted individuals to the Pr[exh] that they would have had if they were not referred.

By adjusting the original scores with this control for endogeneity, we can estimate the true exhaustion rate for the original score. The logistic regression has exhaustion as a dependent variable, with score as the independent variable and the offset, named endoofst, to control for endogeneity.

Logistic regression	Number of obs	=	178246
	Wald chi2(1)	=	3153.80
Log likelihood = -116753.83	Prob > chi2	=	0.0000

exhaust	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
score	3.618608	.0644354	56.16	0.000	3.492317	3.744899
_cons	-1.419276	.0349129	-40.65	0.000	-1.487704	-1.350848
endoofst	(offset)					

To show the performance of the profiling score, we ordered individuals into deciles and calculated the exhaustion rate for each decile along with the standard error. This decile table is how we demonstrate the effectiveness of each model. The decile means are calculated by dividing the percentage of recipients that exhaust benefits for a given decile by 100. For example, in the first decile our mean is 0.4994117, or approximately 49.9 percent, which indicates that approximately 50 percent of benefit recipients in this decile exhausted benefits.

Decile	Mean	Standard Error (Mean)
1	.4994117	.0037426
2	.5670739	.0037091
3	.5924552	.0036845
4	.6079857	.0036509
5	.6290051	.0036219
6	.6438648	.0035828

7	.6527864	.0035666
8	.6694806	.003529
9	.6911517	.0034598
10	.6901045	.0034657
Total	.6242945	.0011471

Updated Profiling Model

The updated model has the same form as the model used to predict score, only the coefficients are generated using 2003 data, and the model includes the offset to control for endogeneity. We also include diagnostic statistics to show how well the model works, including a classification table that looks at the top 62.4 percent of cases (because New Jersey has approximately a 62.4 percent exhaustion rate).

We used the same variables we used to replicate the original profiling score. The resulting model is as follows.

Updated Model Results

Logistic regression	Number of obs	=	178113
	Wald chi2(13)	=	5225.33
Log likelihood = -115528.73	Prob > chi2	=	0.0000

exhaust	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
colgrad	-.2195809	.0139024	-15.79	0.000	-.2468291	-.1923328
tenure	.0281326	.0008863	31.74	0.000	.0263955	.0298697
recnum	1.103466	.4861894	2.27	0.023	.1505526	2.05638
wbr	.0028689	.0000718	39.94	0.000	.0027281	.0030096
lnbyearn	-.5743164	.0118434	-48.49	0.000	-.597529	-.5511037
unemp	.0728332	.0041057	17.74	0.000	.0647863	.0808802
mang_adm	.102375	.0246968	4.15	0.000	.0539701	.1507799
sales	.0670174	.0248367	2.70	0.007	.0183384	.1156965
cler_adm	.1609147	.0209298	7.69	0.000	.119893	.2019363
service	-.148766	.0235624	-6.31	0.000	-.1949475	-.1025845
agr_for	-1.377021	.0405885	-33.93	0.000	-1.456573	-1.297469
cons_prd	-.202511	.0169644	-11.94	0.000	-.2357605	-.1692615
ocmisnum	.0477212	.0209034	2.28	0.022	.0067513	.0886911
_cons	.9018328	.0388581	23.21	0.000	.8256724	.9779932
endoofst	(offset)					

	--------	True	--------	
Classified	D		~D	Total
+	63579		29993	93572
-	47618		36923	84541

Total	111197		66916	178113

Classified + if predicted	Pr(D)	>=	.624
True D defined as exhaust	!= 0		

Sensitivity		Pr(+ D)	57.18%	
Specificity		Pr(-~D)	55.18%	
Positive predictive value		Pr(D +)	67.95%	
Negative predictive value		Pr(~D -)	43.67%	
False + rate for true ~D		Pr(+~D)	44.82%	
False - rate for true D		Pr(- D)	42.82%	
False + rate for classified	+	Pr(~D +)	32.05%	
False - rate for classified	-	Pr(D -)	56.33%	
Correctly classified				56.43%

number of observations	=	178113
area under ROC curve	=	0.5913

The decile table for the updated model is as follows:

Decile	Mean	Standard Error (Mean)
1	.4900629	.0037458
2	.5616754	.003718
3	.5835719	.0036939
4	.5846059	.0036925
5	.6087811	.0036569
6	.6176173	.0036414
7	.6467352	.0035816
8	.6689125	.0035263
9	.7070911	.0034101
10	.7740161	.0031339
Total	.6243059	.0011475

From the original score to the updated model, there was a significant improvement. The decile gradient, which ranged from 0.49 to 0.69 for the original model, improved to 0.49 to 0.77 for the updated model.

Revised Model

The revised model is similar to the updated model, but we attempted to incorporate more of the information in the variable set. We include a continuous version of the education variable and second order terms to capture nonlinear effects. We developed a model with five continuous variables (education, job tenure, weekly benefit rate, log of base year earnings, and country unemployment rate), five second order variables, and ten interaction variables (all the interactions between the four continuous variables). We retained the other variables from the updated model in their original form.

We created the second order variables by first subtracting their mean (centering), and then squaring them. We created the interaction variables by centering and multiplying the ten second order combinations. The means for the four continuous variables are shown below.

stats	educ	tenure	wbr	lnbyearn	unemp
mean	12.25601	4.624428	333.1658	3.058695	5.984065

The logistic regression model results for the revised model are as follows.

Logistic regression	Number of obs	=	178113
	Wald chi2(28)	=	6369.85
Log likelihood = -114755.9	Prob > chi2	=	0.0000

exhaust	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
educ	-.0277699	.0023751	-11.69	0.000	-.0324249	-.0231148
tenure	.0235908	.0015362	15.36	0.000	.0205798	.0266017
recnum	1.174978	.4881747	2.41	0.016	.2181727	2.131782
wbr	.0019483	.0000817	23.84	0.000	.0017881	.0021085
lnbyearn	-.4664727	.0138149	-33.77	0.000	-.4935494	-.4393961
unemp	.0903605	.0044758	20.19	0.000	.081588	.099133
mang_adm	.0820552	.0248014	3.31	0.001	.0334454	.1306651
sales	.0801861	.0249972	3.21	0.001	.0311925	.1291797
cler_adm	.1575941	.0211543	7.45	0.000	.1161324	.1990558
service	-.126855	.0237714	-5.34	0.000	-.173446	-.0802639
agr_for	-1.377801	.0409314	-33.66	0.000	-1.458025	-1.297577
cons_prd	-.2016193	.0172503	-11.69	0.000	-.2354292	-.1678094
ocmisnum	.0446574	.0211467	2.11	0.035	.0032105	.0861042
xe2	-.0040069	.0002868	-13.97	0.000	-.004569	-.0034448
xt2	-.0001627	.0000741	-2.20	0.028	-.0003078	-.0000175
xw2	-3.94e-06	8.11e-07	-4.86	0.000	-5.53e-06	-2.35e-06
xl2	.3815962	.0181718	21.00	0.000	.3459802	.4172122
xu2	-.0285628	.0030579	-9.34	0.000	-.0345563	-.0225694
xet	.0008329	.0002695	3.09	0.002	.0003047	.001361
xew	.0000729	.0000233	3.12	0.002	.0000271	.0001186
xel	-.0145786	.0035122	-4.15	0.000	-.0214623	-.0076948
xeu	.0035905	.0013345	2.69	0.007	.000975	.0062061
xtw	-.0000464	.0000142	-3.28	0.001	-.0000741	-.0000186
xtl	.0235582	.002272	10.37	0.000	.0191051	.0280113
xtu	-.0020638	.0007209	-2.86	0.004	-.0034768	-.0006507
xwl	-.0031613	.0002026	-15.61	0.000	-.0035584	-.0027643
xwu	.0001053	.00006	1.75	0.079	-.0000123	.0002229
xlu	-.0424881	.0100134	-4.24	0.000	-.062114	-.0228622

_cons	1.253384	.0513738	24.40	0.000	1.152694	1.354075
endoofst	(offset)					

Classification Table

	--------	True	--------	
Classified	D		~D	Total
+	60669		26747	87416
-	50528		40169	90697
Total	111197		66916	178113

Classified + if predicted Pr(D) >= .624
True D defined as exhaust != 0

Sensitivity		Pr(+ D)	54.56%	
Specificity		Pr(-~D)	60.03%	
Positive predictive value		Pr(D +)	69.40%	
Negative predictive value		Pr(~D -)	44.29%	
False + rate for true ~D		Pr(+~D)	39.97%	
False - rate for true D		Pr(- D)	45.44%	
False + rate for classified	+	Pr(~D +)	30.60%	
False - rate for classified	-	Pr(D -)	55.71%	
Correctly classified				56.61%

number of observations	=	178113
number of covariate patterns	=	177834
Pearson chi2(177805)	=	178292.65
Prob > chi2	=	0.2066

number of observations	=	178113
area under ROC curve	=	0.6050

The decile table for the revised model is as follows.

Decile	Mean	Standard Error (Mean)
1	.480631	.0037437
2	.5402279	.0037345

3	.5652125	.0037146
4	.5819672	.0036958
5	.6119252	.0036515
6	.6307338	.0036163
7	.6434988	.0035889
8	.6756499	.0035078
9	.7161866	.0033783
10	.7970355	.0030138
Total	.6243059	.0011475

Note that there is an improvement from the updated to the revised model in terms of log likelihood. The decile gradient for the revised model ranges from 0.48 to 0.797, while the updated model ranged from 0.49 to 0.77. Both models are monotonically increasing across all deciles.

Tobit analysis using the variables of the revised model

The following is the procedure we used to generate a Tobit model to predict exhaustion. The Tobit model is similar to the logistic regression model except that it uses information about non-exhaustees, assuming that non-exhaustees who are closer to exhaustion are more similar to exhaustees than those who are further from exhaustion. First, we created a new dependent variable. It is:

100 X (balance remaining/maximum benefit amount)

This variable represents the percent of the allowed benefits left to individuals. Exhaustees have a value of 0 and non-exhaustees have positive balances.

Second, we tested for endogeneity using the same procedure as for the logistic regression analyses. Replication is necessary because of the difference in functional form for the Tobit model. The first model uses only the score as independent variable.

Tobit regression		Number of obs	=	178246
		LR chi2(1)	=	2057.16
		Prob > chi2	=	0.0000
Log likelihood =	-436838.47	Pseudo R2	=	0.0023

tobdep	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
score	-101.1723	2.25331	-44.90	0.000	-105.5888	-96.7559
_cons	37.0132	1.214822	30.47	0.000	34.63218	39.39423
/sigma	63.09744	.2000084			62.70543	63.48945

The second model uses only score and a binary variable for referred status as independent variables.

Tobit regression		Number of obs	=	178246
		LR chi2(2)	=	2085.58
		Prob > chi2	=	0.0000
Log likelihood =	-436824.26	Pseudo R2	=	0.0024

tobdep	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
score	-107.244	2.527161	-42.44	0.000	-112.1972	-102.2908
select	2.650198	.4968582	5.33	0.000	1.676367	3.624029
_cons	39.76307	1.319853	30.13	0.000	37.17619	42.34995
/sigma	63.09013	.1999825			62.69817	63.48209

The change in log likelihood is about 14, which shows uniform endogeneity. Next is the inclusion of interaction effects.

Tobit regression		Number of obs	=	178246
		LR chi2(3)	=	2160.29
		Prob > chi2	=	0.0000
Log likelihood =	-436786.9	Pseudo R2	=	0.0025

tobdep	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
score	-119.0531	2.878037	-41.37	0.000	-124.694	-113.4122
select	-27.76447	3.54989	-7.82	0.000	-34.72217	-20.80677
xrefscore	51.67789	5.970201	8.66	0.000	39.97643	63.37934
_cons	45.9038	1.499389	30.62	0.000	42.96503	48.84256
/sigma	63.07041	.1999132			62.67859	63.46224

The change in log likelihood is about 38, which again demonstrates endogeneity. The offset variable to control for endogeneity is:

-27.76447*select + 51.67789*xrefscore

The Tobit model uses the same independent variables as the revised model and includes the Tobit control for endogeneity. The results are as follows.

Tobit regression		Number of obs	=	178113
		LR chi2(28)	=	7441.38
		Prob > chi2	=	0.0000
Log likelihood =	-434168.82	Pseudo R2	=	0.0085

tobdep	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]

educ	1.061373	.0817449	12.98	0.000	.9011548	1.221591
tenure	-.7152825	.052553	-13.61	0.000	-.8182852	-.6122799
recnum	-24.29749	15.55527	-1.56	0.118	-54.78546	6.190475
wbr	-.0830057	.0028304	-29.33	0.000	-.0885532	-.0774581
lnbyearn	19.46854	.477942	40.73	0.000	18.53178	20.4053
unemp	-2.985137	.1549471	-19.27	0.000	-3.28883	-2.681444
mang_adm	-4.035914	.8616765	-4.68	0.000	-5.724781	-2.347048
sales	-3.027414	.8681353	-3.49	0.000	-4.72894	-1.325889
cler_adm	-5.386447	.7341076	-7.34	0.000	-6.825282	-3.947613
service	4.463505	.8263035	5.40	0.000	2.843969	6.083041
agr_for	39.14603	1.285883	30.44	0.000	36.62573	41.66634
cons_prd	6.841766	.5988393	11.43	0.000	5.668054	8.015477
ocmisnum	-2.771226	.7349764	-3.77	0.000	-4.211764	-1.330689
xe2	.1392198	.0099697	13.96	0.000	.1196794	.1587602
xt2	.005469	.0025079	2.18	0.029	.0005536	.0103844
xw2	.0002188	.0000274	7.98	0.000	.0001651	.0002725
xl2	-13.03713	.6023542	-21.64	0.000	-14.21773	-11.85653
xu2	.7692705	.1059933	7.26	0.000	.561526	.977015
xet	-.038262	.0092839	-4.12	0.000	-.0564583	-.0200657
xew	-.0019081	.000805	-2.37	0.018	-.0034858	-.0003304
xel	.4763954	.1212711	3.93	0.000	.2387067	.7140841
xeu	-.113579	.0462546	-2.46	0.014	-.2042369	-.0229211
xtw	.0017199	.0004864	3.54	0.000	.0007665	.0026733
xtl	-.7842279	.0775656	-10.11	0.000	-.9362547	-.6322012
xtu	.0927014	.0248627	3.73	0.000	.043971	.1414318
xwl	.0965577	.0067014	14.41	0.000	.0834232	.1096923
xwu	-.0040087	.0020561	-1.95	0.051	-.0080386	.0000212
xlu	1.310121	.3428866	3.82	0.000	.6380712	1.982171
_cons	-50.10033	1.788742	-28.01	0.000	-53.60622	-46.59444
tobend	(offset)					
/sigma	61.97888	.1960162			61.59469	62.36307

The decile table for the Tobit model is as follows.

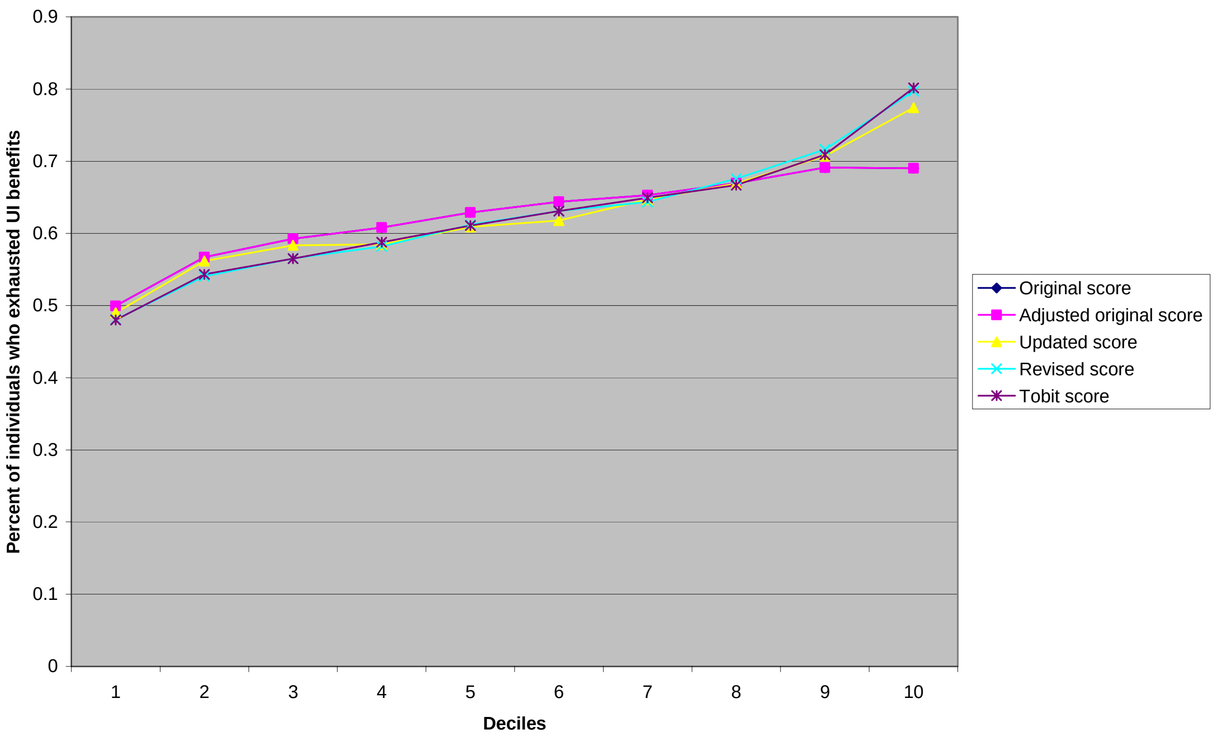
Decile	Mean	Standard Error (Mean)
1	.4800696	.0037435
2	.5432036	.0037326
3	.5648756	.0037149
4	.5875814	.0036886
5	.6106339	.0036537
6	.6306777	.0036164
7	.6491691	.0035759
8	.6667228	.0035322
9	.7088316	.0034042
10	.8013026	.0029899
Total	.6243059	.0011475

Note that the Tobit model cannot be compared with the logistic regression models by log likelihood comparisons. However, from the decile tables, the model appears to be slightly better than the revised model. It ranges from .48 to .80, while the revised model ranged from .48 to .797

We created a summary table of the four decile tables that allows us to compare models. The Tobit model allows only marginal improvement over the revised model. The revised model appears to be as good as any of the other models.

Decile	Original score	Adjusted Original score	Updated mean	Revised mean	Tobit mean
1	.4994117	.4994117	.4900629	.480631	.4800696
2	.5670739	.5670739	.5616754	.5402279	.5432036
3	.5924552	.5924552	.5835719	.5652125	.5648756
4	.6079857	.6079857	.5846059	.5819672	.5875814
5	.6290051	.6290051	.6087811	.6119252	.6106339
6	.6438648	.6438648	.6176173	.6307338	.6306777
7	.6527864	.6527864	.6467352	.6434988	.6491691
8	.6694806	.6694806	.6689125	.6756499	.6667228
9	.6911517	.6911517	.7070911	.7161866	.7088316
10	.6901045	.6901045	.7740161	.7970355	.8013026
Total	.6242945	.6242945	.6243059	.6243059	.6243059

New Jersey Profiling Models



Correlations of the five profiling scores indicate that the updated, revised, and Tobit scores are highly correlated. The strongest correlation is between the revised and Tobit models with a correlation of .9770. The original score and adjusted scores are positively correlated with the other three scores, though not at the same magnitude as the correlation between the other three scores. While the latter three scores are highly correlated, they are not identical, which suggests that there is a significant difference between the models.

	score	prorig	prup	prrev	protobn
score	1.0000				
prorig	0.9721	1.0000			
prup	0.6670	0.7136	1.0000		
prrev	0.5857	0.6293	0.8648	1.0000	
protobn	0.5068	0.5478	0.8369	0.9770	1.0000

We also tested the performance of each model using the following metric.

Percent exhausted of the top 62.4 percent of individuals in the score.

We used 62.4 percent because that was the exhaustion rate for benefit recipients in the data set provided by New Jersey. This metric will vary from about 62.4 percent, for a score that is a random draw, to 100 percent for a score that is a perfect predictor of exhaustion. The scores for the four models are as follows:

Score	% exhausted of those with the top 62.4% of score	Standard error of the score
Original	66.07	.14%
Adjusted	66.04	.14%
Updated	66.04	.14%
Revised	67.58	.14%
Tobit	67.46	.14%

To compare models across SWAs, we developed a metric to gauge classification improvements between our models and the original model. In the below metric, *"Exhaustion"* is the percentage of all benefit recipients in our sample that exhaust benefits. Here we use 62.4 percent for "*Exhaustion*" because that was the exhaustion rate for all benefit recipients for New Jersey. In our metric, "Pr[*Exh*]" is determined by the model with the highest percentage of benefit exhaustees with profiling scores falling in the top X percent of the sample where X percent is determined by the exhaustion rate for all benefit recipients in the sample. For New Jersey "Pr[*Exh*]" is represented by the revised model with a score of 71.3 percent for benefit recipients that exhaust benefits with scores falling in the top 62.4 percent of the score.

In addition to this metric we also applied the equation below, derived by Silverman, Strange, and Lipscombe (2004), for calculating the variance (σ_z^2) of a quotient (p. 1069). This equation allowed us to calculate the variance for our metric, Z = X/Y, which is the quotient of two random variables X (100 - "Pr[*Exh*]") and Y (100 - "*Exhaustion*"). In the equation below, σ_X^2 is the variance of 100 - "Pr[*Exh*]", σ_Y^2 is the variance of 100 - "*Exhaustion,*" $E(X)$ is the mean for (100 - "Pr[*Exh*]"), and $E(Y)$ is the mean for (100- "*Exhaustion*"). By dividing the variance of the quotient of the two random variables (here 100 - "*Exhaustion*" and 100 - "Pr[*Exh*]") by the square root of our observations we were able to determine the standard error of the metric.

$$\text{Metric: } 1 - \frac{100 - \Pr[Exh]}{100 - Exhaustion}$$

$$\text{Variance of Metric: } \sigma_z^2 \approx \frac{\sigma_X^2}{E(Y)^2} + \frac{E(X)^2 \sigma_Y^2}{E(Y)^4} \quad \text{where X = } (100 - \Pr[Exh]) \text{, (Y = } 100 - Exhaustion\text{)}$$

$$\text{Standard error of the metric: } \sqrt{\frac{\sigma_Z^2}{N}}$$

For our metric we use 67.58 percent for "Pr[*Exh*]" and 62.4 percent for *"Exhaustion"* and arrive at a score of 0.137082369, or roughly 13.7 percent, with a standard error of 0.006008 or 0.65 percent. For other SWAs, the statistic is recalculated using the exhaustion rate of that SWA from the given sample and the score from the model with the highest percentage of exhaustion. For SWAs with hypothetically perfect models, this metric will have a value of 1, and for SWAs with models that predict no better than random, the metric will take a value of 0.

SWA	Profiling score	Control for endogeneity?	Exhaustion rate for the state	Number of individuals with the highest profiling score	Exhaustion rate for individuals with high profiling scores	Metric	Variance of the Metric	Standard Error of the metric
New Jersey	original score	Y	62.4	67,030	66.0	0.096	2.947	0.007
New Jersey	revised score	Y	62.4	67,030	67.6	0.137	2.789	0.006

The above table also shows that the revised score is substantially better than the adjusted score.

Analysis of Type I Errors

Type I errors are individuals who are predicted to exhaust (reject the null hypothesis) and do not exhaust (the null hypothesis is actually true). Our analysis will be restricted to the top 62.4 percent of individuals who are predicted to exhaust benefits using the revised model.

Variable	Mean for exhausted	Mean for non-exhausted	T statistic	P value
	N=75,200	N=36,076		
college graduates	0.1014	0.1163	7.5175	0.0000
job tenure	5.4097	5.3742	-0.7663	0.4435
recall status	0.0002	0.0001	-0.9711	0.3315
weekly benefit rate	324.1054	322.8493	-1.6526	0.0984
base year earnings	2.4e+04	2.5e+04	10.8749	0.0000
county unemployment rate	6.2385	6.1882	-6.3755	0.0000
managerial/ administrative	0.0669	0.0671	0.0869	0.9308
sales and related	0.0716	0.0693	-1.4062	0.1597
clerical/administrative support	0.1704	0.1585	-4.9996	0.0000
service occupations	0.0738	0.0754	0.9410	0.3467
agricultural occupations	0.0004	0.0003	-0.2203	0.8256
construction occupations	0.3398	0.3571	5.6879	0.0000
occupation missing	0.1720	0.1697	-0.9467	0.3438

For the table above, note that it includes 75,200 individuals who exhausted benefits and 36,976 who did not. The total of these two types of individuals is 111,276, which is 62.4 percent of the 178,246 individuals in the sample. The Type I analysis shows that certain variables have more explanatory power than others for explaining the difference between Type I errors and correct predictions. For example, the variables for job tenure, recall status, managerial/administrative occupation and agricultural occupation are not that important for explaining the difference between exhaustees and non-exhaustees. More important variables, with low p-values, are college graduate, base year earnings, county unemployment rate, clerical/ administrative support occupation and construction occupation.

References

Silverman, M. P., Strange, W. and Lipscombe, T.C. (2004). The distribution of composite measurements: How to be certain of the uncertainties in what we measure. *American Journal of Physics, 72*(8), 1068-1081

Expanded Analyses of Pennsylvania Profiling Data

ANALYSIS OF PENNSYLVANIA PROFILING DATA

Pennsylvania provided its model structure and a dataset for analysis and model revision. Included in this dataset was a binary variable indicating whether or not benefit recipients were referred to reemployment services. This binary variable allowed us to test for endogeneity within the data and to answer the question - does referral to reemployment services have an effect on the exhaustion of benefits?

To test for endogeneity, we first calculated/ran the logistic regression model where only score (and a constant) was used to predict Pr[exh], their probability of benefit exhaustion.

Logistic Regression Model with score only

Logistic regression	Number of observations	=	223906
	LR chi2(1)	=	1317.60
	Prob > chi2	=	0.0000
Log likelihood = -153875.72	Pseudo R2	=	0.0043

exhaust	Coefficient	Std.	Err.	Z	P>z [95%	Conf.
score	2.592343	.0717106	36.15	0.000	2.451793	2.732894
_cons	-1.133801	.0274493	-41.31	0.000	-1.187601	-1.080001

Next, the variables for referral and exempt were added to determine if they increased explanatory power. The test is a chi-squared test of the difference in the (-2 X log likelihood) statistic for the nested models.

Logistic Regression Model with score, referral, and exempt

Logistic regression	Number of observations	=	223906
	LR chi2(3)	=	3314.48
	Prob > chi2	=	0.0000
Log likelihood = -152877.28	Pseudo R2	=	0.0107

exhaust	Coefficient	Standard error	z	P>z	[95% Conf.	Interval]
score	2.835601	.0806119	35.18	0.000	2.677605	2.993598
refnex	.1078473	.0117285	9.20	0.000	.0848599	.1308348
exempt	-.7580491	.0192067	-39.47	0.000	-.7956935	-.7204046
_cons	-1.201052	.0296161	-40.55	0.000	-1.259098	-1.143005

The addition of the variables “refnex” and “exempt” improves the log likelihood from -153,875.72 to -152,877.28. This represents a significant difference, showing signed or uniform DIF. Now, we add two interaction terms (referral-not-exempt X score, and exempt X score) to test for non-uniform or unsigned DIF.

Logistic Regression Model with score, referral-not-exempt, exempt and their interactions

Logistic regression	Number of observations	=	223906
	LR chi2(5)	=	3357.87
	Prob > chi2	=	0.0000
Log likelihood = -152855.59	Pseudo R2	=	0.0109

exhaust	Coefficient	Standard error	z	P>z	[95% Conf.	Interval]
score	3.126434	.0948357	32.97	0.000	2.940559	3.312308
refnex	.4218879	.0828933	5.09	0.000	.25942	.5843558
exempt	.0027421	.1330698	0.02	0.984	-.2580698	.263554
xexrfnesco	-.784345	.2004544	-3.91	0.000	-1.177228	-.3914616
xexsco	-1.857989	.3193107	-5.82	0.000	-2.483827	-1.232152
_cons	-1.306397	.0347128	-37.63	0.000	-1.374433	-1.238361

Again, the addition of the interaction term changes the log likelihood from -152,877.28 to -152,855.59. This represents a significant difference, showing unsigned or non-uniform DIF. The coefficients suggest that the difference between the referred and non-referred individuals is similar to that shown in Figure 3. For the exempt individuals, the difference is near zero when score is near 0, but with higher levels of score, exempt individuals have lower-than-expected probability of exhausting UI benefits.

Our proposed remedy is to include a variable in the model with a fixed coefficient that controls for the referral and exempt effect. This variable, called an offset variable, or ***offset***, will account for the deviation from the “score - Pr[exhaust]” curve for individuals who are referred or exempted. The value of this variable is derived from the coefficients of the above regression as:

offset = .4218879*refnex+.0027421*exempt-.784345*xexrfnesco-1.857989*xexsco

This value represents the difference between the Pr[exh] for referred and non-referred, and exempt and non-exempt individuals. Adding this variable to the logistic regression as a fixed coefficient variable was done to adjust referred and exempted individuals to the Pr[exh] that they would have had if they were not referred or exempted.

By adjusting the original scores with this control for endogeneity, we estimated the true exhaustion rate for the original score. We calculate the model as follows. The logistic regression has exhaustion as a dependent variable, with score as the independent variable and the offset, named endogeneity control, to control for endogeneity.

Logistic regression	Number of observations	=	223906
	Wald chi2(1)	=	1871.93
Log likelihood = -152855.59	Prob > chi2	=	0.0000

exhaust	Coefficient	Standard error	z	P>z	[95% Conf.	Interval]
score	3.126434	.0722611	43.27	0.000	2.984804	3.268063
_cons	-1.306397	.0276347	-47.27	0.000	-1.36056	-1.252234
endogeneity control	(offset)					

By taking the predictions of the model, ordering and dividing them into deciles, and then for each decile showing the actual exhaustion rate, with its standard error, we obtain the following table that demonstrates the effectiveness of each model.

Decile	Mean	Standard Error (Mean)
1	.3263136	.0030338
2	.3936042	.0033309
3	.4170953	.0033266
4	.4557091	.0033146
5	.4790516	.0033477
6	.489566	.00331
7	.508395	.0033587
8	.4939282	.0033718
9	.5168695	.0033428
10	.5405574	.0033307
Total	.4614749	.0010535

Updated Profiling Model

The updated model has the same form as the original model used to predict score, only the coefficients are generated using 2003 data, and the model includes the offset to control for endogeneity. We also include diagnostic statistics to show how well the model works, including a classification table that looks at the top 46 percent of cases because Pennsylvania has a 46 pecent exhaustion rate.

Updated Model Results

Logistic regression	Number of observations	=	223906
	Wald chi2(8)	=	3538.16
Log likelihood = -151990.66	Prob > chi2	=	0.0000

exhaust	Coefficient	Standard error	z	P>z	[95% Conf.	Interval]
tenind	-.1888852	.0088276	-21.40	0.000	-.2061869	-.1715834
eduind1	-.0925952	.013493	-6.86	0.000	-.1190411	-.0661494
eduind2	.0701369	.0124953	5.61	0.000	.0456464	.0946273
decind	-.3323059	.0237736	-13.98	0.000	-.3789014	-.2857104
lowrr	-.0484037	.016271	-2.97	0.003	-.0802944	-.0165131
hibrr	-.0031713	.078394	-0.04	0.968	-.1568208	.1504781
indexh	4.083298	.077704	52.55	0.000	3.931001	4.235595
tur	-.0314385	.0043355	-7.25	0.000	-.039936	-.022941
_cons	-1.597222	.0422489	-37.81	0.000	-1.680028	-1.514415
endogeneity control	(offset)					

Classification Table

Classified	D	~D	Total
+	63492	60436	123928
-	39835	60143	99978
Total	103327	120579	223906

Classified + if predicted Pr(D)	>=	.46
True D defined as exhaust	!=	0

Sensitivity		Pr(+ D)	61.45%	
Specificity		Pr(-~D)	49.88%	
Positive predictive value		Pr(D +)	51.23%	
Negative predictive value		Pr(~D -)	60.16%	
False + rate for true ~D		Pr(+~D)	50.12%	
False - rate for true D		Pr(- D)	38.55%	
False + rate for classified	+	Pr(~D +)	48.77%	
False - rate for classified	-	Pr(D -)	39.84%	
Correctly classified				55.22%

Logistic model for exhaust, goodness-of-fit test

number of observations	=	223906
number of covariate patterns	=	2228
Pearson chi2(2219)	=	6861.56
Prob > chi2	=	0.0000

number of observations	=	223906
area under ROC curve	=	0.5833

The decile table for the updated model is as follows:

Decile	Mean	Standard Error (Mean)
1	.3122766	.0029876
2	.3623209	.0032684
3	.4295011	.0033629
4	.4502674	.0033355
5	.4760161	.0033377
6	.4844848	.0033322
7	.4891484	.003344
8	.5214427	.0033458
9	.528713	.0033358
10	.5674903	.0033117
Total	.4614749	.0010535

Revised Model

The revised model is the same as the updated model except that seven more variables were added to account for nonlinear and second order interaction effects.

Logistic regression	Number of observations	=	223906
	Wald chi2(15)	=	4102.60
Log likelihood = -151684.36	Prob > chi2	=	0.0000

exhaust	Coefficient	Standard error	z	P>z	[95% Conf.	Interval]
tenind	-.1868556	.0088761	-21.05	0.000	-.2042524	-.1694588
eduind1	-.0968022	.0135224	-7.16	0.000	-.1233056	-.0702987
eduind2	.0675245	.0125174	5.39	0.000	.0429909	.0920581
decind	-.0815156	.0383682	-2.12	0.034	-.156716	-.0063152
lowrr	-.0599267	.0163153	-3.67	0.000	-.0919041	-.0279493
hibrr	-.0258075	.078488	-0.33	0.742	-.1796411	.1280261
indexh	5.015172	.1268003	39.55	0.000	4.766648	5.263696
tur	-.0423947	.0069549	-6.10	0.000	-.0560259	-.0287634
xit	-.2096412	.0774124	-2.71	0.007	-.3613667	-.0579157
xid	-3.772136	.5402018	-6.98	0.000	-4.830912	-2.71336
xtd	.0116573	.0223247	0.52	0.602	-.0320982	.0554129
xiten	-1.996344	.1574447	-12.68	0.000	-2.30493	-1.687758
xtten	.0253426	.0089136	2.84	0.004	.0078723	.042813
xi2	-15.11698	1.167127	-12.95	0.000	-17.4045	-12.82945
xt2	-.0209703	.0017147	-12.23	0.000	-.024331	-.0176096

_cons	-1.873164	.0681795	-27.47	0.000	-2.006793	-1.739535
endogeneity control	(offset)					

Classification Table

	--------	True	--------	
Classified	D		~D	Total
+	73578		71064	144642
-	29749		49515	79264
Total	103327		120579	223906

Classified + if predicted Pr(D) >= .46
True D defined as exhaust != 0

Sensitivity		Pr(+ D)	71.21%	
Specificity		Pr(-~D)	41.06%	
Positive predictive value		Pr(D +)	50.87%	
Negative predictive value		Pr(~D -)	62.47%	
False + rate for true ~D		Pr(+~D)	58.94%	
False - rate for true D		Pr(- D)	28.79%	
False + rate for classified	+	Pr(~D +)	49.13%	
False - rate for classified	-	Pr(D -)	37.53%	
Correctly classified				54.98%

Logistic model for exhaust, goodness-of-fit test

number of observations	=	223906
number of covariate patterns	=	2228
Pearson chi2(2212)	=	6360.96
Prob > chi2	=	0.0000

Logistic model for exhaust

number of observations	=	223906
area under ROC curve	=	0.5879

The decile table for the revised model is as follows.

Decile	Mean	Standard Error (Mean)
1	.2835068	.003012
2	.3783363	.0032347
3	.4261983	.0032915
4	.4586336	.003244
5	.4701638	.0034389
6	.4902339	.003346
7	.4876519	.0033224
8	.5153135	.0031217
9	.5333196	.0035789
10	.577338	.0033472
Total	.4614749	.0010535

Tobit Analysis Using the Variables of the Revised Model

The procedure that follows was used to generate a Tobit model to predict exhaustion. The Tobit model is similar to the logit model except that Tobit uses information about non-exhaustees, assuming that non-exhaustees who are closer to exhaustion are more similar to exhaustees than those claimants who are further from exhaustion. First, we created a new dependent variable, "/sigma."

/sigma = 100 X (allowed benefits – benefits paid)/ allowed benefits

This variable represents the percent of the allowed benefits still available to individuals. Exhaustees have a value of 0. In the data, all negative values were recoded as 0.

Second, we tested for endogeneity using the same procedure as for the logit analyses. Replication is necessary because of the difference in functional form for the Tobit model. The first model uses only the score as independent variable.

Tobit regression		Number of observations	=	223906
		LR chi2(1)	=	889.02
		Prob > chi2	=	0.0000
Log likelihood =	-733011.31	Pseudo R2	=	0.0006

exhvpct	Coefficient	Standard error	t	P>t	[95% Conf.	Interval]
score	-63.35571	2.127225	-29.78	0.000	-67.52502	-59.1864

_cons	32.6816	.8095355	40.37	0.000	31.09494	34.26827
/sigma	55.3712	.1261599			55.12393	55.61847

The second model uses only score, exempt, and referred-not-exempt as independent variables.

Tobit regression		Number of observations	=	223906
		LR chi2(3)	=	3311.91
		Prob > chi2	=	0.0000
Log likelihood =	-731799.87	Pseudo R2	=	0.0023

exhvpct	Coefficient	Standard error	t	P>t	[95% Conf.	Interval]
Score	-67.55848	2.356731	-28.67	0.000	-72.17761	-62.93935
Refnex	-4.896999	.3538844	-13.84	0.000	-5.590604	-4.203395
exempt	22.36194	.5177387	43.19	0.000	21.34718	23.37669
_cons	33.83465	.8611289	39.29	0.000	32.14685	35.52244
/sigma	55.0079	.125249			54.76241	55.25338

The change in log likelihood shows uniform endogeneity. Next is the inclusion of interaction effects.

Tobit regression		Number of observations	=	223906
		LR chi2(5)	=	3395.68
		Prob > chi2	=	0.0000
Log likelihood =	-731757.98	Pseudo R2	=	0.0023

exhvpct	Coefficient	Standard error	t	P>t	[95% Conf.	Interval]
Score	-76.39179	2.778797	-27.49	0.000	-81.83816	-70.94542
Refnex	-9.065158	2.480393	-3.65	0.000	-13.92666	-4.203652
exempt	-9.452034	3.524107	-2.68	0.007	-16.35919	-2.544873
xexrfnesco	11.17242	6.005183	1.86	0.063	-.5975842	22.94243
Xexsco	77.79561	8.513585	9.14	0.000	61.1092	94.48201
_cons	37.02261	1.011061	36.62	0.000	35.04096	39.00426
/sigma	54.99493	.1252164			54.74951	55.24035

The change in log likelihood again demonstrates endogeneity. The offset variable to control for endogeneity is:

offset = -9.065158*ref-9.452034*exempt+11.17242*xexrfnesco+77.79561*xexsco

The Tobit model uses the same independent variables as the revised model and includes the control for endogeneity.

Tobit regression		Number of observations	=	223906
		LR chi2(15)	=	2995.07
		Prob > chi2	=	0.0000
Log likelihood =	-730963.51	Pseudo R2	=	0.0020

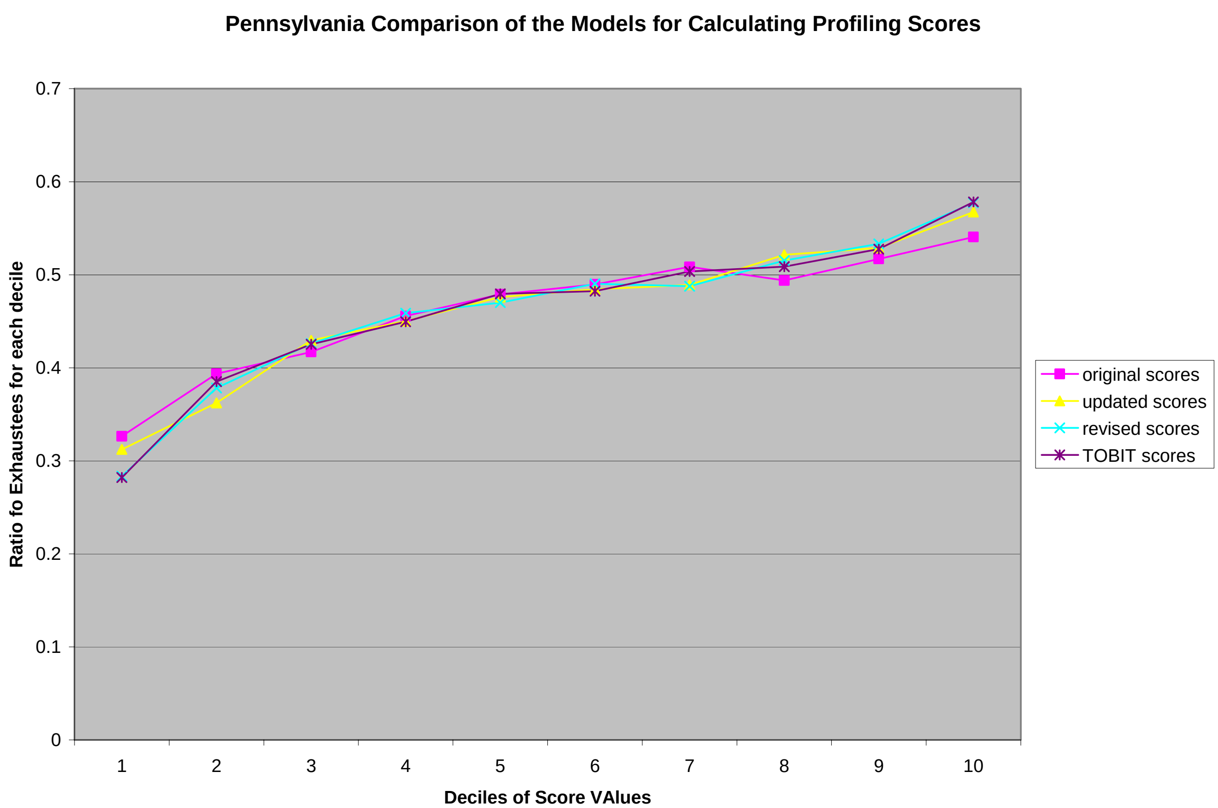
exhvpct	Coefficient	Standard error	t	P>t	[95% Conf.	Interval]
tenind	4.621223	.2603629	17.75	0.000	4.110919	5.131528
eduind1	3.088008	.3889418	7.94	0.000	2.325692	3.850324
eduind2	-2.403472	.3715285	-6.47	0.000	-3.131658	-1.675285
decind	1.480894	1.11586	1.33	0.184	-.7061634	3.667951
lowrr	1.437	.4829383	2.98	0.003	.4904536	2.383547
hibrr	4.656828	2.261252	2.06	0.039	.2248323	9.088824
indexh	-127.455	3.659758	-34.83	0.000	-134.628	-120.282
tur	1.020195	.1998597	5.10	0.000	.6284755	1.411915
xit	13.52186	2.133034	6.34	0.000	9.341166	17.70255
xid	141.3555	15.53334	9.10	0.000	110.9105	171.8004
xtd	-1.305497	.6269963	-2.08	0.037	-2.534394	-.0766006
xiten	60.77506	4.471539	13.59	0.000	52.01096	69.53916
xtten	-.6976938	.2540387	-2.75	0.006	-1.195603	-.1997845
xi2	266.5333	34.07283	7.82	0.000	199.7514	333.3152
xt2	.5510001	.0475255	11.59	0.000	.4578514	.6441488
_cons	53.83535	1.962353	27.43	0.000	49.98919	57.68151
endogeneity control	(offset)					
/sigma	54.75564	.124555			54.51151	54.99976

The decile table for the Tobit model is as follows.

Decile	Mean	Standard Error (Mean)
1	.2820718	.0029993
2	.3851224	.0032586
3	.4253426	.0032817
4	.4496224	.0031531
5	.4794263	.0034658
6	.482314	.003434
7	.5036359	.0031605
8	.5088421	.0034105
9	.5275927	.0034569
10	.5782828	.0033163
Total	.4614749	.0010535

We created a summary table of the four decile tables that allows us to compare models. The Tobit model allows only marginal improvement over the revised model. The revised model is best.

Decile	Original score	Updated score	Revised score	Tobit score
1	.3263136	.3122766	.2835068	.2820718
2	.3936042	.3623209	.3783363	.3851224
3	.4170953	.4295011	.4261983	.4253426
4	.4557091	.4502674	.4586336	.4496224
5	.4790516	.4760161	.4701638	.4794263
6	.489566	.4844848	.4902339	.482314
7	.508395	.4891484	.4876519	.5036359
8	.4939282	.5214427	.5153135	.5088421
9	.5168695	.528713	.5333196	.5275927
10	.5405574	.5674903	.577338	.5782828
Total	.4614749	.4614749	.4614749	.4614749



Correlations of the four profiling scores indicate that all model scores are positively correlated, as is to be expected. While the scores are positively correlated, they are not identical, which suggests that there are differences between the models. Here the strongest correlation exists between the revised and Tobit models with a correlation of 0.9894.

	original score	updated score	revised score	tobit score
original score	1.0000			
updated score	0.5511	1.0000		
revised score	0.5066	0.9463	1.0000	
tobit score	0.5080	0.9327	0.9894	1.0000

We also tested the performance of each model using the metric below.

Percent exhausted of the top 46.1 percent of individuals in the score.

We used 46.1 percent because the exhaustion rate for benefit recipients in the Pennsylvania dataset was 46.1 percent. This metric will vary from about 46.1 percent, for a score that is a random draw, up to 100 percent for a score that is a perfect predictor of exhaustion. The scores for the four models are as follows:

Score	% exhausted of those with the top 46.1% of score	Standard error of the score
Original	49.33	0.15727
Updated	52.29	0.15493
Revised	52.48	0.15547
Tobit	52.39	0.15542

We note that the revised score performed better than the updated and Tobit scores. The original score performed worst, and the updated score performed slightly worse than the revised score.

To compare models across SWAs, we developed a metric to gauge classification improvements between our models and the original model. In the metric below, "*Exhaustion*" is the percentage of all benefit recipients in our sample that exhaust benefits. Here we use 46.1 percent for "*Exhaustion*" because the exhaustion rate for all benefit recipients for Pennsylvania was 46.1 percent. "Pr[*Exh*]" in our metric is determined by the model with the highest percentage of benefit exhaustees with profiling scores falling in the top X percent, of the sample where X percent is determined by the exhaustion rate for all benefit recipients in the sample. For Pennsylvania, "Pr[*Exh*]" is represented by the revised model with a score of 52.48 percent for benefit recipients that exhaust benefits with scores falling in the top 46.1 percent.

In addition to this metric, we also applied the equation below, derived by Silverman, Strange, and Lipscombe (2004), for calculating the variance (σ_z^2) of a quotient (p. 1069). This equation allowed us to calculate the variance for our metric, Z = X/Y, which is the quotient of two random variables X (100 - "Pr[*Exh*]") and Y (100 - "*Exhaustion*"). In the equation below, σ_X^2 is the variance of 100 - "Pr[*Exh*]," σ_Y^2 is the variance of 100 - "*Exhaustion,*" $E(X)$ is the mean for (100 - "Pr[*Exh*]"), and $E(Y)$ is the mean for (100- "*Exhaustion*"). By dividing the variance of the quotient of the two random variables (here 100 - "*Exhaustion*" and 100 - "Pr[*Exh*]") by the square root of our observations we were able to determine the standard error of the metric.

Metric = 1 – (100 – Pr[*Exh*])/(100 – *Exhaustion*)

Variance of Metric: $\sigma_z^2 \approx \frac{\sigma_X^2}{E(Y)^2} + \frac{E(X)^2 \sigma_Y^2}{E(Y)^4}$ where X = $(100 - \Pr[Exh])$, Y = $(100 - Exhaustion)$

Standard error of the metric: $\sqrt{\frac{\sigma_Z^2}{N}}$

For our metric, "Pr[*Exh*]" is 52.48 percent and "*Exhaustion*" is 46.1 percent. We used these to calculate a score of 0.1311, or roughly 13.11 percent, with a standard error of 0.004340011. For SWAs with hypothetically perfect models, this metric will have a value of 1, and for SWAs with models that predict no better than random, the metric will take a value of 0.

SWA	Profiling score	Control for endogeneity?	Exhaustion rate for the state	Number of individuals with the highest profiling score	Exhaustion rate for individuals with high profiling scores	Metric	Variance of the Metric	Standard Error of the metric
Pennsylvania	original score	Y	46.1	103,172	51.2	0.095	1.564	0.004
Pennsylvania	revised score	Y	46.1	103,172	52.5	0.118	1.527	0.004

Type I Errors Analysis

For this analysis, Type I errors occur when individuals who are predicted to exhaust (reject the null hypothesis), do not exhaust (the null hypothesis is actually true). The analysis is restricted to the top 46.1 percent of individuals who are predicted to exhaust benefits using the revised model.

Variable	Mean for exhausted	Mean for non-exhausted	T statistic	P value
	N=54,154	N=49,018		
Tenure with most recent employer	0.4471	0.4022	14.5700	0.0000
Education less than 12 years	0.0640	0.0654	-0.8947	0.3710
Education of 16 or more years	0.2503	0.2346	5.8819	0.0000
Declining industry	0.0254	0.0241	1.3262	0.1848
Low benefit replacement rate	0.1071	0.1054	0.9064	0.3647
High benefit replacement rate	0.0020	0.0017	1.2687	0.2045
Industry exhaustion rate	0.4676	0.4693	-8.1571	0.0000
Total unemployment rate of area	5.5065	5.5039	0.5369	0.5913

For the above table, 54,154 individuals exhausted benefits and 49,018 did not. The total of these two types of individuals is 103,172, which is 46.1 percent of the 223,906 individuals in the sample. The Type I analysis shows that certain variables have more explanatory power than others for explaining the difference between Type I errors and correct predictions. For example, the area unemployment rate, low education level, and low benefit replacement rate variables are not that important for explaining the difference between exhaustees and non-exhaustees. More important variables, with low p-values, are tenure with most recent employer, education – college grad+, and industry exhaustion rate.

Expanded Analyses of Texas Profiling Data

ANALYSIS OF TEXAS PROFILING DATA

Reported Profiling Model

Texas uses a statistical model whose functional form is a logistic regression to select individuals for participation in the WPRS Program. The model was last updated in September 2003 with the North American Industry Classification System (NAICS) replacing the Standard Industrial Classification (SIC) system and the Standard Occupational Classification (SOC) system replacing the Dictionary of Occupational Titles (DOT).

The first step in analyzing both the model used and the data was to order the profiling data into a decile table as shown below. The decile means (the average for each group representing 10 percent) in this table are calculated by dividing the percentage of recipients that exhaust Unemployment Insurance (UI) benefits for a given decile by 100. For example, in the first decile our mean is 0.3120462, or 31.2 percent, which indicates that approximately 31 percent of benefit recipients in this decile exhausted benefits.

Decile	Mean	Standard Error (Mean)
1	.3120462	.0023265
2	.3797816	.0024018
3	.4156162	.0024895
4	.4265862	.0024906
5	.4619196	.0025132
6	.4787928	.0024786
7	.5114555	.0025492
8	.5475704	.0024834
9	.596076	.0024753
10	.6780035	.0023531
Total	.4803744	.0007935

After creating this decile table, we attempted to replicate these scores using the data and coefficients for the variables given in the document "Rapid Reemployment Model." While we were able to identify all variables from the dataset, two factors limited our ability to replicate the profiling scores. First, there was no constant provided with the model. To address this, through trial and error of picking constant values, we estimated a constant for the model of 0.2775. This enabled us to replicate the profiling scores for most cases. Second, there were 433 cases, out of a sample of 396,447, for which data were missing. Therefore, our analysis will be based on the 396,014 cases for which we had complete information.

Even for the cases with complete information, our replication of the SWA profiling score was significantly different from that which the SWA provided. There may be two reasons for this difference. First, the given coefficients were rounded off to 2 or 3 significant digits. For a model with 19 variables, this rounding could, in some cases, make a large difference in the estimated profiling score. However, there remained some cases with large differences. Second, there may be cases for which data were not accurate. Therefore, we assume that some individuals may have inaccurate information for at least one variable.

The table below shows the characteristics of the difference between our predicted score and the given score. The second column shows that 1 percent of the difference on the low side is -0.1109866 or less, and that 10 percent of the difference on the low side is -0.045519 or less. The 50th percentile, or the median, differs only by .0001864, which is fairly close. On the high side, 10 percent of the cases have a difference between actual and replicated profiling score of 0.053146 or greater. On the whole, our ability to replicate the given profiling score was within about .05 for more than 80 percent of the cases. The third and fourth columns of the table contain other univariate statistics of the difference variable.

Difference between predicted and given profiling scores

	Percentiles		
1%	-.1109866		
5%	-.0665765		
10%	-.045519	Observations	396014
25%	-.011548	Sum of Weight	396014
50%	.0001864	Mean	.0017419
		Std. Dev.	.0428359
75%	.0138439		
90%	.053146	Variance	.0018349
95%	.0770493	Skewness	.2779308
99%	.1318981	Kurtosis	9.56145

Texas included a binary variable indicating whether or not benefit recipients were referred to reemployment services; therefore, we were able to test for endogeneity within the data regarding whether referral to reemployment services had an effect on the exhaustion of benefits. We proceeded on the assumption that the given profiling score is what Texas used in its WPRS referral system for 2003.

To test for endogeneity, we first calculated the logistic regression model where only “score” and a “constant” are used to predict exhaustion.

Logistic Regression Model with score only

Logistic regression	Number of observations	=	396447
	LR chi2(1)	=	17098.79
	Prob > chi2	=	0.0000
Log likelihood = -265941.25	Pseudo R2	=	0.0311

Exhaust	Coefficient	Standard error	z	P>z	[95% Conf.	Interval]
Score	3.853365	.0303001	127.17	0.000	3.793978	3.912752
_cons	-1.995095	.0154028	-129.53	0.000	-2.025284	-1.964906

Adding the variable for "referral" tested for a uniform referral effect. The test is a chi-squared test of difference in the (-2 X log likelihood) statistic for the nested models.

Logistic Regression Model with score and referral

Logistic regression	Number of observations	=	396447	Logistic regression
	LR chi2(2)	=	17104.72	
	Prob > chi2	=	0.0000	
Log likelihood = -265938.29	Pseudo R2	=	0.0312	Log likelihood = -265938.29

Exhaust	Coefficient	Standard error	z	P>z	[95% Conf.	Interval]
Score	3.851421	.0303101	127.07	0.000	3.792014	3.910827
Refer	-.0183026	.007518	-2.43	0.015	-.0330376	-.0035677
_cons	-1.980377	.016542	-119.72	0.000	-2.012799	-1.947955

The addition of the variable "refer" improves the log likelihood from -265,941.25 to -265,938.29. The difference in log likelihood is 2.94, and the chi-square test for significance is two times this difference with one degree of freedom. This analysis shows a significant difference, showing signed or uniform effect. We added an interaction term (referral X score) to test for a non-uniform or unsigned effect.

Logistic Regression Model with score, referral and an interaction term

Logistic regression	Number of observations	=	396447
	LR chi2(3)	=	17120.02
	Prob > chi2	=	0.0000
Log likelihood = -265930.64	Pseudo R2	=	0.0312

Exhaust	Coefficient	Standard error	z	P>z	[95% Conf.	Interval]
Score	4.046741	.058563	69.10	0.000	3.93196	4.161523
Refer	.1153608	.0350337	3.29	0.001	.0466961	.1840255
Refer X score	-.2673757	.0684468	-3.91	0.000	-.401529	-.1332224
_cons	-2.078348	.0300881	-69.08	0.000	-2.13732	-2.019377

Again, the addition of the interaction term changes the log likelihood from -265,938.29 to -265,930.64. The difference in log likelihood shows an unsigned or non-uniform effect in addition to the signed effect.

The offset variable is calculated from the referral and interaction variables times their coefficients as:

offset = .1153608*refer - .2673757*score

This value represents the difference between the Pr[exh] for referred and non-referred individuals. Adding this variable to the logit as a fixed coefficient variable adjusts referred and exempted individuals to the Pr[exh] that they would have had if they were not referred.

By adjusting the original scores with this control for endogeneity, we estimated the true exhaustion rate for the original score. The logit regression has exhaustion as a dependent variable, with score as the independent variable and the offset, named endovar, to control for endogeneity.

Logistic regression	Number of observations	=	396447
	Wald chi2(1)	=	17831.05
Log likelihood = -265930.64	Prob > chi2	=	0.0000

exhaust	Coefficient	Standard error	z	P>z	[95% Conf.	Interval]
score	4.046741	.0303052	133.53	0.000	3.987344	4.106138
_cons	-2.078348	.0154047	-134.92	0.000	-2.108541	-2.048156
endovar	(offset)					

By taking the predictions of the model, ordering and dividing them into deciles, and then for each decile showing the actual exhaustion rate, with its standard error, we obtain the following table that demonstrates the effectiveness of each model.

Profiling Means and Standard Error of Means by Decile

Decile	Mean	Standard Error (Mean)
1	.3129018	.0023235
2	.3784102	.0024286
3	.4162552	.0024553
4	.4261504	.0025116
5	.4616296	.0025031
6	.4794217	.0024943
7	.5101999	.0025307
8	.5468143	.0024918
9	.5970523	.0024683
10	.6775371	.0023529
Total	.4803744	.0007935

Updated Profiling Model

The updated model has the same form as the model used to predict score, only the coefficients are generated using 2003 data, and the model includes the offset to control for endogeneity. Diagnostic statistics are included to show how well the model works, including a classification table that looks at the top 48 percent of cases because that was Texas' exhaustion rate.

Updated Model Results

Logistic regression	Number of observations	=	396014
	Wald chi2(19)	=	17652.32
Log likelihood = -265,658.95	Prob > chi2	=	0.0000

exhaust	Coefficient	Standard error	z	P>z	[95% Conf.	Interval]
eqwksreg	-.0852572	.0008736	-97.60	0.000	-.0869694	-.0835451
tenlong	.3735053	.0135625	27.54	0.000	.3469233	.4000874
tenshort	-.3614415	.0079099	-45.69	0.000	-.3769446	-.3459384
delay1	.097212	.0086662	11.22	0.000	.0802266	.1141974
delay2	.3870738	.0093073	41.59	0.000	.3688318	.4053158
metbea	.1029851	.0072996	14.11	0.000	.0886781	.117292
turm2	5.378269	.1791041	30.03	0.000	5.027232	5.729307
pt	.1966226	.0382476	5.14	0.000	.1216585	.2715866
lnaww	-.2169386	.0077563	-27.97	0.000	-.2321406	-.2017365
logwba2	.4811158	.0124413	38.67	0.000	.4567314	.5055003
info	.2604191	.0197951	13.16	0.000	.2216214	.2992167
manufact	.1492092	.0111637	13.37	0.000	.1273287	.1710898
oserv	.1453133	.0204281	7.11	0.000	.105275	.1853516
transwre	.1062135	.0204164	5.20	0.000	.0661981	.1462289

accfserv	-.1610647	.0206739	-7.79	0.000	-.2015848	-.1205446
tranmove	-.1594981	.0133486	-11.95	0.000	-.185661	-.1333353
foodprep	-.013593	.0220039	-0.62	0.537	-.0567199	.0295338
persserv	.2510918	.019733	12.72	0.000	.2124157	.2897678
heasupp	-.1153656	.0288519	-4.00	0.000	-.1719143	-.0588169
_cons	.1317931	.0493866	2.67	0.008	.0349972	.228589
endovar	(offset)					

Classification Table

	--------	True	--------	
Classified	D		~D	Total
+	102757		77164	179921
-	87441		128652	216093
Total	190198		205816	396014

Classified + if predicted	Pr(D)	>=	.48
True D defined as exhaust	!= 0		

Sensitivity		Pr(+ D)	54.03%	
Specificity		Pr(-~D)	62.51%	
Positive predictive value		Pr(D +)	57.11%	
Negative predictive value		Pr(~D -)	59.54%	
False + rate for true ~D		Pr(+~D)	37.49%	
False - rate for true D		Pr(- D)	45.97%	
False + rate for classified	+	Pr(~D +)	42.89%	
False - rate for classified	-	Pr(D -)	40.46%	
Correctly classified				58.43%

number of observations	=	396014
area under ROC curve	=	0.6166

The decile table for the updated model is as follows:

Decile	Mean	Standard Error (Mean)
1	.3163224	.0023369
2	.3746875	.0024324
3	.4068229	.0024685
4	.4357213	.0024917
5	.4561248	.0025029
6	.4820464	.0025109
7	.5137497	.0025116
8	.5436847	.002503
9	.5971819	.0024647

10	.6764728	.0023509
Total	.480281	.0007939

From the original score to the updated model, there was a significant improvement. The decile gradient, which ranged from a low of 0.31 to a high of 0.68 for the original model, declined slightly to a low of 0.31 to a high of 0.67 for the updated model. Also, the updated model shows a monotonic increase in ability to predict exhaustion. Thus, decile shows a higher exhaustion rate than the previous one.

Revised Model

The revised model is similar to the updated model; it incorporates more of the information in the variable set. Second-order terms were included to capture nonlinear and discontinuous effects. We made some changes to limit multicollinearity, thus improving the consistency of the model. The revised model consists of the following variables.

1) Categorical variables for:
    a) Long and short tenure
    b) Long and short delay
    c) Metroplex region
    d) Industry codes indicating employment in information, manufacturing, other services, transportation and warehousing, or accommodation and food services
    e) Occupation codes indicating employment in transportation and moving, food preparation, personal care and service, and health care support.
2) Binary variable indicating claimant's need for public transportation
3) Continuous variables for potential duration of benefits, local unemployment rate, natural log of weekly benefit amount, and a variable for the log of wage replacement rate, which we created
4) Second-order variables for potential duration of benefits and local unemployment rate. Note: The second-order variables for the natural log of weekly benefit amount and the natural log of wage replacement rate were collinear and added little new information
5) Five interaction variables for all possible interactions between the continuous variables except for the interaction between the natural log of weekly benefit amount and wage replacement rate

The second-order was created by first centering the variables, by subtracting their mean, and squaring them. The interaction variables were created by centering and multiplying the four second-order combinations. The means for the four continuous variables are shown below.

stats	eqwksreg	turm2	logwrr	logwba2
mean	21.17213	.0659975	-.871123	5.470707

The revised model is as follows:

Logistic regression	Number of observations	=	396014
	Wald chi2(26)	=	18380.12
Log likelihood = -265,114.54	Prob > chi2	=	0.0000

Exhaust	Coefficient	Standard error	z	P>z	[95% Conf.	Interval]
eqwksreg	-.0709764	.0011989	-59.20	0.000	-.0733263	-.0686265
tenlong	.3883972	.013637	28.48	0.000	.3616692	.4151251
tenshort	-.3447177	.007934	-43.45	0.000	-.3602681	-.3291674
delay1	.1023993	.0086852	11.79	0.000	.0853766	.1194219
delay2	.3965806	.0093421	42.45	0.000	.3782704	.4148909
metbea	.0877413	.0075076	11.69	0.000	.0730268	.1024559
turm2	7.618689	.2540258	29.99	0.000	7.120808	8.11657
pt	.182516	.0381749	4.78	0.000	.1076946	.2573374
logwba2	.1762326	.0112668	15.64	0.000	.15415	.1983151
info	.2807952	.0198679	14.13	0.000	.2418549	.3197354
manufact	.1544734	.0111798	13.82	0.000	.1325614	.1763855
oserv	.1311824	.020436	6.42	0.000	.0911287	.1712362
transwre	.1032244	.0204489	5.05	0.000	.0631453	.1433036
accfserv	-.1608104	.0206414	-7.79	0.000	-.2012668	-.120354
tranmove	-.1626694	.0133726	-12.16	0.000	-.1888793	-.1364595
foodprep	-.0196018	.0219647	-0.89	0.372	-.0626519	.0234483
persserv	.2461699	.0197114	12.49	0.000	.2075363	.2848035
heasupp	-.1113396	.0288778	-3.86	0.000	-.167939	-.0547403
eqwks2	.0035772	.0001889	18.94	0.000	.0032069	.0039474
trm2	-75.20079	6.116247	-12.30	0.000	-87.18842	-63.21317
logwrr	.2412488	.0085946	28.07	0.000	.2244037	.258094
xeqwrr	.0258452	.001211	21.34	0.000	.0234716	.0282188
xeqtrm	-.3521697	.0386875	-9.10	0.000	-.4279958	-.2763437
xeqlg	-.0326464	.0018581	-17.57	0.000	-.0362883	-.0290045
xtrmlg	3.649509	.4233222	8.62	0.000	2.819813	4.479205
xtrmwrr	.29173	.4403165	0.66	0.508	-.5712745	1.154734
_cons	.163165	.0582598	2.80	0.005	.0489778	.2773521
endovar	(offset)					

Classification Table

	--------	True	--------	
Classified	D		~D	Total
+	100647		73965	174612

-	89551		131851	221402
Total	190198		205816	396014

Classified + if predicted Pr(D) >= .480
True D defined as exhaust != 0

Sensitivity		Pr(+ D)	52.92%	
Specificity		Pr(-~D)	64.06%	
Positive predictive value		Pr(D +)	57.64%	
Negative predictive value		Pr(~D -)	59.55%	
False + rate for true ~D		Pr(+~D)	35.94%	
False - rate for true D		Pr(- D)	47.08%	
False + rate for classified	+	Pr(~D +)	42.36%	
False - rate for classified	-	Pr(D -)	40.45%	
Correctly classified				58.71%

number of observations	=	396014
area under ROC curve	=	0.6205

The decile table for the revised model is as follows.

Decile	Mean	Standard Error (Mean)
1	.3085955	.0023212
2	.3679107	.0024233
3	.4043585	.0024662
4	.434484	.0024909
5	.4634984	.0025059
6	.4860361	.0025116
7	.5137244	.0025116
8	.5428009	.0025033
9	.5986465	.0024632
10	.6827605	.0023387
Total	.480281	.0007939

Note that there is an improvement from the updated to the revised model in terms of log likelihood. However, the decile gradient for the revised model and the updated model shows only minimal difference. Both models are monotonically increasing across all deciles.

Tobit analysis using the variables of the revised model

The following procedure was used to generate a Tobit model to predict exhaustion. The Tobit model is similar to the logit model except that it uses information about non-exhaustees, assuming that non-exhaustees who are closer to exhaustion are more similar to exhaustees than those who are further from exhaustion. First, we created a new dependent variable, "/sigma."

/sigma = 100 X (maximum benefit amount – benefits paid)/ maximum benefit amount

This variable represents the percent of the allowed benefits left to individuals. Exhaustees have a value of 0. In the data, all negative values were recoded as 0.

Second, we tested for endogeneity using the same procedure as for the logit analyses. Replication is necessary because of the difference in functional form for the Tobit model. The first model uses only the score as independent variable.

Tobit regression		Number of observations	=	396447
		LR chi2(1)	=	18351.92
		Prob > chi2	=	0.0000
Log likelihood =	-1274342.8	Pseudo R2	=	0.0071

tobit dependent var.	Coefficient	Standard error	t	P>t	[95% Conf.	Interval]
score	-129.5669	.9669814	-133.99	0.000	-131.4622	-127.6716
_cons	72.06959	.4800877	150.12	0.000	71.12864	73.01055
/sigma	59.43342	.1038993			59.22978	59.63706

The second model uses only score and a binary variable for referred status as independent variables.

Tobit regression		Number of observations	=	396447
		LR chi2(2)	=	18406.41
		Prob > chi2	=	0.0000
Log likelihood =	-1274315.5	Pseudo R2	=	0.0072

tobit dependent var.	Coefficient	Standard error	t	P>t	[95% Conf.	Interval]
score	-129.404	.9671306	-133.80	0.000	-131.2996	-127.5085
refer	1.770434	.2398955	7.38	0.000	1.300246	2.240622
_cons	70.66097	.5164904	136.81	0.000	69.64867	71.67328
/sigma	59.42635	.1038864			59.22273	59.62996

The change in log likelihood shows uniform endogeneity. Next is the inclusion of interaction effects.

Tobit regression		Number of observations	=	396447
		LR chi2(3)	=	18418.81
		Prob > chi2	=	0.0000
Log likelihood =	-1274309.3	Pseudo R2	=	0.0072

tobit dependent var.	Coefficient	Standard error	t	P>t	[95% Conf.	Interval]
score	-134.9548	1.850961	-72.91	0.000	-138.5827	-131.327
refer	-1.966589	1.088124	-1.81	0.071	-4.09928	.166101
score X refer	7.603824	2.159826	3.52	0.000	3.37063	11.83702
_cons	73.39708	.9333018	78.64	0.000	71.56784	75.22633
/sigma	59.42583	.1038852			59.22222	59.62945

The change in log likelihood again demonstrates endogeneity. The offset variable to control for endogeneity is:

offset = -1.966589*refer + 7.603824*score times refer

The Tobit model uses the same independent variables as the revised model, and includes the Tobit control for endogeneity. The results are as follows.

Tobit regression		Number of observations	=	396014
		LR chi2(26)	=	20751.32
		Prob > chi2	=	0.0000
Log likelihood =	-1272661.1	Pseudo R2	=	0.0081

tobit dependent var.	Coefficient	Standard error	t	P>t	[95% Conf.	Interval]
eqwksreg	2.405508	.0381114	63.12	0.000	2.330811	2.480205
tenlong	-11.99592	.4418282	-27.15	0.000	-12.86189	-11.12995
tenshort	9.246602	.2470913	37.42	0.000	8.76231	9.730894
delay1	-2.797	.2762329	-10.13	0.000	-3.338409	-2.255592
delay2	-12.87464	.3032737	-42.45	0.000	-13.46904	-12.28023
metbea	-2.656668	.2392148	-11.11	0.000	-3.125522	-2.187814
turm2	-301.366	7.983454	-37.75	0.000	-317.0133	-285.7186
pt	-4.674928	1.243558	-3.76	0.000	-7.112264	-2.237593
logwba2	-8.648269	.3555935	-24.32	0.000	-9.345222	-7.951317
info	-9.694697	.6402673	-15.14	0.000	-10.9496	-8.439792
manufact	-5.01057	.359218	-13.95	0.000	-5.714626	-4.306513

oserv	-4.481407	.6587477	-6.80	0.000	-5.772532	-3.190281
transwre	-2.431678	.6551927	-3.71	0.000	-3.715836	-1.14752
accfserv	5.992467	.6511633	9.20	0.000	4.716207	7.268728
tranmove	5.996153	.4232011	14.17	0.000	5.166691	6.825614
foodprep	1.599792	.6980129	2.29	0.022	.2317081	2.967877
persserv	-7.556716	.6404074	-11.80	0.000	-8.811895	-6.301537
heasupp	7.073391	.8995265	7.86	0.000	5.310346	8.836437
eqwks2	-.1252639	.0060941	-20.56	0.000	-.137208	-.1133197
trm2	2754.226	195.026	14.12	0.000	2371.981	3136.471
logwrr	-5.992173	.2597402	-23.07	0.000	-6.501256	-5.48309
xeqwrr	-.6482221	.0378365	-17.13	0.000	-.7223806	-.5740637
xeqtrm	14.74313	1.25252	11.77	0.000	12.28823	17.19803
xeqlg	.9918048	.0595822	16.65	0.000	.8750255	1.108584
xtrmlg	-136.8592	13.50226	-10.14	0.000	-163.3232	-110.3951
xtrmwrr	-16.67146	13.44361	-1.24	0.215	-43.02053	9.67761
_cons	18.69611	1.830804	10.21	0.000	15.10779	22.28443
endogeneity control	(offset)					
/sigma	59.36851	.1038132			59.16503	59.57198

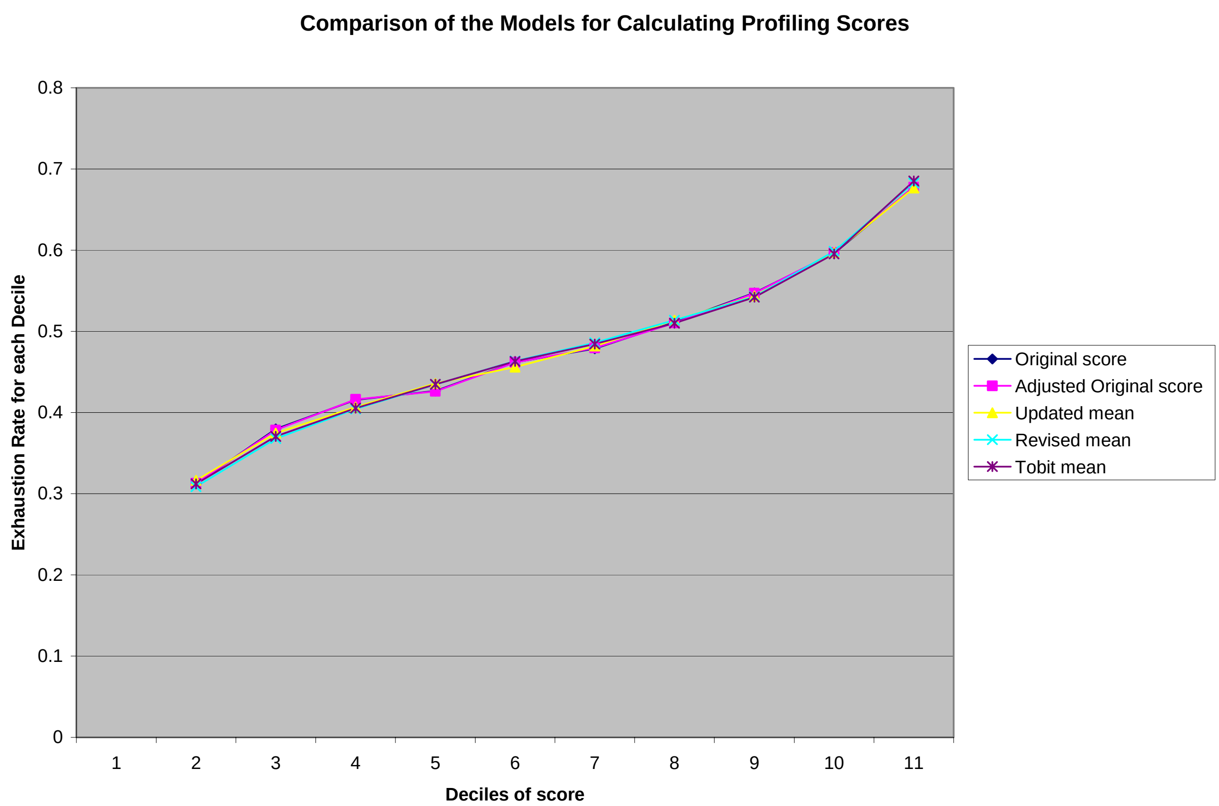
The decile table for the Tobit model is as follows.

Decile	Mean	Standard Error (Mean)
1	.3120549	.0023283
2	.3705621	.0024269
3	.4054191	.0024672
4	.4346607	.002491
5	.4630691	.0025057
6	.48442	.0025113
7	.5099871	.0025121
8	.5421696	.0025036
9	.5953638	.0024665
10	.685109	.0023341
Total	.480281	.0007939

Note that the Tobit model cannot be compared with the logit models by log likelihood comparisons. However, from the decile tables, the model does not appear to be significantly better than the revised model.

We created a summary table of the four decile tables that allows us to compare models. The Tobit model allows only marginal improvement over the revised model. The updated or revised model will yield better results in predicting benefit exhaustion.

Decile	Original Score	Original score (Adjusted for Endogeneity)	Updated score	Revised score	Tobit score
1	.3120462	.3129018	.3163224	.3085955	.3120549
2	.3797816	.3784102	.3746875	.3679107	.3705621
3	.4156162	.4162552	.4068229	.4043585	.4054191
4	.4265862	.4261504	.4357213	.434484	.4346607
5	.4619196	.4616296	.4561248	.4634984	.4630691
6	.4787928	.4794217	.4820464	.4860361	.48442
7	.5114555	.5101999	.5137497	.5137244	.5099871
8	.5475704	.5468143	.5436847	.5428009	.5421696
9	.596076	.5970523	.5971819	.5986465	.5953638
10	.6780035	.6775371	.6764728	.6827605	.685109
Total	.4803744	.480281	.480281	.480281	.480281



Correlations of the four profiling scores indicate that all model scores are highly correlated. The original score is highly correlated (positively) with the other three scores. While the latter three scores are highly correlated, they are not identical, which suggests that there is a significant difference between the models.

	original score	updated score	revised score	tobit score
original score	1.0000			
updated score	0.8977	1.0000		
revised score	0.8710	0.9698	1.0000	
tobit score	0.8789	0.9677	0.9864	1.0000

Note that the strongest correlation is between the revised and Tobit models with a correlation score of almost one. As expected, there is also a very strong positive correlation between the updated, revised, and Tobit models. However, these correlations are not as strong as the relationship between the revised model and the Tobit model.

We also tested the performance of each model using the metric below.

Percent exhausted of the top 48 percent of individuals in the score.

We used 48 percent because the exhaustion rate for benefit recipients in the Texas dataset was 48 percent. This metric will vary from about 48 percent, for a score that is a random draw, to 100 percent for a score that is a perfect predictor of exhaustion. The scores for the four models are as follows:

Score	% exhausted of those with the top 48% of score	Standard error of the score
Original	56.57	0.11353
Updated	56.65	0.11360
Revised	56.87	0.11353
Tobit	56.73	0.11357

We note that the revised score performed better than the updated score. The original score performed worst, and the updated score performed slightly worse than the revised and Tobit scores.

To compare models across SWAs, we developed a metric to gauge classification improvements between our models and the original model. In the metric below, "*Exhaustion*" is the percentage of all benefit recipients in our sample that exhaust benefits. Here we use 48 percent for "*Exhaustion*" because the exhaustion rate for all benefit recipients for Texas was 48 percent. In our metric, "Pr[*Exh*]" is determined by the model with the highest percentage of benefit exhaustees with profiling scores falling in the top X percent of the sample, where X percent is determined by the exhaustion rate for all benefit recipients in the sample. For Texas, "Pr[*Exh*]" is represented by the revised model with a score of 56.87 percent for benefit recipients that exhaust benefits with scores falling in the top 48 percent.

In addition to this metric, we also applied the equation below, derived by Silverman, Strange, and Lipscombe (2004), for calculating the variance (σ_z^2) of a quotient (p. 1069). This equation allowed us to calculate the variance for our metric, Z = X/Y, which is the quotient of two random variables X (100 - "Pr[*Exh*]") and Y (100 - "*Exhaustion*"). In the equation below, σ_X^2 is the variance of 100 - "Pr[*Exh*]," σ_Y^2 is the variance of 100 - "*Exhaustion*," $E(X)$ is the mean for (100 - "Pr[*Exh*]"), and $E(Y)$ is the mean for (100- "*Exhaustion*"). By dividing the variance of the quotient of the two random variables (here 100 - "*Exhaustion*" and 100 - "Pr[*Exh*]") by the square root of our observations we were able to determine the standard error of the metric.

Metric = 1 – (100 – Pr[*Exh*])/(100 – *Exhaustion*)

Variance of Metric: $\sigma_z^2 \approx \frac{\sigma_X^2}{E(Y)^2} + \frac{E(X)^2 \sigma_Y^2}{E(Y)^4}$, where X = ($100 - \Pr[Exh]$), (Y = $100 - Exhaustion$)

Standard error of the metric: $\sqrt{\frac{\sigma_Z^2}{N}}$

For our metric, "Pr[*Exh*]" is 56.87 percent and "*Exhaustion*" is 48 percent. We used these to calculate a score of 0.169991817, or roughly 17 percent, with a standard error of 0.002849646. For SWAs with hypothetically perfect models, this metric will have a value of 1, and for SWAs with models that predict no better than random, the metric will take a value of 0.

SWA	Profiling score	Control for endogeneity?	Exhaustion rate for the state	Number of individuals with the highest profiling score	Exhaustion rate for individuals with high profiling scores	Metric	Variance of the Metric	Standard Error of the metric
Texas	original score	Y	48.0	190,270	56.6	0.165	1.555	0.003
Texas	revised score	Y	48.0	190,270	56.9	0.170	1.545	0.003

Analysis of Type I Errors

For this analysis, Type I errors occur when individuals who are predicted to exhaust (reject the null hypothesis) and do not exhaust (the null hypothesis is actually true). The analysis is restricted to the top 48 percent of individuals who are predicted to exhaust benefits using the revised model.

Variable	Mean for exhausted	Mean for non-exhausted	T statistic	P value
	N = 108,222	N = 82,073		
Potential Duration	17.7026	18.6265	38.0622	0.0000
Tenure of 10 or more years	0.1106	0.1113	0.4754	0.6345
Tenure of less than one year	0.4733	0.4302	-18.7288	0.0000
Delay of 2-6 weeks	0.1933	0.1987	2.9133	0.0036
Delay of 6 or more weeks	0.2967	0.2516	-21.7987	0.0000
Metroplex economic region	0.3077	0.3113	1.7206	0.0853
Local unemployment rate	0.0703	0.0694	-9.7000	0.0000
Public transportation needed	0.0132	0.0124	-1.6114	0.1071
Average weekly wage (log)	6.1254	6.1241	-0.5200	0.6031
Weekly benefit amount (log)	5.3889	5.3773	-5.8280	0.0000
Information industry sector	0.0386	0.0396	1.1452	0.2521
Manufacturing sector	0.1311	0.1288	-1.4718	0.1411
Other service industry sector	0.0361	0.0361	0.0855	0.9319
Transportation and warehousing industry	0.0334	0.0327	-0.7726	0.4398
Accommodation and food services industry	0.0258	0.0288	3.9985	0.0001
Transportation and moving occupations	0.0608	0.0619	1.0084	0.3133
Food preparation occupations	0.0278	0.0291	1.6694	0.0950
Personal care and service occupations	0.0474	0.0490	1.5937	0.1110
Healthcare support occupations	0.0090	0.0080	-2.2022	0.0277

For the above table, 108,222 individuals exhausted benefits and 82,073 did not. The total of these two types of individuals is 190,295, which is 48 percent of the 396,447 individuals in the sample. The Type I analysis shows that certain variables have more explanatory power than others for explaining the difference between Type I errors and correct predictions. For example, the variables for long tenure, average weekly wage, and other service industry sector are not that important for explaining the difference between exhaustees and non-exhaustees. More important variables, with lower p-values, are potential duration, tenure of less than one year and delay of six or more weeks.

Expanded Analyses of West Virginia Profiling Data

Analysis of West Virginia Data

Our first step was to replicate the given scores using the data and variable coefficients provided for the model. West Virginia provided data in three separate data sets. The first was for individuals who received services. The second was for individuals who were profiled but did not receive services, and the third was individuals who were not profiled. We combined the first two data sets for our analysis of the effectiveness of the profiling score.

From the given data, we identified and replicated variables and categories for weekly benefit allowance, wage base, file lag, reopens, occupation code, industry code, education level, month of filing, and other income. One possible source of data corruption was our construction of the variable file lag, or the difference between the separation date and the 'begin benefit' year date. We found many cases where the result was less than 0, so we cut all cases where the value was less than -9. We also cut all values that were greater than 450, as these individuals would not have had an opportunity to monetarily qualify for UI benefits. In constructing these variables, we noticed that there were 5,136 cases with missing data out of a total of 34,913 individuals. Our replicated score correlated with the provided score at .87.

We first developed a decile table for the original score. This table shows for each decile the actual exhaustion rate, with its standard error and allows us to demonstrate the effectiveness of each model. It is:

Original score deciles	mean	se(mean)
1	.2116266	.0069132
2	.2552277	.0073801
3	.3091898	.0078209
4	.3562428	.0081051
5	.37611	.0081997
6	.4039508	.0083036
7	.4428531	.0084082
8	.4696101	.0084516
9	.4801031	.0084545
10	.5611923	.0084024
Total	.3865895	.0026062

We included a binary variable that indicated whether or not benefit recipients were referred to re-employment services. This binary variable will allow us to test for endogeneity within our data and will answer the question - does referral to re-employment services have an effect on the exhaustion of benefits? To test for endogeneity, we first calculated the logit model where only score (and a constant) is used to predict Pr[exh].

Logit Model with score only

Logistic regression	Number of obs	=	34913
	LR chi2(1)	=	1455.34
	Prob > chi2	=	0.0000
Log likelihood = -22566.217	Pseudo R2	=	0.0312

sumexhst	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
pexhprob	.0426529	.0011478	37.16	0.000	.0404033	.0449025
_cons	-1.968648	.0423624	-46.47	0.000	-2.051676	-1.885619

Adding the variable for referral tests for a uniform referral effect. The test would be a chi-squared test of difference in the (-2 X log likelihood) statistic for the nested models.

Logit Model with score and referral

Logistic regression	Number of obs	=	34913
	LR chi2(2)	=	1473.72
	Prob > chi2	=	0.0000
Log likelihood = -22557.026	Pseudo R2	=	0.0316

sumexhst	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
pexhprob	.0412903	.001189	34.73	0.000	.0389599	.0436207
ref	.114108	.0266666	4.28	0.000	.0618424	.1663736
_cons	-2.004697	.0432422	-46.36	0.000	-2.089451	-1.919944

The addition of the variable "ref" improved the log likelihood from -22566.217 to -22557.026. The difference in log likelihood was significant, which is significant at the .05 level. Our next step was to test for non-uniform effects. We added an interaction term (referral X score) to test for a non-uniform or unsigned effect.

Logit Model with score, referral and an interaction term

Logistic regression	Number of obs	=	34913
	LR chi2(3)	=	1475.07
	Prob > chi2	=	0.0000
Log likelihood = -22556.35	Pseudo R2	=	0.0317

sumexhst	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]

pexhprob	.0444177	.0029442	15.09	0.000	.0386471	.0501883
ref	.23449	.1070069	2.19	0.028	.0247603	.4442196
scorref	-.0037394	.0032179	-1.16	0.245	-.0100464	.0025676
_cons	-2.102373	.0946569	-22.21	0.000	-2.287897	-1.916849

The addition of the interaction term changes the log likelihood from -22557.026 to -22556.35. The difference was not significant. The analysis indicates that there is only a need to control for uniform endogeneity. The offset variable is as follows:

.114108*ref

After correcting for endogeneity, we obtain the following decile table.

prorigdec	mean	se(mean)
1	.2124857	.0069234
2	.25666	.0073937
3	.3070979	.007805
4	.3553009	.0081026
5	.382235	.0082267
6	.3981667	.0082862
7	.4372852	.0083956
8	.4743626	.0084525
9	.4800917	.0084569
10	.5623031	.0083977
Total	.3865895	.0026062

Updated Model

The updated model for West Virginia uses the same variables as used in the original model to predict the profiling score, only the coefficients are generated using 2003 data. We also included diagnostic statistics to show how well the model works, including a classification table that looks at the top 38.7 percent of cases (because West Virginia had approximately a 38.7 percent exhaustion rate for the sample).

There were two variables dropped from the analysis due to multicollinearity, or that the variation in the variables was replicated by other variables in the model. One was education level below high school graduate. The other was NAICS industry 233 to 235. The resulting model was as follows.

Logistic regression	Number of obs	=	29777
	Wald chi2(48)	=	2178.28
Log likelihood = -18833.247	Prob > chi2	=	0.0000

exhaust	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
wba	.0029882	.0002335	12.80	0.000	.0025305	.003446
wagebase	-8.08e-06	1.37e-06	-5.90	0.000	-.0000108	-5.40e-06
ten1	.7436879	.0506253	14.69	0.000	.6444642	.8429115
ten2	.5150458	.0558257	9.23	0.000	.4056294	.6244622
ten3	.5122289	.0402284	12.73	0.000	.4333826	.5910751
ten4	.3701485	.0313851	11.79	0.000	.3086348	.4316622
fillag2	.002649	.000219	12.09	0.000	.0022197	.0030783
reopens	-.4928575	.024942	-19.76	0.000	-.541743	-.4439721
soca	.3750771	.2404267	1.56	0.119	-.0961505	.8463047
socb	.0611577	.2392343	0.26	0.798	-.407733	.5300483
socc	.1707481	.2375245	0.72	0.472	-.2947914	.6362876
socd	.3442268	.238466	1.44	0.149	-.1231579	.8116115
soce	.3127174	.2369227	1.32	0.187	-.1516425	.7770774
socg	-.0630185	.2374472	-0.27	0.791	-.5284066	.4023695
soch	-.0844695	.2412895	-0.35	0.726	-.5573881	.3884492
soci	.0966113	.2373195	0.41	0.684	-.3685264	.5617491
socj	-.038083	.2377118	-0.16	0.873	-.5039894	.4278235
socl	-1.227142	.2462532	-4.98	0.000	-1.709789	-.7444942
naicsa	-.1460809	.2552339	-0.57	0.567	-.6463303	.3541684
naicsb	-.5651295	.1669446	-3.39	0.001	-.892335	-.2379241
naicse	.0405749	.1642364	0.25	0.805	-.2813226	.3624723
naicsf	.1499015	.1648961	0.91	0.363	-.173289	.473092
naicsg	-.191624	.1611328	-1.19	0.234	-.5074385	.1241905
naicsh	-.2697996	.1747613	-1.54	0.123	-.6123255	.0727262
naicsi	.1007729	.2266578	0.44	0.657	-.3434681	.545014
naicsj	.2096941	.1720147	1.22	0.223	-.1274486	.5468368
naicsk	-.1635723	.1977593	-0.83	0.408	-.5511733	.2240288
naicsl	-.2944647	.1610682	-1.83	0.068	-.6101526	.0212232
naicsm	-.0740427	.1627558	-0.45	0.649	-.3930381	.2449528
naicsn	-.4838695	.1897004	-2.55	0.011	-.8556754	-.1120636
naicso	-.432979	.166882	-2.59	0.009	-.7600618	-.1058962
naicsp	.0849415	.170601	0.50	0.619	-.2494303	.4193133
naicsq	-.3549825	.1800176	-1.97	0.049	-.7078106	-.0021544
naicsr	-.206361	.1609367	-1.28	0.200	-.5217911	.1090691
ed2	-.1697102	.0379417	-4.47	0.000	-.2440746	-.0953458
ed3	-.4020231	.0572163	-7.03	0.000	-.5141649	-.2898812
bybmo1	-.0235924	.0539444	-0.44	0.662	-.1293214	.0821366
bybmo2	.0616336	.0605959	1.02	0.309	-.0571322	.1803993
bybmo3	.2367095	.0616057	3.84	0.000	.1159646	.3574545
bybmo4	.3594653	.0607978	5.91	0.000	.2403037	.4786269
bybmo5	.0485156	.0665144	0.73	0.466	-.0818503	.1788814
bybmo6	-.2084052	.0597431	-3.49	0.000	-.3254996	-.0913109
bybmo7	.1857606	.0591185	3.14	0.002	.0698905	.3016306
bybmo8	.1801518	.0615319	2.93	0.003	.0595515	.3007521
bybmo9	.0034562	.0705178	0.05	0.961	-.1347561	.1416685
bybmo10	.252192	.0617218	4.09	0.000	.1312196	.3731645

bybmo11	-.0446778	.0596928	-0.75	0.454	-.1616736	.072318
othintot	-1.325398	.1048464	-12.64	0.000	-1.530893	-1.119903
_cons	-.926875	.2890298	-3.21	0.001	-1.493363	-.360387
endovar	(offset)					

	--------	True	--------	
Classified	D		~D	Total
+	8621		8101	16722
-	3595		9460	13055
Total	12216		17561	29777

Sensitivity		Pr(+ D)	70.57%	
Specificity		Pr(-~D)	53.87%	
Positive predictive value		Pr(D +)	51.55%	
Negative predictive value		Pr(~D -)	72.46%	
False + rate for true ~D		Pr(+~D)	46.13%	
False - rate for true D		Pr(- D)	29.43%	
False + rate for classified	+	Pr(~D +)	48.45%	
False - rate for classified	-	Pr(D -)	27.54%	
Correctly classified				60.72%

number of observations	=	29777
area under ROC curve	=	0.6721

The decile table for the updated model is as follows:

prupdec	mean	se(mean)
1	.175957	.0069789
2	.2437878	.0078693
3	.2971793	.0083761
4	.3399395	.0086831
5	.3895232	.0089374
6	.4308261	.0090758
7	.4662412	.0091445
8	.5238415	.0091535
9	.5815984	.009041
10	.6536782	.0087218
Total	.4102495	.0028505

From the original score to the updated model, there was a significant improvement. The decile gradient, which ranged from .21 to .56 for the original model (corrected for endogeneity) improved to .17 to .65 for the updated model.

Revised Model

The revised model is similar to the updated model, but we incorporated more of the information in the variable set. We substituted continuous variables for tenure and education instead of the categorical versions in the original model. We added four variables for counties # 11, 39, 81 and 107, which are the counties with about 5 percent or more of the population. These variables account for geographical effects. We also included second order terms to capture nonlinear and discontinuous effects, but we did not include second order and interaction terms for the variable wagebase in order to limit multicollinearity. Wagebase was highly correlated with weekly benefit amount.

To reduce multicollinearity, we eliminated four variables for occupations with SOC codes 310-399, 430-439, 470-479, and 510-519. These variables had the highest collinearity with other variables, with variance inflation factors of 40 or greater in our sample.

We created the second order variables by first centering the variables, by subtracting their mean, and squaring them. This gave us four variables to measure non-linear effects. We created the interaction variables by centering and multiplying the five variables, resulting in six additional variables. The means for the four continuous variables are shown below.

Variable	Obs	Mean	Std. Dev.	Min	Max
Wba	34913	192.5633	102.8431	24	358
Tenure	31485	3.092965	6.150329	0	61
Educate	34913	12.50483	1.952646	0	27
File lag	29777	36.8926	58.19218	-9	444

The logit model results for the revised model are as follows.

Logistic regression	Number of obs	=	29777
	Wald chi2(53)	=	1831.05
Log likelihood = -19060.609	Prob > chi2	=	0.0000

Exhaust	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
wba	.0033525	.0002351	14.26	0.000	.0028918	.0038133
wagebase	-6.49e-06	1.42e-06	-4.58	0.000	-9.27e-06	-3.71e-06
tenure2	.0717911	.00482	14.89	0.000	.062344	.0812382

fillag2	.0053138	.0004182	12.71	0.000	.0044943	.0061334
educate	-.0436911	.0077132	-5.66	0.000	-.0588087	-.0285736
soca	.2276896	.0532177	4.28	0.000	.1233848	.3319944
socb	-.0969952	.0482557	-2.01	0.044	-.1915747	-.0024157
socd	.2300526	.0444252	5.18	0.000	.1429809	.3171244
soch	-.2289532	.0583534	-3.92	0.000	-.3433238	-.1145825
socj	-.2019862	.0427502	-4.72	0.000	-.2857751	-.1181973
socl	-1.372821	.0764903	-17.95	0.000	-1.522739	-1.222903
naicsa	-.1696616	.2482049	-0.68	0.494	-.6561343	.3168111
naicsb	-.6009846	.1656591	-3.63	0.000	-.9256704	-.2762987
naicse	.0091071	.1626834	0.06	0.955	-.3097466	.3279607
naicsf	.1616165	.1630974	0.99	0.322	-.1580485	.4812814
naicsg	-.1036812	.159973	-0.65	0.517	-.4172226	.2098602
naicsh	-.2544863	.1732963	-1.47	0.142	-.5941408	.0851683
naicsi	.1865665	.2251364	0.83	0.407	-.2546928	.6278257
naicsj	.3354638	.1710194	1.96	0.050	.0002719	.6706556
naicsk	-.0798549	.1964173	-0.41	0.684	-.4648258	.305116
naicsl	-.2160792	.1598408	-1.35	0.176	-.5293614	.0972031
naicsm	.0169084	.1612332	0.10	0.916	-.2991029	.3329198
naicsn	-.4029611	.1881527	-2.14	0.032	-.7717336	-.0341887
naicso	-.3040127	.1653424	-1.84	0.066	-.6280778	.0200525
naicsp	.1644536	.1694502	0.97	0.332	-.1676628	.49657
naicsq	-.2838175	.1788067	-1.59	0.112	-.6342722	.0666372
naicsr	-.2482247	.1595283	-1.56	0.120	-.5608944	.064445
bybmo1	-.0575788	.0537554	-1.07	0.284	-.1629375	.0477799
bybmo2	.037415	.0603838	0.62	0.536	-.080935	.155765
bybmo3	.2128922	.0614294	3.47	0.001	.0924926	.3332917
bybmo4	.3138914	.0604653	5.19	0.000	.1953815	.4324013
bybmo5	-.0035062	.0660587	-0.05	0.958	-.1329789	.1259665
bybmo6	-.204477	.0595692	-3.43	0.001	-.3212306	-.0877235
bybmo7	.1455612	.0589068	2.47	0.013	.0301061	.2610163
bybmo8	.1819153	.0612726	2.97	0.003	.0618232	.3020074
bybmo9	.030705	.0702562	0.44	0.662	-.1069946	.1684046
bybmo10	.2403364	.0614284	3.91	0.000	.1199389	.3607339
bybmo11	-.0183833	.0594613	-0.31	0.757	-.1349252	.0981587
othintot	-1.312701	.1084094	-12.11	0.000	-1.52518	-1.100223
cnty11	-.2606691	.0567545	-4.59	0.000	-.3719058	-.1494324
cnty39	.0455275	.0378433	1.20	0.229	-.0286439	.1196989
cnty81	-.032068	.0567446	-0.57	0.572	-.1432855	.0791494
cnty107	.0466289	.0510532	0.91	0.361	-.0534335	.1466914
xten2	-.0018176	.0002334	-7.79	0.000	-.0022752	-.0013601
xwba2	-9.18e-06	1.62e-06	-5.65	0.000	-.0000124	-6.00e-06
xedu2	.001283	.0017081	0.75	0.453	-.0020649	.0046308
xfil2	-.0000155	1.94e-06	-7.97	0.000	-.0000193	-.0000117
xtwba	-.0000145	.0000307	-0.47	0.636	-.0000747	.0000457
xtedu	-.0015697	.0011548	-1.36	0.174	-.0038332	.0006937
xtfil	-.0000953	.0000321	-2.96	0.003	-.0001583	-.0000323
xwbaedu	.0000701	.0000722	0.97	0.331	-.0000714	.0002117
xwbafil	6.07e-06	2.30e-06	2.64	0.008	1.57e-06	.0000106

xedufil	.0000135	.000115	0.12	0.906	-.0002119	.0002389
_cons	-.4862913	.1886342	-2.58	0.010	-.8560077	-.116575
endovar	(offset)					

Classification Table

	--------	True	--------	
Classified	D		~D	Total
+	8292		8002	16294
-	3924		9559	13483
Total	12216		17561	29777

Sensitivity		Pr(+ D)	67.88%	
Specificity		Pr(-~D)	54.43%	
Positive predictive value		Pr(D +)	50.89%	
Negative predictive value		Pr(~D -)	70.90%	
False + rate for true ~D		Pr(+~D)	45.57%	
False - rate for true D		Pr(- D)	32.12%	
False + rate for classified	+	Pr(~D +)	49.11%	
False - rate for classified	-	Pr(D -)	29.10%	
Correctly classified				59.95%

number of observations	=	29777
area under ROC curve	=	0.6553

The decile table for the revised model is as follows.

prrevdec	mean	se(mean)
1	.1796508	.007036
2	.259906	.0080383
3	.3270651	.0085983
4	.3557272	.0087756
5	.3841504	.0089145
6	.4378778	.0090929
7	.4685925	.0091473
8	.5063801	.0091632

9	.5503694	.0091173
10	.6328519	.008836
Total	.4102495	.0028505

This model appears to be similar to the updated model.

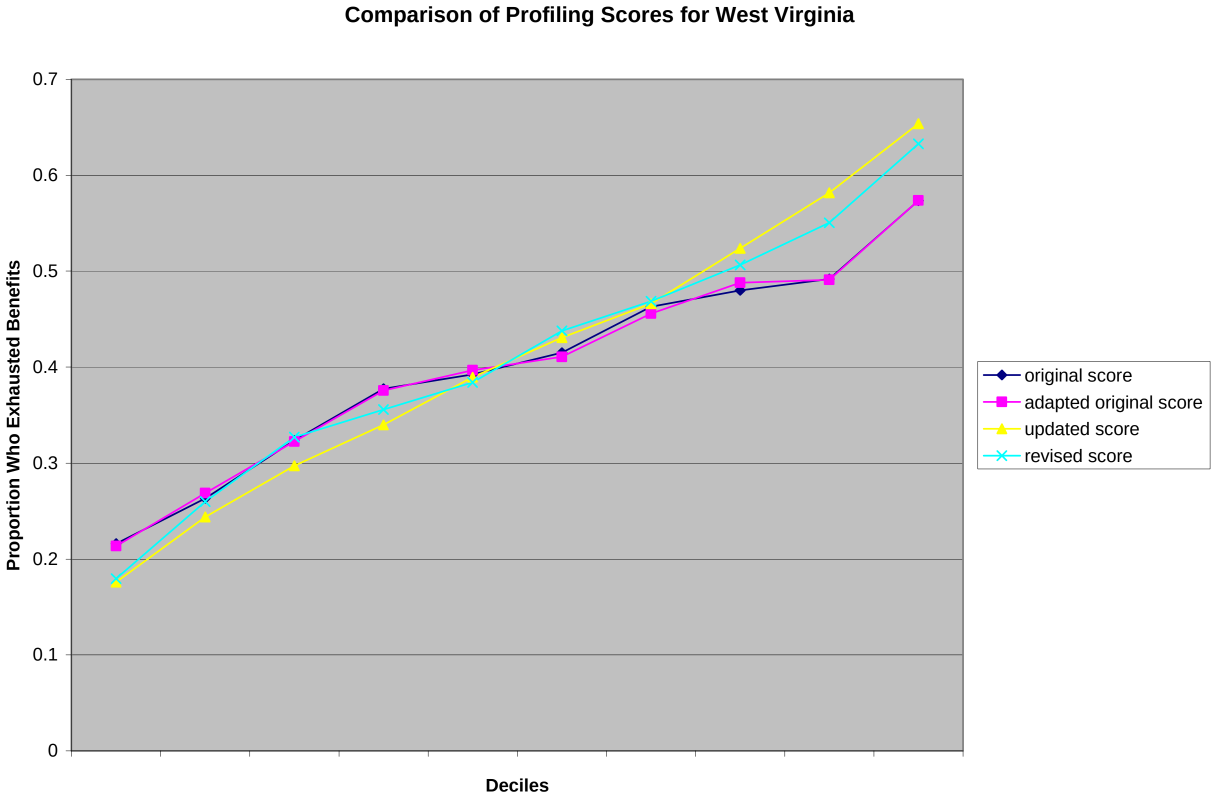
Tobit analysis using the variables of the revised model

For West Virginia, the Tobit analysis is not possible because the total benefit allowance was not provided. We cannot calculate a dependent variable for the percent of allowable benefits paid.

Summary Tables

We created a summary table of the four decile tables that allows us to compare models. To make the models comparable, we only included cases with full information. For this subsample, the exhaustion rate is 41 percent, as indicated by the bottom row of the table. While there was considerable improvement between the adapted and updated models there was no improvement with the revised model. The updated score appears to be the best model for the data available.

Decile	Original score	Original score adapted for endogeneity	Updated score	Revised score
1	.2160804	.2135395	.175957	.1796508
2	.2632411	.2686275	.2437878	.259906
3	.3236351	.3225689	.2971793	.3270651
4	.3774373	.3756047	.3399395	.3557272
5	.3924802	.3968833	.3895232	.3841504
6	.4150641	.4106452	.4308261	.4378778
7	.4629278	.4558684	.4662412	.4685925
8	.4799627	.4879032	.5238415	.5063801
9	.4918478	.4909475	.5815984	.5503694
10	.5734245	.5737608	.6536782	.6328519
Total	.4102495	.4102495	.4102495	.4102495



Correlations of the four profiling scores indicate that all model scores are positively correlated, as is to be expected. While the scores are positively correlated, they are not identical, which suggests that there are differences between the models.

	pexhprob	prorig	prup	prrev
pexhprob	1.0000			
prorig	0.9932	1.0000		
prup	0.6399	0.6465	1.0000	
prrev	0.6540	0.6626	0.8429	1.0000

We also tested the performance of each model using the following metric.

Percent exhausted of the top 41 percent of individuals in the score.

We used 41 percent because that is the exhaustion rate for benefit recipients with full information in the data set provided by West Virginia. This metric will vary from about 41 percent, for a score that is a random draw, to 100 percent for a score that is a perfect predictor of exhaustion. The scores for the four models are as follows:

Score	% exhausted of those with the top 41% of score	Standard error of the score
Original	.50692	.0045245
Adapted	.5070042	.0045252
Updated	.5536899	.0044991
Revised	.5373904	.0045126

The updated model performs the best.

To compare models across SWAs, we developed a metric to gauge classification improvements between our models and the original model. In the metric below, *"Exhaustion"* is the percentage of all benefit recipients in our sample that exhaust benefits. Here we use 41 percent for "*Exhaustion*" because the exhaustion rate for all benefit recipients for West Virginia was 41 percent. In our metric, "Pr[*Exh*]" is determined by the model with the highest percentage of benefit exhaustees with profiling scores falling in the top X percent of the sample where X percent is determined by the exhaustion rate for all benefit recipients in the sample. For West Virginia, "Pr[*Exh*]" is represented by the updated model with a score of 55.37 percent for benefit recipients that exhaust benefits with scores falling in the top 41 percent.

In addition to this metric, we also applied the equation below, derived by Silverman, Strange, and Lipscombe (2004), for calculating the variance (σ_z^2) of a quotient (p. 1069)[iii]. This equation allowed us to calculate the variance for our metric, Z, which is the quotient of two random variables X and Y where X = 100 - Pr[*Exh*] and Y = 100 - "*Exhaustion.*" In the equation below, σ_X^2 is the variance of 100 - Pr[*Exh*], σ_Y^2 is the variance of 100 - "*Exhaustion,*" $E(X)$ is the mean for 100 - Pr[*Exh*], and $E(Y)$ is the mean for 100 - "*Exhaustion.*" By dividing the variance of the quotient of the two random variables (here 100 - "*Exhaustion*" and 100 - "Pr[*Exh*]") by the square root of our observations, we were able to determine the standard error of the metric.

$$\text{Metric: } 1-\left(\frac{100-\Pr[Exh]}{100-Exhaustion}\right)$$

$$\text{Variance of Metric: } \sigma_z^2 \approx \frac{\sigma_X^2}{E(Y)^2}+\frac{E(X)^2\sigma_Y^2}{E(Y)^4}$$

$$\text{Standard error of the metric: } \sqrt{\frac{\sigma_Z^2}{N}}$$

For our metric, we use 55.4 percent for "Pr[*Exh*]" for the updated model and 50.7 percent for "Pr[*Exh*]" for the original adapted model. *"Exhaustion"* for both was 41 percent. The model metrics are shown below. For other SWAs, the statistic is recalculated using the exhaustion rate of that SWA from the given sample and the score from the model with the highest percentage of exhaustion. For SWAs with hypothetically perfect models, this metric will have a value of 1, and for SWAs with models that predict no better than random, the metric will take a value of 0.

SWA	Profiling score	Control for endogeneity?	Exhaustion rate for the state	Number of individuals with the highest profiling score	Exhaustion rate for individuals with high profiling scores	Metric	Variance of the Metric	Standard Error of the metric
West Virginia	original score	Y	41.0	12,209	50.7	0.164	1.205	0.010
West Virginia	updated score	Y	41.0	12,209	55.4	0.243	1.109	0.010

Analysis of Type I Errors

Type I errors are individuals who are predicted to exhaust (reject the null hypothesis) and do not exhaust (the null hypothesis is actually true). Our analysis will be restricted to the top 41 percent of individuals who are predicted to exhaust benefits using the updated model. We use the variables included in the updated model.

Variable	Mean for exhausted	Mean for non-exhausted	T statistic	P value
	N=6,760	N=5,449		
Weekly benefit amount	242.0283	235.5159	-3.8482	0.0001
Wages in base year	2.6e+04	2.6e+04	-0.3489	0.7272
Job tenure of 10 years or greater	0.1967	0.1542	-6.1281	0.0000
Job tenure of 6 to 9 years	0.1058	0.0943	-2.0886	0.0368
Job tenure of 1 to 2 years	0.2296	0.2200	-1.2549	0.2095
Job tenure of less than 1 year	0.3457	0.3814	4.0773	0.0000
File lag	42.6956	43.4436	0.5800	0.5620
SOC occupation code 110 to 139	0.1036	0.1070	0.6164	0.5376
SOC occupation code 150 to 299	0.0858	0.0859	0.0174	0.9862
SOC occupation code 310 to 399	0.1093	0.1121	0.4923	0.6225
SOC occupation code 410 to 419	0.1308	0.1255	-0.8605	0.3895
SOC occupation code 430 to 439	0.2349	0.2276	-0.9565	0.3389
SOC occupation code 450 to 459	0.0021	0.0018	-0.2924	0.7700
SOC occupation code 470 to 479	0.0654	0.0778	2.6597	0.0078
SOC occupation code 490 to 499	0.0404	0.0429	0.7045	0.4811
SOC occupation code 510 to 519	0.1575	0.1393	-2.8131	0.0049
SOC occupation code 530 to 539	0.0700	0.0796	2.0271	0.0427
SOC occupation code 550 to 559	0.0000	0.0000	.	.
SOC occupation code not listed above	0.0003	0.0004	0.2160	0.8290
Industry with NAICS code 111 to 115	0.0030	0.0035	0.5142	0.6071
Industry with NAICS code 211 to 213	0.0337	0.0367	0.8888	0.3741

Industry with NAICS code 221	0.0114	0.0050	-3.8484	0.0001
Industry with NAICS code 233 to 235	0.0000	0.0000	.	.
Industry with NAICS code 311 to 327	0.1006	0.0934	-1.3302	0.1835
Industry with NAICS code 331 to 339	0.1164	0.0949	-3.8326	0.0001
Industry with NAICS code 421 to 454	0.1657	0.1727	1.0281	0.3039
Industry with NAICS code 481 to 493	0.0217	0.0231	0.5119	0.6087
Industry with NAICS code 511 to 514	0.0098	0.0081	-0.9814	0.3264
Industry with NAICS code 521 to 525	0.0692	0.0604	-1.9687	0.0490
Industry with NAICS code 531 to 533	0.0101	0.0136	1.8041	0.0712
Industry with NAICS code 541, 551, 561, 562, or 611	0.1095	0.1198	1.7919	0.0732
Industry with NAICS code 621 to 624	0.1278	0.1397	1.9160	0.0554
Industry with NAICS code 711 to 713	0.0056	0.0042	-1.0909	0.2753
Industry with NAICS code 721 to 722	0.0274	0.0314	1.3107	0.1900
Industry with NAICS code 811 to 814	0.0574	0.0497	-1.8627	0.0625
Industry with NAICS code 921 to 928	0.0120	0.0092	-1.4961	0.1346
Industry with NAICS code not listed above	0.1188	0.1347	2.6360	0.0084
Education less than 12 years	0.1355	0.1290	-1.0508	0.2934
Education 12 to 15 years	0.7593	0.7565	-0.3656	0.7147
Education 16 to 28 years	0.1355	0.1290	-1.0508	0.2934
Begin benefits in January	0.0948	0.0945	-0.0581	0.9537
Begin benefits in February	0.0864	0.0769	-1.8996	0.0575
Begin benefits in March	0.1037	0.0987	-0.9030	0.3665
Begin benefits in April	0.1030	0.1075	0.8213	0.4115
Begin benefits in May	0.0485	0.0573	2.1536	0.0313
Begin benefits in June	0.0612	0.0499	-2.7019	0.0069
Begin benefits in July	0.0999	0.0980	-0.3406	0.7334
Begin benefits in August	0.1013	0.1033	0.3609	0.7182
Begin benefits in September	0.0527	0.0560	0.8036	0.4217
Begin benefits in October	0.0864	0.0943	1.5242	0.1275
Begin benefits in November	0.0725	0.0831	2.1913	0.0284
Begin benefits in December	0.0896	0.0804	-1.8196	0.0688
Other income indicator	0.0009	0.0039	3.4700	0.0005

For the above table, note that it includes 6,760 individuals who exhausted benefits and 5,449 who did not. The total of these two types of individuals is 12,209, which is 41 percent of the 29,777 individuals in the sample. The Type I analysis shows that certain variables have more explanatory power than others for explaining the difference between Type I errors and correct predictions. For example, the variables for weekly benefit amount, job tenure of 10 years or greater, job tenure of less than one year, SOC occupation 470 to 479 and NAICS code 221 are important for explaining the difference between exhaustees and non-exhaustees. Less important variables, with low p-values, are wages in base year and file lag.

[1] Silverman, M. P., Strange, W. and Lipscombe, T.C. (2004). The distribution of composite measurements: How to be certain of the uncertainties in what we measure. *American Journal of Physics, 72*(8), 1068-1081.
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