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A New WPRS Profiling Model for Michigan

Abstract

The Worker Profiling and Reemployment Services (WPRS) system was established nationwide following the 1993 enactment of Public Law 103-152. The law requires state employment security agencies to profile new claimants for regular unemployment insurance (UI) benefits to identify those most likely to exhaust their regular benefits, and refer them to reemployment services to promote a faster transition to new employment. In November 1994, the Michigan Employment Security Commission (MESC) began profiling new UI claimants with technical assistance from the W. E. Upjohn Institute for Employment Research

Since WPRS profiling was introduced in Michigan much has changed, but the same model was in use until very recently. The MESC has been abolished, with UI now administered by the Michigan Bureau of Workers' and Unemployment Compensation (MBWUC). The process of taking UI claims has shifted from in-person interviews at local offices around the state to telephone claims taken by staff at three call centers to be located in Detroit, Grand Rapids, and Saginaw. Michigan has also changed from being a wage-request state for UI eligibility determination to a wage-reporting state. This means that each claimant's full benefit year UI entitlement is now known at the time that eligibility is established, a fact that permits new approaches to WPRS modeling. The MBWUC is also switching to using the new Standard Occupation Code (SOC) and North American Industrial Classification System (NAICS). Furthermore, UI has become a partner in new one-stop centers for employment services established in each workforce development area in the state as required by the Workforce Investment Act (WIA) of 1998.

To develop a new Michigan WPRS profiling model which is in harmony with the new institutional realities, the MBWUC once again chose to partner with the W.E. Upjohn Institute for Employment Research. This brief paper offers a new WPRS model for Michigan which improves on the original model by applying lessons learned nationwide in the years since WPRS models were first implemented. A variety of alternative specifications were considered, the best of these was proposed as the new Michigan WPRS model. Michigan has since implemented this model and is now using it to profile UI claimants for referral to reemployment services promoting a speedy return to work.

I. Background

The Worker Profiling and Reemployment Services (WPRS) system was established nationwide following the 1993 enactment of Public Law 103-152. The law requires state employment security agencies to establish and utilize a system of profiling all new claimants for regular unemployment insurance (UI) benefits. Profiling is designed to identify UI claimants who are most likely to exhaust their regular benefits, so they may be provided reemployment services to help them make a faster transition to new employment.

In November 1994, the Michigan Employment Security Commission (MESC) began profiling new UI claimants to identify those at risk of long-term unemployment. To do this, MESC adopted a statistical methodology that ranks dislocated workers according to their likelihood of exhausting UI benefits. MESC developed the methodology with technical assistance from the W.E. Upjohn Institute for Employment Research (Eberts and O'Leary 1996). In January 1995, the first cohort of profiled unemployment insurance recipients were referred to reemployment services.

The same profiling model implemented in Michigan eight years ago is still being used to refer UI claimants to WPRS services. However, nearly all other aspects of UI in Michigan have changed in the intervening years. The MESC has been abolished. It was replaced by the Michigan Unemployment Agency, and now UI is administered by the Michigan Bureau of Workers' and Unemployment Compensation (MBWUC). Within the next few months, the process of taking UI claims will shift from in-person interviews at local offices around the state to telephone claims taken by staff at three call centers to be located in Detroit, Grand Rapids, and Saginaw. Furthermore, UI has become a partner in new one-stop centers for employment services established in each workforce development area in the state as required by the Workforce Investment Act (WIA) of 1998.

When the Michigan WPRS was first implemented in 1994, linkages between UI and the employment service and Job Training Partnership Act (JTPA) agencies were either established or strengthened in each local labor market (Eberts and O'Leary 1997). Those relationships which have flowered in the WIA one-stop centers are crucial for maintaining active reemployment efforts for those at greatest risk of long-term UI benefit receipt. Currently, UI claimants who are neither job attached nor union hiring hall members are required to register for job search with Michigan Works to establish benefit eligibility. With UI call centers, the Internet, employer-filed claims, and mail claims available in the near future, personal interaction with claimants will be greatly reduced. Under this new system, a WPRS referral to orientation may be the most active reemployment assistance that many UI claimants will experience during a new spell of joblessness.

Also since 1994, Michigan has changed from a wage-request state for UI eligibility determination to a wage-reporting state. This means that each claimant's full benefit year UI entitlement is now known at the time eligibility is established, a fact that will permit new approaches to WPRS modeling. When call centers are implemented, MBWUC will also switch to using the new Standard Occupation Code (SOC) and North American Industrial Classification System (NAICS).

To develop a new Michigan WPRS profiling model that is in harmony with the new institutional realities, MBWUC has once again chosen to partner with the W.E. Upjohn Institute for Employment Research. This brief paper offers a new WPRS model for Michigan, which improves on the original model by applying lessons learned nationwide in the years since WPRS models were first implemented. A variety of alternative specifications were considered; the best of these is proposed as the new Michigan WPRS model.

The purpose of this paper is to provide MBWUC staff, with a detailed description of the new profiling model that we recommend the state adopt. In the next section we briefly review the existing Michigan WPRS profiling model and the describe the profiling and referral process as it existed when WPRS was originally implemented. Section III summarizes the findings from two evaluations of WPRS, which help in understanding the expected effects of the program. Section IV delineates the recommendations from a study sponsored by the U.S. Department of Labor data to identify the best ways to simplify and improve the statistical profiling models. This section is followed by a description of the data used to estimate the new profiling model. Section VI presents the specification of the new model and its variations. Section VII contrasts the two top variations of the new model using several criteria, which shows why we recommend one model over the others. The final section offers a brief summary.

II. The Original Michigan WPRS System

Unemployed workers who are issued a first payment within five weeks of filing a claim are eligible for profiling in Michigan. As in all states, profiling in Michigan entails a two-stage process (this section is drawn from Eberts and O'Leary 1996). First, UI recipients who are expecting to be recalled to their previous jobs or who are members of a union hall are dropped from the pool of workers to be profiled. These two groups are excluded because they are not expected to undertake an active independent job search. Second, among the remaining UI recipients, some are identified as the best candidates for early reemployment services. Michigan, like most states, performs the second sorting using a statistical model that ranks claimants by their likelihood of exhausting regular UI benefits.[1] Beneficiaries are then referred to orientation and reemployment services in order of their ranking until the capacity of local agencies to serve them is depleted.

The profiling model is run at the state level, and profiling scores are generated for each eligible worker statewide. To implement profiling, each local office draws from the statewide ranking of profiled UI claimants who live in their jurisdiction. Each office arrays the selected individuals from highest to lowest predicted probability of exhausting UI benefits. Service providers (or coordinating organization) determine the maximum number of claimants who can be served in a given period, based on the funds that office receives for the WPRS program.

[1]Kelso (1998), Dickinson et al. (1999), and Dickinson, Decker, and Kreutzer (2002) report that only a few states use nonstatistical characteristics to refer UI claimants to WPRS services.

Profiled UI claimants are referred to service providers based on their probability of benefit exhaustion and the referral agreement.[2] After assessing the referred claimant's needs, the service provider offers a set of reemployment services best suited to the individual claimant.

The original Michigan WPRS statistical model includes a UI claimant's personal characteristics: educational attainment, industry and occupation of last job held, and tenure on last job. Industry and occupation codes are also included to reflect differences in demand for labor across these sectors and occupations as well as differences in worker qualifications, particularly across occupations. If the plastics industry, for example, is experiencing a downturn in the state, then workers who have been employed in that sector may have more difficulty finding reemployment than those in a sector experiencing growth. The occupational indicators followed the codes in the Dictionary of Occupational Titles (DOT). These codes, which provide indicators of the people and things complexity of occupations, were also included in the statistical model to provide additional detail on the requirements of the job held by the UI beneficiaries. Service delivery areas (SDAs), defined for administering Job Training Partnership Act (JTPA) programs, were included in the statistical model to identify local labor markets, with the understanding that local economic conditions, and other local circumstances, may differ across these regions of the state.

Based on this model, the probability assigned to each eligible UI recipient is a weighted average of the effects of each of these characteristics on the likelihood an individual exhausts UI benefits. The weights reflect the relationship between these variables and the likelihood of exhaustion at the time the model is estimated. Since these relationships may change over time, it is necessary to reestimate the model periodically.

For purposes of the WPRS in Michigan, all individuals who receive first payments within the same week are considered as one group. UI recipients within this group are ranked according to their predicted probability of exhausting. Those estimated to be most likely to exhaust are placed at the head of the queue for reemployment services.

Once a week, each local MESC office receives a list of profiled and ranked eligible UI recipients who are beneficiaries through that office. The list includes the name, social security number, and estimated probability of exhausting UI benefits for each profiled beneficiary. The ranking of eligible UI recipients on the list is derived from the statewide estimation of the probability of exhausting UI benefits. The local beneficiary with the highest state ranking is placed first on the list followed by the beneficiary with the next highest state ranking and so forth.

The number of UI recipients actually referred to reemployment services at any specific local office depends upon the amount of resources received by that office to provide WPRS services. Since funding to local offices is largely based on labor market conditions, one would expect that those local offices with the greatest need should be able to serve a larger proportion

[2]Black et al. (2003) devised a rationing rule to accommodate local WPRS capacity that provides for an ideal impact evaluation.

of their UI claimants. UI recipients from local offices with tight labor markets or with industries experiencing few layoffs will have statewide rankings much lower than those from local offices with high unemployment rates, and they will serve a smaller proportion of beneficiaries through the WPRS.

III. Evaluation of the Effectiveness of WPRS

The purpose of WPRS is to identify UI beneficiaries who are most likely to exhaust their regular UI benefits and to direct them to reemployment services as quickly as possible so that they can actively pursue reemployment. Two evaluations have been conducted to determine the success of this program. A national evaluation of WPRS, sponsored by the U.S. Department of Labor, was based on claimant-level data from a sample of states (Dickinson et al. 1999; Dickinson, Decker, and Kreutzer 2002). In each of the study states (Connecticut, Illinois, Kentucky, Maine, New Jersey, and South Carolina), labor market outcome data were compiled from administrative records on all new initial UI claimants between July 1995 and December 1996 who were eligible for referral to mandatory WPRS job search assistance (JSA). The combined samples included 92,401 profiled and referred claimants, and 295,920 claimants who were profiled but not referred to WPRS JSA. The impact estimates were statistically significant in all states except South Carolina. For those five states with statistically significant results, the largest impact was −0.98 weeks in Maine, with the other impacts ranging from −0.21 to −0.41 weeks of UI benefits.

The State of Kentucky also sponsored an assessment of their WPRS system. A feature of the Kentucky evaluation that sets it apart from the national evaluation was that the evaluation design was incorporated into the profiling modeling and implementation process. This allowed for the randomized assignment of claimants to treatment and control groups—an improvement over the design of the national evaluation. A team of economists at the Center for Business and Economic Research at the University of Kentucky developed the profiling model and conducted the evaluation (Berger, et al. 1997; Black et al. 2003).

To accommodate the random assignment of claimants, the Kentucky approach to profiling divides the predicted UI exhaustion distribution into 20 groups spanning 5 percentile points each. Each week the local WPRS capacity is met within one of the 20 groups. For example, for a particular week, sufficient capacity was available to accommodate claimants from the top three percentile groups, but there was not enough capacity to extend the referrals into the fourth percentile group. Thus, claimants were randomly selected from the percentile group, which was third from the top until the capacity was exhausted. The authors referred to this group as the profiling tie group (PTG). Justification for this approach is based on the fact that the precision of the profiling model is such that it is not possible to distinguish statistically at any reasonable confidence level between individuals in that group. Therefore, randomization is appropriate for assigning claimants to JSA.

From among these PTGs, experimental treatment and control groups were formed to conduct an evaluation of the WPRS in Kentucky. Data were collected starting from the very beginning of WPRS implementation in Kentucky, October 1994 through June 1996. The PTGs yielded a total sample of 1,981, with 1,236 of these assigned to mandatory WPRS JSA.

The impact estimates for WPRS in Kentucky were more dramatic. With regard to the three outcomes of interest, the estimated impacts were a reduction of 2.2 weeks of UI, a reduction of $143 in UI benefits per beneficiary, and an increase of $1,054 per beneficiary in earnings during the UI benefit year. The differences in these estimates from those of the national WPRS evaluation are most likely due to the fact that Black et al. (2003) essentially confined their comparisons within PTGs, thereby achieving a closer counterfactual. Dickinson et al. (1999) compared those assigned to WPRS, who had the highest probability of benefit exhaustion, with all those profiled but not referred, including many with very low exhaustion probabilities. This meant that the comparison group in the national evaluation was likely to have a shorter mean benefit duration than program participants, even in the absence of WPRS services. The ideal approach is to use beneficiaries from the same percentile group to make the comparison between the outcomes of those who were referred to orientation with those who were not.

The two studies suggest that WPRS has been successful in meeting its original purpose. Findings from these evaluations are important not only for providing a better understanding of the overall effect of the program, but also for helping states improve the precision of their profiling models and the effectiveness of their service delivery systems. In a separate evaluation of the U.S. Department of Labor's Significant Improvement Demonstration Grants (SIGs), which were awarded to 11 states, it was recommended that states continue to find ways to improve their models (Needels, Corson, and Van Noy 2002). In addition to updating and revising the model more often, they also recommended that states improve their models through assessing the performance of their own WPRS system. The Kentucky approach offers an excellent framework in which to integrate an evaluation design into the profiling process. The approach is efficient, inexpensive, and incorporates a random assignment technique, which is regarded as the most reliable method of evaluation. We recommend that such an approach be incorporated into the implementation of the new profiling model.

IV. Lessons Learned from WPRS Modeling

A. Recommendations from a Study Sponsored by the U.S. Department of Labor

In addition to sponsoring an evaluation of the WPRS, the U.S. Department of Labor commissioned a study to identify the best ways to simplify and improve statistical WPRS models (Black, et al. 2002). Our proposed model takes into consideration the lessons learned from this study.

The study identified five areas in which the model can be simplified without reducing predictive performance: 1) use ordinary least squares (OLS) instead of logit, probit, or tobit (quantal choice models); 2) define the dependent variable as the proportion of entitlement used; 3) drop the local labor market values of the unemployment rate and industry employment; 4) add covariates that contribute to the predictive power of the model; and 5) there is no need to have separate models for separate regions of the state-use dummies. The study also recommended that using UI administrative records, which are maintained at a high standard, would improve the precision of the model.

We briefly summarize the reasons that the authors of the study gave for each of their five recommendations and then indicate whether or not we have incorporated these features into the new model that we propose. First, the study concluded that the functional form for the model should be linear. The authors found no evidence that the more involved statistical techniques, such as tobit, logit, or probit, outperformed the simple linear probability model (applying OLS to estimate a dichotomous dependent variable). Therefore, they recommended the use of OLS for both dichotomous and continuous dependent variables. We will adopt this recommendation for the new model.

Second, the study suggested that the dependent variable should be a continuous variable that measures the fraction of weeks of entitled benefits that the claimant has drawn. This measure is calculated as the actual benefits drawn divided by the total amount of benefits the claimant is entitled to in his/her current benefit year. Unlike the dichotomous variable that indicates whether or not a beneficiary has drawn his/her total entitlement, the fraction of benefits drawn differentiates among those who have not yet exhausted. The authors contend that this additional information can improve the predictive power of the model. Their results, however, show little difference in predictive power between the two models. Furthermore, they report discrepancies in the construction of the continuous variable across the three states for which they analyzed data. Therefore, while we offer a model that uses the continuous variable for comparison purposes, we recommend adoption of the model that uses a dichotomous variable indicating whether or not the individual has exhausted benefits.

Third, the study recommended dropping the local labor market values of the unemployment rate and industry employment. The reason behind this suggestion is that virtually all claimants applying for UI in a given WIA area at a given time face the same unemployment rate. Consequently, the regional variation in unemployment rates will not help distinguish among workers applying in the same WIA area at the same time. We recognized this problem when developing the original model and left it out of the specification, and we will do so again in the new model. We retain the occupation and industry variables, however, to reflect structural differences in labor demand and supply in the various occupations and sectors.

Fourth, the study found that a few additional variables improved the predictive power of the model. In addition to the variables that we included in the original Michigan model, the U.S. Department of Labor study suggests considering a few others: 1) UI benefits exhausted in the most recent prior UI spell, 2) an indicator for previous UI claims, 3) welfare dependency, 4) food stamps recipiency, public transportation available for getting to work, 5) JTPA (or WIA) eligibility, 6) quarterly wages within the last year, and 7) enrolled in school or employed at time of claim. Some variables from this list were not available from Michigan's administrative records to include in the model. Others were tried but were not statistically significant and did not add to the predictive power of the model. We included variables 1 and 5 (in the form of base wages) from the list above. In addition, we included reasons for job separation and length of UI entitlement.

Fifth, the study found that estimating separate models for different regions of the state did not improve the predictive power of the model. We had come to a similar conclusion when experimenting with different specifications, and thus will estimate a single model for the state of Michigan. We do include regional indicators, associated with each WIA area, which account for "shifts" in the probability of exhaustion across regions but which do not incorporate possible differences in the coefficients of the variables across regions.

B. Model Specification Changes Related to Intervening Events

The occurrence of three events since the original model was developed prompts the need for additional changes to the specification. First, the occupation variables in the original model were based on the Dictionary of Occupational Titles (DOT). These codes included detailed descriptions of the degree of complexity encompassed by the various occupations in relating to people and in manipulating things. DOT codes are being replaced with standard occupation codes based on the O*Net occupational classification system. Consequently, the detailed descriptions of occupations with respect to people and things are no longer available and must be deleted from the model.

The second event is the simple fact that WPRS has been in operation since 1994 and has shown in the evaluations that it has had a significant impact on exhaustion rates, at least for the states studies. Thus, the model must now include an indicator for those beneficiaries who have been profiled and referred to orientation. The original model was estimated on data that recorded the experience of beneficiaries before WPRS was implemented. But any reestimation of the model since then must take into account the effect of the program on the behavior of the claimants. As described in the previous section, WPRS has been shown to reduce the duration of UI benefits by as much as 2.2 weeks. Therefore, those claimants who are profiled and referred to orientation will on average have a different duration than those who were not referred to orientation. If there were no way to distinguish between the two groups, the model would be misspecified, thus reducing its predictive power.[3]

The third event is the initiation of extended benefits during the period in which the new model was estimated. The recent economic downturn and the increased difficulty experienced by displaced workers in finding jobs prompted Congress and the President to establish the Temporary Extended Unemployment Compensation (TEUC), which provides claimants who have exhausted regular state benefits up to 13 weeks of additional benefits. Under federal law, unemployed workers may qualify for benefits if they 1) are not currently working full time, 2)

[3]However, empirical studies have found that the degree of misspecification from using such data is usually minor and does not significantly affect the parameter estimates (Olsen et al. 2002). This finding may appear to run counter to the evaluation results, which found a significant effect of WPRS on exhaustion rates. The difference in results can be explained by the fact that entering the referral indicator in the model is not a valid method of testing for the impact of the program, due to selection bias and other factors. The orientation variable is not used to calculate the profiling score, since it, of course, is not observed at the time profiling takes place.

have exhausted all rights to regular state UI benefits, 3) have no entitlement to other UI benefits, and 4) have a new or additional claim for state UI benefits and a benefit year ending after March 10, 2001. An additional period of TEUC, called TEUC-X , is payable if the state's insured unemployment rate (IUR) reaches 4.0 percent or higher at the time a jobless worker exhausts his/her original TEUC benefits. These benefits are the same length and amount as offered under the TEUC. Jobless workers will generally receive the same weekly benefit amount in TEUC as they did in their most recent regular state UI claim and be eligible for half the number of weeks to which they were entitled in their most recent benefit year. The first week for which TEUC was payable was the week ending March 16, 2002. TEUC was still in effect at the time this paper was written. Figure 1 shows the jump in the percentage of claimants establishing TEUC entitlements soon after the program was implemented. The percentage climbed steadily until 50 percent of the beneficiaries established entitlements. The same pattern occurred for TEUC-X but with small percentages. Therefore, it is important to account for this program in the new model.

By offering claimants an additional 13 weeks of benefits beyond the regular entitlement, those who are eligible to establish this extended entitlement may be more likely to exhaust their regular benefits than those who are not eligible. Studies have shown that extended benefits tend to increase the rate of UI benefit exhaustion (Woodbury 1997, p. 245; Jurajda and Tannery 2003). Therefore, estimating the model on data that include a period in which the TEUC is in effect requires the ability to sort out the effect of extended benefits on the likelihood of exhausting regular benefits. The difficulty in doing so is the inability to distinguish between those who, during their benefit year, recognized that benefits could be extended beyond the regular period and those who did not have this option. It is compounded by the inability to separate out the effects of economic downturns (demand conditions) on reemployment from the effects of extended benefits (supply response). However, since we are not concerned about estimating the separate effect of extended benefits on exhaustion (that is, to separate its effect from the other variables in the model), we need only to enter separate categorical variables for each week. In this way, we have taken into account the effect of any event unique to that week on the probability of exhaustion. These events, of course, include among other things, the claimant's eligibility for extended benefits. Therefore, the recommended model includes categorical weekly variables.[4]

V. Data for Estimating a New Michigan WPRS Model

The MBWUC provided data on UI claimants who filed on or after October 1, 2000. The reason for this starting date is that this is the time that the MBWUC started using quarterly wage record information to determine UI eligibility. Prior to that time, Michigan used a wage request system, which relied on contacting employees for weekly wages and separation information whenever a former employee filed a claim for jobless benefits. For consistency of data, it is necessary to start the estimation when the wage record system was initiated, after October 2000. Wage record data are also the only source of information on the full benefit year of UI

[4]The categorical variables are used in the estimation to avoid omitted variable bias in the other coefficients. The categorical variables, however, are not used to estimate the profiling scores when the model is implemented.

entitlement, which other studies (as well as our estimation) have shown to be an important variable. Under the old Michigan wage request system, the full potential benefit year compensation might never be known for a claimant drawing less than 26 weeks of benefits. The data extract provides information on valid claims that ended after September 30, 2001, which means that the claims started on or after October 1, 2000. A claim is valid if the claimant met all monetary (sufficient earnings and hours) and nonmonetary (not fired, quit, etc.) conditions for establishing a valid UI claim.

Table 1 summarizes the number of profiled claimants in our sample by the week ending date of their first payment. Table 2 shows the frequencies of benefit durations in our sample. More than 50 percent of claimants in the sample exhausted their initial entitlement. Table 3 shows the number of profiled workers in each of the 24 workforce development areas (WDA) of the State of Michigan. WDA 19 includes the City of Detroit.

VI. Variables included in the New Michigan WPRS Model

Specification of the new proposed Michigan WPRS profiling model is shown in Table 4. The table contrasts the variables used in the original model with those used in the new model. The major difference is the addition of five variables that were not available at the time the previous model was developed. These variables include: base wages, entitlement length, exhausted benefits in prior UI spell, reasons for separation, and referred to orientation, as well as the weekly categorical variables described above. Adding these variables is justified as a way to better model the behavior of claimants with respect to exhausting benefits. Base wages are added in order to offer additional information about the individuals prior job, since the level of compensation reflects a person's qualifications relative to other individuals in the same sector and occupation. It also indicates the likelihood that an individual is able to find a job with similar attributes. The entitlement length suggests the claimant's prior attachment to work. The reason for including the referral to orientation has been discussed in the previous section. The variable indicating whether the claimant exhausted benefits in a prior UI spell is added to the model to reflect behavioral tendencies of the claimant. The reasons-for-separation variables are included to distinguish among those claimants who were laid off from those who quit or were fired, since there appears to be a difference in the likelihood of exhausting benefits depending upon the reason for separation. The weekly categorical variables are included to account for the idiosyncratic effects of weekly events on the probability of exhausting benefits, particularly the availability of extended benefits. The means for the estimation sample are shown in Table 5.

We also experimented with various combinations of the new variables. We found, however, that the full model outperformed the models that included only subgroups of the variables listed above. In particular the weekly categorical variables, which were included to account for TEUC, helped to improve the model. Table 6 shows the correlation between the three most promising models, with and without the weekly variables. We see that the logit and the OLS estimation of the specification with UI exhaustion as the dependent variable yield virtually identical rankings, which is the reason we recommend the simpler estimation technique of OLS. Also, although the addition of the weekly variables increases the fit of the models, it does not change the ranking significantly, as indicated by the higher correlations between those two variations of the model.

VII. Choosing the Appropriate Dependent Variable

Accepting the full set of variables as the preferred specification, the remaining issue with regard to specification is the choice of the dependent variable. The original model, along with most state profiling models, used a dichotomous dependent variable indicating whether or not a beneficiary exhausted his/her benefits. Black et. al. (2002) experimented with the fraction of benefits drawn in a benefit year and recommended it as an alternative measure. We also will experiment with the two forms of the dependent variables and show that, according to several criteria, the alternative measure (fraction of benefits drawn) is not superior and, in most cases slightly inferior to the model with exhaustion as the dependent variable.

Estimates of the two models are shown in Tables 7 and 8.[5] We find that the coefficients are similar across the two specifications, particularly for the claimant's personal characteristics such as tenure and education. Estimates suggest that claimants with more tenure (up until about 26 years as a result of the negative sign on the tenure squared term) and education are less likely to exhaust benefits. Those referred to orientation are more likely to exhaust benefits. This result seems counterintuitive to what we learned from the evaluations. However, the positive sign may reflect the fact that those claimants who were referred to orientation were most likely to exhaust benefits during their previous claim (according to the statistical profiling model) and thus may have the same tendency in this benefit period.[6] It is interesting that the coefficients for the first two reasons for separation—lack of work and quit/fired—differ between the two models. The exhaustion model (Model A) suggests that those who quit or are fired are more likely to exhaust benefits, while the fraction-of-benefits model (Model B) suggests the opposite. The signs are reversed for the lack-of-work variable. The coefficients on both variables are statistically significant in each model.

The relationship between the predicted values and key variables can be illustrated by graphing these relationships by constructed percentiles. We choose three variables—tenure at the last employer, college graduation, and exhaustion of prior UI spell—and construct 20 percentile groups in order to record the percentage of college graduates and the prior exhaustion rates across the distribution. For illustrative purposes, we use only the predicted values from Model A, recognizing that the same relationships hold for Model B. As shown in Figure 2, prior exhaustion is positively related to the profiling score, with most of the variation affecting the upper end of the profiling score distribution. Figure 3 shows that college graduation and the profiling score are negatively correlated, with the percentage gradually falling throughout the

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[5]The dichotomous variables, such as those used for education, separation, occupations, industries, and WIA areas, are normalized against the mean instead of against an omitted variable from each of the groups of variables. Therefore, all categories are included in the tables, as opposed to the customary omission of one variable from each group.

[6]The positive sign on the orientation coefficient may reflect selection bias, which underscores the need for random assignment when evaluating the WPRS program.

distribution while the profiling score increases. As shown in Figure 4, tenure exhibits a quadratic relationship with the profiling score, which is the reason for entering that variable as a quadratic. In the graph, we see that tenure increases throughout the distribution until it begins to decrease after reaching the 16th percentile group (the top 25 percent of the distribution).

In order to judge the predictive power of the various models, it is appropriate to base these comparisons on out-of-sample predictions generated by each model. Out-of-sample validation involves excluding a random sample from the data used for model estimation, and then using that sample to check the forecasting accuracy of the model. Following Black et al. (2002), the validation sample is constructed by randomly selecting claimants who filed claims in four different weeks—one week from each of four quarters of data. This process generated a sample of 15,074, which is 7 percent of the estimation sample. The means of the explanatory variables for the validation sample are displayed in Table 9.

A. Selection Criteria of Minimizing False Positives[7]

A statistical profiling model ranks individual claimants according to their estimated probability of exhausting benefits (or the fraction of benefits drawn, as is the case with Model B). Therefore, referrals to orientation are drawn first from the top of the distribution of predicted values, working down through the distribution until the capacity of the system to serve individuals has been met. Therefore, an optimal profiling model is one in which the model precisely selects for referral all individuals who would, if not referred, exhaust their benefits. Models that generate a greater number of false positives (that is, those who were identified by the model as exhausting but did not) yield less efficient profiling procedures.

Two costs result from imprecise estimates, as shown in Table 10. The first cost is from false negatives. These are individuals who were not referred to orientation because their profiling score was below the cutoff point, but should have been. By exhausting their benefits, they draw more UI benefits than they would if referred to orientation, thus costing the UI system additional dollars and reducing the prospect of returning to work. According to the Kentucky evaluation results, individuals are likely to stay on UI 2.2 weeks longer, collect $143 more in UI benefits and forego $1,054 in earnings during the UI benefit year than if they would have been referred.

The second cost relates to false positives. These are individuals who were identified as having a high probability of exhausting benefits and referred to services but would have likely found a job without assistance before exhausting benefits. The cost associated with this group is the opportunity cost of occupying a position in the orientation session (and subsequent services) that could have been used by someone who would have actually exhausted benefits without this

[7]The authors which to thank Tim Bartik for suggesting the framework for this criterion.

assistance. There is also the cost of delaying an individual's job search activities and asking an individual to participate in a program that he or she may not have wanted to attend.[8]

Therefore, it is obvious from Table 10 that the goal of an optimal profiling model is to minimize the number of claimants who are false positives in the upper range of the profiling distribution from which people are drawn to attend orientation. The converse of this goal is to maximize the number of true positives, that is, those who are identified as exhausting benefits who actually do exhaust.

As a way of using this criterion to compare the two models, first suppose that capacity exists to serve 3,000 people per week out of 20,000 people profiled. Following the procedure used by Kentucky, these 20,000 are divided into 20 groups of 1,000 each, that is, into 20 groups each with an interval of five percentile points. Selection for referral to orientation starts with the top percentile group of 1,000 and then works down the distribution until all the slots are filled. Table 11 displays the cumulative number of claimants who are profiled as exhausting benefits and who actually exhausted, for each of the two models. In order to refer 3,000 people to orientation, all 1,000 people from each of the first three groups are selected. If Model A were used to identify who among the claimants is likely to exhaust benefits, 2,074 people (or 69.1 percent) would have actually exhausted (true positives). If Model B were used to profile the claimants, 2,064 (68.8 percent) would be identified correctly. The difference is 10 people who are accurately identified as exhausting. For this part of the distribution, the models are comparable in meeting the goal of referring to orientation as many people as possible who would actually exhaust benefits.

It should be noted that statistical profiling does much better than randomly selecting claimants from the entire pool of 20,000. Under random selection, the probability of referring someone to orientation who would have actually exhausted benefits is 52 percent (the mean percentage of exhaustees in the sample).[9] The two models exceed this rate by at least 16.8 percentage points. For the 3,000 assigned, this means that an additional 504 people have been accurately identified as exhausting, thus significantly reducing the cost of misclassification. For example, wrongly classifying this group of 3,000 people would cost the system $72,072 per benefit year in additional UI payments (504 × $143), according to the Kentucky evaluation, since the false positives are taking up space in the programs that could have been used by those who actually exhausted.

[8]Under the Personal Reemployment Account, these costs become even more significant to both the individual claimant and the system. According to the PRA proposal, a claimant is entitled to up to $3,000 if they are eligible. One criteria of eligibility is to have a high probability of exhausting benefits. If a false positive occurs for someone with a high probability of exhausting benefits, then that individual becomes entitled to the $3,000 account, which, since there are limited funds, would prevent someone who was actually more likely to exhaust benefits from receiving the funds.

[9]Random selection may not be the decision rule used instead of profiling. Traditionally, referral decisions are based on the judgment of front-line staff. It is interesting to note, however, that Gueron and Pauly (1991) cite two studies that show little correlation between the job-readiness ratings by frontline staff and participants' performance in the program.

Suppose that capacity is increased to 3,500. To add 500 more claimants, profiled workers would be drawn from the next lowest percentile group—the 17th. However, only half of the 1,000 people included in this group can be accommodated. One solution would be to randomly draw 500 people from the group. This approach is similar to the one suggested by Black et. al (2001) and used by Kentucky. Following Black's terminology, the 17th percentile group is referred to as the profiling tie group, since not everyone from this percentile group is referred to orientation due to limited capacity. Under Model A, 65.7 percent of the 500 people drawn from the 17th percentile would actually exhaust benefits, whereas under Model B, 65.1 percent would exhaust. Of the 500 people drawn, the difference between the two models in the number of people drawn who actually would exhaust benefits is very small, only 3 people.

An alternative approach is to draw the 500 claimants sequentially from highest to lowest profiling score from within the 17th percentile group until the 500 referrals are reached. A convenient way to contrast the two approaches is to divide those claimants in the profiling tie group (17th percentile group in the case of the previous example) into decile groups (10 groups of equal number of claimants). We consider only the distribution generated from Model A in order to illustrate the differences between the two sampling techniques. Table 12 displays the number of actual exhaustees for each decile group within the 17th percentile group. Drawing from the top half of the distribution to obtain 500 additional referrals results in 66.8 percent of those drawn actually exhausting benefits. This proportion is slightly more than the 65.7 percent of actual exhaustees that was obtained by randomly selecting from the entire 1,000 claimants within the 17th percentile. However, whether one approach is superior to another for any portion along the distribution of profiling scores depends upon the idiosyncrasies of those claimants.[10]

B. Steepness of the Distribution

The criterion of maximizing the number of referrals who actually would exhaust benefits is comprised of two parts. The first is the steepness of the distribution, which is the ability to distinguish among claimants according to their likelihood of exhausting benefits. The second is the accuracy of that prediction, as measured by the percentage of individuals along each segment of the distribution that actually exhausts benefits. First consider the steepness of the distribution for the two profiling models. Steepness is one of the primary criteria used by Black et. al (2002) to select profiling models.[11] A profiling model with a steeper distribution is able to distinguish

[10]As will be shown later in the paper, the actual exhaustion rates do not perfectly track the predicted probability of exhausting benefits. As shown in Table 12, the actual exhaustion rate is higher in the 17th percentile than in neighboring percentiles, whereas it should decline continuously from top to bottom of the top of the distribution. One possible reason for the nonmonotonic nature of the actual exhaustion rate for small segments of the distribution is the relatively small sample size for each percentile—750. The model was estimated on a sample of more than 200,000 claimants. In reality, however, WIA areas will be drawing relatively small samples each week and should expect some anomalies as shown here. It should also be noted that the actual exhaustion rate when Model B is used to delineate the 17th percentile is even less monotonic when compared to the exhaustion rate of the neighboring percentiles.

[11]Steepness of the distribution is one of the criteria that we used to select the original profiling model for Michigan.

among the UI claimants more precisely. Figures 5 and 6 display the predicted probabilities derived from Model A and Model B, respectively, estimated on the validation sample. Note that both curves follow a logistic function. The distribution generated by Model A ranges from 0.17 to 0.92, while the distribution generated by Model B spans a shorter interval from 0.51 to 0.99. Figure 7 compares the steepness of the two distributions by dividing the distributions into 20 percentile groups and indexing the lowest value (upper cutoff value for the lowest percentile group) of each distribution to 1. The points plotted in Figure 3 are the upper percentile values for each of the 20 groups. It is apparent from this graph that predicting exhaustion events (Model A) generates a distribution that is considerably steeper than predicting the fraction of benefits (Model B). The ending value for Model A is 77 percent greater than the beginning value, whereas the ending value for Model B is only 28 percent greater than its beginning value. Based on this measure, the slope of Model A's distribution is 2.7 times steeper than that of Model B.

Since most claimants who are referred to orientation are drawn from the top 25 percent of the distribution, it is also instructive to take a closer look at this portion of the curve. Once again using upper percentile values for each of the 20 groups, it is evident that, for the upper 25 percent of the distribution, the distribution of the predicted values of Model A is steeper than that of Model B. The difference between the cutoff values for the 20th percentile group and the 15th is 0.119 for Model A versus 0.077 for Model B. Thus the spread of the distribution for Model A is 55 percent greater than that of Model B for this upper quarter of the distribution.

C. Accuracy of the Model

To measure the accuracy of each model, we follow an approach referred to as the running sum of proportion of ones (exhausting benefits equals one), or CUSUM.[12] Ideally for our purposes, the profiling score should perfectly distinguish between those who exhaust and those who do not exhaust. If this were true, the relationship between the profiling score and the event of exhausting benefits would be such that all those who exhaust would be in the top portion of the distribution of predicted exhaustion probabilities and all those who do not exhaust would be in the lower portion of the distribution. Thus, there would be no interspersing of those who exhausted with those who did not exhaust. In this case, plotting the running sums of ones against the continuous profiling score would yield a pyramid-shaped graph with its peak at the sample proportion of those who exhausted. Figures 8 and 9 show the graphs of the running sum of ones for each model. The graphs show a pronounced inverted U-shaped plot for each model, indicating a strong positive monotonic relationship. The trend for each model is confirmed by a highly statistically significant linear cusum statistic (7.72 for Model A and 7.27 for Model B).

Examining the upper 25 percent of the distribution, as shown in Figures 10 and 11, shows a less pronounced inverted U-shaped relationship, but the statistic shows a highly statistically significant linear relationship, with Model B exhibiting a slightly higher statistic than Model A (3.41 for Model A and 4.45 for Model B). Therefore, according to this measure of fit, the two

[12]See the description of CUSUM in the *STATA Reference Manual*, Release 6, Volume One, pp. 285–288.

models are comparable in their relationship between the exhaustion event and the profiling score.

D. Comparing How Each Model Ranks Claimants

While the two models are comparable with respect to fitting the data and satisfying the criteria of maximizing the number of referrals who would actually exhaust benefits, their ranking of specific individuals according to their profiling scores differs. Thus, some individuals referred to orientation by one model may not be referred to orientation by the other model. The rank correlation of the profiling scores generated from the two models is 0.885. A score of 1.00 indicates that each model ranked individuals identically.

To see the effect of the different rankings on referrals to orientation, we return to the previous example of selecting 3,000 claimants for referrals. As shown in Table 11, selecting claimants from the 18th, 19th, and 20th percentile groups would meet this capacity. Table 13 shows the overlap between the two models in selecting claimants as well as the outliers. Cross tabulations were derived for each of the 20 percentile groups, but we show only the 13th percentile group and higher, since this is the region of the distribution that is affected by the selection of referrals. We find an overlap of 2,423 (or 80.8 percent of) individuals who were in the 18th through 20th percentile groups for each model. If referrals are based on Model A, then 576 individuals would have been included in the top 3 percentile groups who would not have been included if Model B were used. Conversely, Model A does not include 570 people in the top 3 percentile groups that Model B would have included. Since the outliers under Model B vis-á-vis Model A extend farther down in the distribution than the outliers under Model A, the exhaustion rate of the Model B outliers is slightly lower than that of the outliers under Model A (60.8 percent versus 61.7 percent).

E. Contrasting the Preferred New Model with the Original Model

The original model and the new model assign different profiling scores to the same people, thus yielding significantly different rankings. Using the same out-of-sample group of claimants, we find that the rank-order correlation coefficient is 0.33, which is considerably lower than the ideal value of 1.00, which indicates all individuals are ranked the same by each model. The value of 0.33 is also much lower than the rank correlation coefficient between the two versions of the new model.

We also find that the distribution of profiled scores between the new and original models differs. As shown in Figure 12, the new model is considerably steeper than the original model and tends to increase more monotonically than the original model. The new model is about 40 percent steeper than the original model for the entire distribution and 15 percent steeper for the top 25 percent of the distribution. Therefore, adding the variables included in the new model improves the performance of the model based on this simple criteria of model performance. The performance of the model is also improved by updating the estimates of the coefficients.

VIII. Summary

The Michigan Bureau of Workers' and Unemployment Compensation has asked the Upjohn Institute to revise and update the statistical profiling model that it uses to identify UI claimants who are most likely to exhaust their regular benefits. The Institute developed the original model, which Michigan has used since 1995. Several studies sponsored by the U.S. Department of Labor underscore the need to reestimate profiling models periodically and to update them if new variables are made available. The new model that we propose includes new variables that are now available since Michigan became a wage-record state. In addition, the new model is estimated using the most recent data available. The proposed model predicts the probability that a UI beneficiary exhausts his or her regular benefits. An alternative specification was explored that predicts the fraction of benefits drawn during the benefit year. Both models incorporate most of the suggestions outlined in the report by Black et al. (2002) sponsored by the U.S. Department of Labor. While the two models are fairly comparable according to several criteria, we recommend adopting the model based that predicts the exhaustion of benefits (Model A). This model performed slightly better, and it is easier to interpret.

We also recommend that the profiling model be implemented following the method recommended by Black et al. (2002) and used by Kentucky. This method divides the distribution of profiling scores into 20 percentile groups and refers claimants to orientation starting with the group with the highest profiling scores and working down the distribution. When the capacity of the service providers is met within a specific percentile group, claimants are randomly drawn from that group, referred to as the profiling tie group, until capacity is met. We showed that this approach yields results that are similar to that obtained from using a sequential selection approach. This approach is justified because the models are not sufficiently precise to distinguish among claimants within a given percentile group with an acceptable statistical significance. It also provides MBWUC with a valuable evaluation tool that can be used to periodically revise the profiling model and to improve the effectiveness of the WPRS system.

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Table 1 Number of Profiled Workers, Exhaustion Rate, and Fraction of Entitlement Used, by Date of First UI Payment

	Estimation sample			Validation sample		
Week ending date of first payment	Sample size	Exhaustion rate	Fraction of entitlement used	Sample size	Exhaustion rate	Fraction of entitlement used
7-Oct-00	1645	0.5605	0.7583			
14-Oct-00	1285	0.5440	0.7493			
21-Oct-00	1381	0.5583	0.7601			
28-Oct-00	1363	0.5657	0.7676			
4-Nov-00	1686	0.5623	0.7817			
11-Nov-00	72	0.6250	0.8075	1665	0.5351	0.7721
18-Nov-00	1847	0.5322	0.7778	63	0.4762	0.7185
25-Nov-00	1179	0.5191	0.7656	27	0.5185	0.6937
2-Dec-00	1483	0.5192	0.7698	2	0.5000	0.5962
9-Dec-00	1726	0.5110	0.7600			
16-Dec-00	1154	0.4905	0.7541			
23-Dec-00	1117	0.5031	0.7519			
30-Dec-00	1197	0.5313	0.7484			
6-Jan-01	2220	0.5279	0.7556			
13-Jan-01	2751	0.5049	0.7538			
20-Jan-01	2331	0.4848	0.7343			
27-Jan-01	2550	0.4624	0.7101			
3-Feb-01	2329	0.4693	0.7127			
10-Feb-01	3136	0.4790	0.7213			
17-Feb-01	2242	0.4777	0.7189	1	0.0000	0.5385
24-Feb-01	2306	0.4679	0.7178			
3-Mar-01	2324	0.4819	0.7158			
10-Mar-01	166	0.4518	0.6920	2399	0.5227	0.7444
17-Mar-01	2374	0.5430	0.7664	87	0.4713	0.7252
24-Mar-01	2459	0.5336	0.7538	44	0.4773	0.7355
31-Mar-01	2059	0.5294	0.7518	6	0.8333	0.8590
7-Apr-01	3637	0.5428	0.7571			
14-Apr-01	142	0.4648	0.6890	1988	0.5302	0.7517
21-Apr-01	2114	0.5553	0.7681	59	0.4407	0.6724
28-Apr-01	2334	0.5338	0.7572	38	0.5789	0.7642
5-May-01	2380	0.5458	0.7649	9	0.5556	0.6410
12-May-01	2054	0.5755	0.7751			
19-May-01	1938	0.5681	0.7740			
26-May-01	2014	0.5645	0.7665			
2-Jun-01	1475	0.5715	0.7679			
9-Jun-01	2297	0.5485	0.7477			
16-Jun-01	1956	0.5557	0.7559			
23-Jun-01	2041	0.5654	0.7606			
30-Jun-01	1695	0.5971	0.7850			
7-Jul-01	3186	0.6058	0.7829			
14-Jul-01	2242	0.6258	0.7891			
21-Jul-01	2065	0.5835	0.7619			

Table 1 (Continued)

Week ending date of first payment	Estimation sample			Validation sample		
	Sample size	Exhaustion rate	Fraction of entitlement used	Sample size	Exhaustion rate	Fraction of entitlement used
28-Jul-01	1822	0.6153	0.7815			
4-Aug-01	2022	0.6078	0.7816			
11-Aug-01	2059	0.5872	0.7622			
18-Aug-01	101	0.6733	0.8297	1754	0.6009	0.7702
25-Aug-01	1709	0.6220	0.7796	70	0.5714	0.7987
1-Sep-01	1794	0.6472	0.8062	28	0.6786	0.8559
8-Sep-01	2069	0.6191	0.7877	5	0.6000	0.6923
15-Sep-01	1883	0.6325	0.8001			
22-Sep-01	2159	0.6373	0.8021			
29-Sep-01	3136	0.5858	0.7679			
6-Oct-01	3593	0.5967	0.7802			
13-Oct-01	145	0.6207	0.8047			
20-Oct-01	61	0.6393	0.8174			
27-Oct-01	10	0.7000	0.8615			
3-Nov-01	1	0.0000	0.1923			
17-Nov-01	3	0.0000	0.1031			
1-Dec-01	1	1.0000	1.0000			
	102520	0.5517	0.7607	8245	0.5434	0.7569

Table 2 Number of Profiled Workers and Proportion of Entitlement Used, by Weeks of Benefits Drawn

	Estimation Sample		Validation Sample	
Weeks of Benefits Drawn	Sample Size	Proportion of Entitlement Used	Sample Size	Proportion of Entitlement Used
1	1003	0.0416	75	0.0401
2	3611	0.0850	296	0.0862
3	1823	0.1242	165	0.1195
4	3390	0.1654	297	0.1666
5	1681	0.2026	145	0.1990
6	3066	0.2457	240	0.2479
7	1629	0.2863	122	0.2828
8	2607	0.3310	227	0.3317
9	1427	0.3663	122	0.3577
10	2453	0.4150	182	0.4132
11	1277	0.4468	94	0.4590
12	2432	0.5001	194	0.4923
13	1278	0.5498	102	0.5559
14	2681	0.6397	227	0.6374
15	2033	0.7793	153	0.7745
16	3197	0.7702	258	0.7795
17	2357	0.8377	173	0.8523
18	3479	0.8383	234	0.8268
19	2426	0.8907	165	0.8890
20	3279	0.8820	266	0.8697
21	2140	0.9204	188	0.9192
22	3039	0.9151	250	0.9164
23	2002	0.9489	163	0.9386
24	3058	0.9548	251	0.9551
25	2176	0.9834	195	0.9803
26	42991	1.0000	3462	1.0000
Total	102535	0.7607	8246	0.7569

Table 3 Number of Profiled Workers, Exhaustion Rate and Fraction of Entitlement Used by WIA Area

		Estimation Sample			Validation Sample		
		Sample Size	Exhaustion Rate	Fraction of Entitlement Used	Sample Size	Exhaustion Rate	Fraction of Entitlement Used
1	WIA Area, Western UP	864	0.5671	0.8055	70	0.5571	0.7944
2	WIA Area, Central UP	981	0.5178	0.7615	73	0.5205	0.7373
3	WIA Area, Eastern UP	352	0.5199	0.7590	33	0.3939	0.6778
4	WIA Area, North West	3765	0.4874	0.7372	316	0.4937	0.7394
5	WIA Area, North East	2101	0.5621	0.7988	181	0.5912	0.8356
6	WIA Area, West Central	1755	0.5197	0.7562	147	0.5102	0.7806
7	WIA Area, Region 7B	1185	0.5932	0.8010	77	0.5974	0.8046
8	WIA Area, Muskegon-Oceana	3122	0.5208	0.7454	196	0.5714	0.7818
9	WIA Area, Ottawa County	2273	0.4809	0.7142	148	0.4932	0.7515
10	WIA Area, ACSET	6505	0.5191	0.7352	598	0.5268	0.7355
11	WIA Area, Central	2003	0.5142	0.7463	176	0.4375	0.6963
12	WIA Area, Saginaw-Midland-Bay	5087	0.5546	0.7697	384	0.5599	0.7650
13	WIA Area, Thumb	2393	0.5687	0.7781	153	0.5948	0.7788
14	WIA Area, Capital	1508	0.4973	0.7305	116	0.4655	0.7085
15	WIA Area, Genesee-Shiawassee	3840	0.5646	0.7702	310	0.5548	0.7756
16	WIA Area, Livingston County	913	0.4907	0.7201	69	0.5217	0.7664
17	WIA Area, Oakland County	12869	0.5225	0.7378	1066	0.5122	0.7325
18	WIA Area, Macomb-St. Clair	11709	0.5415	0.7501	998	0.5381	0.7547
19	WIA Area, Wayne-Monroe	26469	0.6060	0.7883	2002	0.5919	0.7800
20	WIA Area, Washtenaw County	2283	0.4823	0.7161	170	0.4294	0.6849
21	WIA Area, Calhoun ISO	1924	0.5405	0.7632	183	0.5355	0.7203
22	WIA Area, South Central	2848	0.5488	0.7523	221	0.5204	0.7574
23	WIA Area, Kalamazoo-St. Joseph	3229	0.5636	0.7635	359	0.5655	0.7521
24	WIA Area, Berrien-Cass-Van Buren	2386	0.5746	0.7783	188	0.5213	0.7564
999	Out-of-State Resident	171	0.4971	0.7091	12	0.5000	0.7656
Total	Overall	102535	0.5517	0.7607	8246	0.5433	0.7569

Table 4 Variables in the Original and New Michigan WPRS Profiling Models

Original Model	New Model	Comments
y = UI exhaustion (1, 0)	y = UI exhaustion (1, 0)	Use OLS instead of logit
Education - 5	Education - 5	LTHS, HS, SC, ColGrad, Adv
Tenure - 2	Tenure - 2	Tenure, tenure squared
Occupation - 9 DOT	Occupation - 10 SOC	Coding system changed
Industry - 11 SIC	Industry - 20 NAICS	Coding system changed
SDA - 25 areas	WIA - 24 areas + out of state claim	Coding system changed
Complexity - 6		No longer available
	Variables added	
	Base_wages	Earnings in UI base period
	Entitle_length	Maximum UI weeks available
	Exhaust_prior	Exhausted previous UI spell
	Orient_ref*	Proxy for referred to WPRS
	Weekly categorical variable	Controls for weekly events such as TEUC
	sep_reason	Reasons for job separation
	byb___*	Weekly time indicator

NOTE: Variables marked with an asterisk (*) are included in the regression model but are not used to calculate the profiling score for each individual.

Table 5 Means of the Estimation Sample (Client Inflow: October 1, 2000–September 30, 2001)

Variable	Description	Means	Standard Deviation
tenure	Tenure at last employer (years)	3.540	5.760
$tenure^2$	Tenure squared	45.840	154.720
educ1	Education, less than high school	0.135	0.340
educ2	Education, high school graduate	0.529	0.499
educ3	Education, some college	0.216	0.411
educ4	Education, college graduate	0.084	0.277
educ5	Education, advanced	0.035	0.184
exhaust_prior	Exhausted recent prior unemployment claim	0.168	0.374
base_wages	Base period wages ($1000)	28.440	21.340
entitle	Entitlement length (weeks)	24.670	2.910
orient_ref	Referred to orientation	0.054	0.226
sep_reason1	Separation reason, lack of work	0.793	0.405
sep_reason2	Separation reason, quit/fired	0.194	0.395
sep_reason3	Separation reason, still employed	0.002	0.042
sep_reason4	Separation reason, other	0.011	0.106
soc1113	Occup (SOC), Management, Business, Financial	0.068	0.251
soc1529	Occup (SOC), Professional and Related Occ	0.105	0.307
soc3139	Occup (SOC), Services	0.039	0.193
soc41	Occup (SOC), Sales and Related Occ	0.034	0.180
soc43	Occup (SOC), Office, Administrative Support	0.120	0.325
soc45	Occup (SOC), Farming, Fishing and Forestry	0.029	0.170
soc47	Occup (SOC), Construction and Extraction	0.070	0.255
soc49	Occup (SOC), Installation, Maintenance, Repair	0.019	0.138
soc51	Occup (SOC), Production	0.390	0.488
soc53	Occup (SOC), Trans and Material Moving	0.126	0.331
indnaics1	Ind (NAICS): Agric,, Forestry, Fishing	0.006	0.077
indnaics2	Ind (NAICS): Mining	0.005	0.073
indnaics3	Ind (NAICS): Utilities	0.001	0.028
indnaics4	Ind (NAICS): Construction	0.098	0.298
indnaics5	Ind(NAICS): Production	0.339	0.473
indnaics6	Ind (NAICS): Wholesale Trade	0.049	0.216
indnaics7	Ind (NAICS): Retail Trade	0.083	0.276
indnaics8	Ind (NAICS): Transportation, Warehousing	0.039	0.193
indnaics9	Ind (NAICS): Information	0.018	0.133
indnaics10	Ind (NAICS): Finance and Insurance	0.024	0.154
indnaics11	Ind (NAICS): Real Estate, Rental, Leasing	0.013	0.112
indnaics12	Ind (NAICS): Prof, Scientific, Technical	0.074	0.262
indnaics13	Ind (NAICS): Company/Enterprise Management	0.003	0.055
indnaics14	Ind (NAICS): Admin, Support and Waste Mgmt	0.113	0.316
indnaics15	Ind (NAICS): Educational Services	0.012	0.108
indnaics16	Ind (NAICS): Health Care/Social Assistance	0.04	0.20
indnaics17	Ind (NAICS): Art, Entertainment, Recreation	0.014	0.117
indnaics18	Ind (NAICS): Accommodation and Food Services	0.367	0.188
indnaics19	Ind (NAICS): Other Services (Except Pub Admin)	0.023	0.148
indnaics20	Ind (NAICS): Public Administration	0.010	0.097

Table 6 Estimation Sample Correlation of Rankings by Model Specification (Client Inflow: October 1, 2000–September 30, 2001)

	Logit, Exhaust, New	Logit, Exhaust, New Plus Dummies	OLS, Exhaust, New	OLS, Exhaust, New Plus Dummies	OLS, Fraction, New	OLS, Fraction, New Plus Dummies
Logit, Exhaust, New	1.0000	0.8735	0.9999	0.8714	0.8907	0.7941
Logit, Exhaust, New Plus Dummies	0.8735	1.0000	0.8735	0.9999	0.7811	0.8884
OLS, Exhaust, New	0.9999	0.8735	1.0000	0.8715	0.8903	0.7936
OLS, Exhaust, New Plus Dummies	0.8714	0.9999	0.8715	1.0000	0.7785	0.8878
OLS, Fraction, New	0.8907	0.7811	0.8903	0.7785	1.0000	0.8853
OLS, Fraction, New Plus Dummies	0.7941	0.8884	0.7936	0.8878	0.8853	1.0000

Validation Sample Correlation of Rankings by Model Specification

	Logit, Exhaust, New	Logit, Exhaust, New Plus Dummies	OLS, Exhaust, New	OLS, Exhaust, New Plus Dummies	OLS, Fraction, New	OLS, Fraction, New Plus Dummies
Logit, Exhaust, New	1.0000	0.9941	0.9999	0.9942	0.8884	0.8671
Logit, Exhaust, New Plus Dummies	0.9941	1.0000	0.9939	0.9999	0.9128	0.9000
OLS, Exhaust, New	0.9999	0.9939	1.0000	0.9941	0.8879	0.8665
OLS, Exhaust, New Plus Dummies	0.9942	0.9999	0.9941	1.0000	0.9125	0.8997
OLS, Fraction, New	0.8884	0.9128	0.8879	0.9125	1.0000	0.9955
OLS, Fraction, New Plus Dummies	0.8671	0.9000	0.8665	0.8997	0.9955	1.0000

Table 7 Model A
New Michigan Profiling Model Specification Adding Dummies and Restrictions
OLS Regression on 0/1 Exhaustion Dummy as Dependent Variable
Client Inflow: October 1, 2000–September 30, 2001

Variable	Description	Parameter Estimate	Standard Error	t-statistic
Intercept	Intercept	0.82600	0.00974	84.79
tenure	Tenure at Last Employer (Years)	0.01009	0.00051	19.62
$tenure^2$	Tenure Squared	-0.00019	0.00002	10.33
educ1	Education, Less Than High School	0.02896	0.00279	10.38
educ2	Education, High School Graduate	0.00271	0.00104	2.61
educ3	Education, Some College	-0.00823	0.00205	4.01
educ4	Education, College Graduate	-0.03030	0.00374	8.10
educ5	Education, Advanced	-0.02904	0.00588	4.94
exhaust_prior	Exhausted Recent Prior Unemployment Claim	0.14826	0.00292	50.70
base_wages	Base Period Wages ($1000)	-0.00134	0.00006	21.21
entitle	Entitlement Length (Weeks)	-0.01269	0.00041	30.84
orient_ref	Referred to Orientation	0.03894	0.00498	7.82
sep_reason1	Separation Reason, Lack of Work	-0.00251	0.00058	4.37
sep_reason2	Separation Reason, Quit/Fired	0.01023	0.00230	4.45
sep_reason3	Separation Reason, Still Employed	-0.03041	0.02528	1.20
sep_reason4	Separation Reason, Other	0.00613	0.00999	0.61
soc1113	Occup (SOC), Management, Business, Financial	0.00223	0.00416	0.54
soc1529	Occup (SOC), Professional and Related Occ	-0.00076	0.00334	0.23
soc3139	Occup (SOC), Services	0.00667	0.00572	1.16
soc41	Occup (SOC), Sales and Related Occ	-0.00019	0.00591	0.03
soc43	Occup (SOC), Office, Administrative Support	0.00706	0.00303	2.33
soc45	Occup (SOC), Farming, Fishing and Forestry	-0.05131	0.00811	6.33
soc47	Occup (SOC), Construction and Extraction	-0.01574	0.00425	3.70
soc49	Occup (SOC), Installation, Maintenance, Repair	-0.00594	0.00765	0.78
soc51	Occup (SOC), Production	0.00658	0.00151	4.36
soc53	Occup (SOC), Trans and Material Moving	-0.00787	0.00314	2.51
indnaics1	Ind (NAICS): Agric,, Forestry, Fishing	0.02393	0.01411	1.70
indnaics2	Ind (NAICS): Mining	-0.17222	0.01632	10.55
indnaics3	Ind (NAICS): Utilities	0.03425	0.03789	0.90
indnaics4	Ind (NAICS): Construction	-0.02751	0.00351	7.84
indnaics5	Ind (NAICS): Manufacturing	-0.00291	0.00165	1.76
indnaics6	Ind (NAICS): Wholesale Trade	0.01592	0.00475	3.35
indnaics7	Ind (NAICS): Retail Trade	0.00405	0.00368	1.10
indnaics8	Ind (NAICS): Transportation, Warehousing	-0.02450	0.00542	4.52
indnaics9	Ind (NAICS): Information	0.03622	0.00796	4.55
indnaics10	Ind (NAICS): Finance and Insurance	0.03555	0.00689	5.16
indnaics11	Ind (NAICS): Real Estate, Rental, Leasing	0.01186	0.00947	1.25
indnaics12	Ind (NAICS): Prof, Scientific, Technical	0.02813	0.00393	7.15
indnaics13	Ind (NAICS): Company/Enterprise Management	-0.01638	0.01952	0.84
indnaics14	Ind (NAICS): Admin, Support and Waste Mgmt	0.00996	0.00306	3.26
indnaics15	Ind (NAICS): Educational Services	-0.01726	0.00992	1.74
indnaics16	Ind (NAICS): Health Care/Social Assistance	-0.00562	0.00539	1.04

Table 7 (Continued)

Variable	Description	Parameter Estimate	Standard Error	t-statistic
indnaics17	Ind (NAICS): Art, Entertainment, Recreation	-0.02645	0.00913	2.90
indnaics18	Ind (NAICS): Accommodation and Food Services	-0.01217	0.00585	2.08
indnaics19	Ind (NAICS): Other Services (Except Pub Admin)	0.03583	0.00706	5.08
indnaics20	Ind (NAICS): Public Administration	-0.01467	0.01094	1.34
wia1	WIA Area, Western UP	-0.00086	0.01245	0.07
wia2	WIA Area, Central UP	-0.04219	0.00880	4.79
wia3	WIA Area, Eastern UP	-0.04293	0.01265	3.39
wia4	WIA Area, North West	-0.06385	0.00591	10.80
wia5	WIA Area, North East	0.00752	0.00811	0.93
wia6	WIA Area, West Central	-0.04117	0.00837	4.92
wia7	WIA Area, Region 7B	0.00185	0.00835	0.22
wia8	WIA Area, Muskegon-Oceana	-0.04281	0.00667	6.42
wia9	WIA Area, Ottawa County	-0.04900	0.00719	6.82
wia10	WIA Area, ACSET	-0.01395	0.00378	3.68
wia11	WIA Area, Central	-0.07847	0.00748	10.48
wia12	WIA Area, Saginaw-Midland-Bay	0.00007	0.00546	0.01
wia13	WIA Area, Thumb	0.00683	0.00628	1.09
wia14	WIA Area, Capital	-0.05616	0.00603	9.31
wia15	WIA Area, Genesee-Shiawassee	0.01489	0.00459	3.24
wia16	WIA Area, Livingston County	-0.02457	0.01046	2.35
wia17	WIA Area, Oakland County	-0.00180	0.00326	0.55
wia18	WIA Area, Macomb-St. Clair	0.01158	0.00307	3.77
wia19	WIA Area, Wayne-Monroe	0.04232	0.00207	20.42
wia20	WIA Area, Washtenaw County	-0.04111	0.00823	4.99
wia21	WIA Area, Calhoun ISO	-0.03035	0.00696	4.36
wia22	WIA Area, South Central	-0.00806	0.00594	1.36
wia23	WIA Area, Kalamazoo-St. Joseph	0.00141	0.00648	0.22
wia24	WIA Area, Berrien-Cass-Van Buren	0.01692	0.00700	2.42
wia999	Out-of-State Resident	0.01574	0.00989	1.59
byb100100	YB = 10-01-2000	0.02337	0.00919	2.54
byb100800	BYB = 10-08-2000	0.02384	0.01010	2.36
byb101500	BYB = 10-15-2000	0.02087	0.00996	2.09
byb102200	BYB = 10-22-2000	0.02525	0.00960	2.63
byb102900	BYB = 10-29-2000	-0.00871	0.00826	1.06
byb111200	BYB = 11-12-2000	0.00001	0.00797	0.00
byb111900	BYB = 11-19-2000	-0.02013	0.00937	2.15
byb112600	BYB = 11-26-2000	-0.02347	0.00828	2.83
byb120300	BYB = 12-03-2000	-0.02577	0.00757	3.40
byb121000	BYB = 12-10-2000	-0.04553	0.00845	5.39
byb121700	BYB = 12-17-2000	-0.09099	0.00762	11.94
byb122400	BYB = 12-24-2000	-0.06613	0.00615	10.76
byb123100	BYB = 12-31-2000	-0.02240	0.00702	3.19
byb010701	BYB = 01-07-2001	-0.03657	0.00552	6.62

Table 7 (Continued)

Variable	Description	Parameter Estimate	Standard Error	t-statistic
byb011401	BYB = 01-14-2001	-0.05105	0.00645	7.92
byb012101	BYB = 01-21-2001	-0.06646	0.00611	10.88
byb012801	BYB = 01-28-2001	-0.05193	0.00656	7.92
byb020401	BYB = 02-04-2001	-0.04442	0.00628	7.08
byb021101	BYB = 02-11-2001	-0.05281	0.00712	7.42
byb021801	BYB = 02-18-2001	-0.05283	0.00719	7.35
byb022501	BYB = 02-25-2001	-0.04744	0.00709	6.69
byb031101	BYB = 03-11-2001	-0.00908	0.00728	1.25
byb031801	BYB = 03-18-2001	-0.01433	0.00728	1.97
byb032501	BYB = 03-25-2001	-0.01809	0.00806	2.25
byb040101	BYB = 04-01-2001	0.00744	0.00628	1.19
byb041501	BYB = 04-15-2001	-0.00763	0.00793	0.96
byb042201	BYB = 04-22-2001	-0.00287	0.00772	0.37
byb042901	BYB = 04-29-2001	0.02296	0.00741	3.10
byb050601	BYB = 05-06-2001	0.02464	0.00791	3.11
byb051301	BYB = 05-13-2001	0.03056	0.00793	3.85
byb052001	BYB = 05-20-2001	0.01089	0.00808	1.35
byb052701	BYB = 05-27-2001	0.03973	0.00909	4.37
byb060301	BYB = 06-03-2001	0.01838	0.00733	2.51
byb061001	BYB = 06-10-2001	0.01854	0.00824	2.25
byb061701	BYB = 06-17-2001	0.03279	0.00775	4.23
byb062401	BYB = 06-24-2001	0.04036	0.00829	4.87
byb070101	BYB = 07-01-2001	-0.04744	0.00457	10.39
byb070801	BYB = 07-08-2001	0.00531	0.00650	0.82
byb071501	BYB = 07-15-2001	0.04503	0.00774	5.82
byb072201	BYB = 07-22-2001	0.06967	0.00848	8.21
byb072901	BYB = 07-29-2001	0.06820	0.00819	8.32
yb080501	BYB = 08-05-2001	0.06451	0.00802	8.04
byb081901	BYB = 08-19-2001	0.06990	0.00872	8.02
byb082601	BYB = 08-26-2001	0.09578	0.00851	11.25
byb090201	BYB = 09-02-2001	0.08128	0.00820	9.91
byb090901	BYB = 09-09-2001	0.10588	0.00831	12.74
byb091601	BYB = 09-16-2001	0.07383	0.00773	9.55
byb092301	BYB = 09-23-2001	0.06076	0.00671	9.06
byb093001	BYB = 09-30-2001	0.07111	0.00627	11.34
	Education Restriction	-5.313e-11		
	Separation Reason Restriction	1.835e-10		
	Occupation Restriction	-5.592e-11		
	Industry Restriction	-1.248e-10		
	WIA Area Restriction	-1.899e-10		
	BYB Restriction	-1.901e-10		
	Adjusted R-Square: 0.0455			

Table 8 Model B
New Michigan Profiling Model Specification Adding Dummies and Restrictions
OLS Regression on Fraction of Benefits Used/Exhausted as Dependent Variable
Client Inflow: October 1, 2000–September 30, 2001

Variable	Description	Parameter Estimate	Standard Error	t-statistic
Intercept	Intercept	0.93900	0.00633	148.27
tenure	Tenure at Last Employer (Years)	0.00578	0.00033	17.29
$tenure^2$	Tenure Squared	-0.00010	0.00001	8.60
educ1	Education, Less Than High School	0.01784	0.00181	9.84
educ2	Education, High School Graduate	0.00161	0.00068	2.37
educ3	Education, Some College	-0.00541	0.00133	4.05
educ4	Education, College Graduate	-0.01859	0.00243	7.64
educ5	Education, Advanced	-0.01501	0.00382	3.93
exhaust_prior	Exhausted Recent Prior Unemployment Claim	0.09147	0.00190	48.12
base_wages	Base Period Wages ($1000)	-0.00086	0.00004	20.95
entitle	Entitlement Length (Weeks)	-0.00766	0.00027	28.63
orient_ref	Referred to Orientation	0.03055	0.00324	9.44
sep_reason1	Separation Reason, Lack of Work	0.00239	0.00037	6.38
sep_reason2	Separation Reason, Quit/Fired	-0.00875	0.00149	5.86
sep_reason3	Separation Reason, Still Employed	-0.01123	0.01643	0.68
sep_reason4	Separation Reason, Other	-0.01576	0.00649	2.43
soc1113	Occup (SOC), Management, Business, Financial	-0.00488	0.00270	1.81
soc1529	Occup (SOC), Professional and Related Occ	-0.00703	0.00217	3.24
soc3139	Occup (SOC), Services	-0.00212	0.00372	0.57
soc41	Occup (SOC), Sales and Related Occ	-0.01144	0.00384	2.98
soc43	Occup (SOC), Office, Administrative Support	0.00031	0.00197	0.16
soc45	Occup (SOC), Farming, Fishing and Forestry	-0.01434	0.00527	2.72
soc47	Occup (SOC), Construction and Extraction	0.00682	0.00276	2.47
soc49	Occup (SOC), Installation, Maintenance, Repair	-0.00979	0.00497	1.97
soc51	Occup (SOC), Production	0.00456	0.00098	4.64
soc53	Occup (SOC), Trans and Material Moving	-0.00111	0.00204	0.54
indnaics1	Ind (NAICS): Agric,, Forestry, Fishing	0.04480	0.00917	4.88
indnaics2	Ind (NAICS): Mining	-0.00418	0.01061	0.39
indnaics3	Ind (NAICS): Utilities	0.02314	0.02464	0.94
indnaics4	Ind (NAICS): Construction	0.02149	0.00228	9.42
indnaics5	Ind (NAICS): Manufacturing	-0.00707	0.00107	6.58
indnaics6	Ind (NAICS): Wholesale Trade	0.00129	0.00309	0.42
indnaics7	Ind (NAICS): Retail Trade	-0.00606	0.00239	2.53
indnaics8	Ind (NAICS): Transportation, Warehousing	-0.02254	0.00352	6.40
indnaics9	Ind (NAICS): Information	0.01689	0.00518	3.26
indnaics10	Ind (NAICS): Finance and Insurance	0.01644	0.00448	3.67
indnaics11	Ind (NAICS): Real Estate, Rental, Leasing	0.00180	0.00616	0.29
indnaics12	Ind (NAICS): Prof, Scientific, Technical	0.01348	0.00256	5.27
indnaics13	Ind (NAICS): Company/Enterprise Management	-0.04273	0.01269	3.37
indnaics14	Ind (NAICS): Admin, Support and Waste Mgmt	0.00486	0.00199	2.45
indnaics15	Ind (NAICS): Educational Services	-0.01949	0.00645	3.02
indnaics16	Ind (NAICS): Health Care/Social Assistance	-0.01835	0.00350	5.24

Table 8 (Continued)

Variable	Description	Parameter Estimate	Standard Error	t-statistic
indnaics17	Ind (NAICS): Art, Entertainment, Recreation	0.01641	0.00593	2.77
indnaics18	Ind (NAICS): Accommodation and Food Services	-0.01335	0.00380	3.51
indnaics19	Ind (NAICS): Other Services (Except Pub Admin)	0.01297	0.00459	2.83
indnaics20	Ind (NAICS): Public Administration	0.01243	0.00711	1.75
wia1	WIA Area, Western UP	0.02025	0.00809	2.50
wia2	WIA Area, Central UP	0.00134	0.00572	0.23
wia3	WIA Area, Eastern UP	-0.00230	0.00822	0.28
wia4	WIA Area, North West	-0.02592	0.00384	6.74
wia5	WIA Area, North East	0.02396	0.00527	4.54
wia6	WIA Area, West Central	-0.01641	0.00544	3.02
wia7	WIA Area, Region 7B	0.01995	0.00543	3.67
wia8	WIA Area, Muskegon-Oceana	-0.02824	0.00433	6.52
wia9	WIA Area, Ottawa County	-0.03093	0.00467	6.62
wia10	WIA Area, ACSET	-0.01137	0.00246	4.62
wia11	WIA Area, Central	-0.04513	0.00487	9.27
wia12	WIA Area, Saginaw-Midland-Bay	0.00628	0.00355	1.77
wia13	WIA Area, Thumb	0.01302	0.00408	3.19
wia14	WIA Area, Capital	-0.03610	0.00392	9.20
wia15	WIA Area, Genesee-Shiawassee	0.00987	0.00298	3.31
wia16	WIA Area, Livingston County	-0.01600	0.00680	2.35
wia17	WIA Area, Oakland County	-0.00241	0.00212	1.14
wia18	WIA Area, Macomb-St. Clair	0.00629	0.00199	3.15
wia19	WIA Area, Wayne-Monroe	0.01948	0.00135	14.46
wia20	WIA Area, Washtenaw County	-0.02819	0.00535	5.27
wia21	WIA Area, Calhoun ISO	-0.01611	0.00453	3.56
wia22	WIA Area, South Central	-0.00719	0.00386	1.86
wia23	WIA Area, Kalamazoo-St. Joseph	-0.00588	0.00421	1.40
wia24	WIA Area, Berrien-Cass-Van Buren	0.01084	0.00455	2.38
wia999	Out-of-State Resident	-0.01047	0.00643	1.63
byb100100	BYB = 10-01-2000	-0.00276	0.00597	0.46
byb100800	BYB = 10-08-2000	0.00380	0.00656	0.58
byb101500	BYB = 10-15-2000	0.00405	0.00648	0.63
byb102200	BYB = 10-22-2000	0.00658	0.00624	1.05
byb102900	BYB = 10-29-2000	0.00034	0.00537	0.06
byb111200	BYB = 11-12-2000	0.01466	0.00518	2.83
byb111900	BYB = 11-19-2000	0.00884	0.00609	1.45
byb112600	BYB = 11-26-2000	0.00535	0.00538	0.99
byb120300	BYB = 12-03-2000	0.01266	0.00492	2.57
byb121000	BYB = 12-10-2000	0.00211	0.00550	0.38
byb121700	BYB = 12-17-2000	-0.04993	0.00496	10.08
byb122400	BYB = 12-24-2000	-0.06329	0.00400	15.83
byb123100	BYB = 12-31-2000	-0.00651	0.00456	1.43
byb010701	BYB = 01-07-2001	0.00758	0.00359	2.11
byb011401	BYB = 01-14-2001	-0.00899	0.00419	2.14

Table 8 (Continued)

Variable	Description	Parameter Estimate	Standard Error	t-statistic
byb012101	BYB = 01-21-2001	-0.03183	0.00397	8.02
byb012801	BYB = 01-28-2001	-0.02486	0.00427	5.83
byb020401	BYB = 02-04-2001	-0.02027	0.00408	4.97
byb021101	BYB = 02-11-2001	-0.02762	0.00463	5.97
byb021801	BYB = 02-18-2001	-0.02905	0.00468	6.21
byb022501	BYB = 02-25-2001	-0.02969	0.00461	6.44
byb031101	BYB = 03-11-2001	0.00490	0.00473	1.04
byb031801	BYB = 03-18-2001	0.00256	0.00474	0.54
byb032501	BYB = 03-25-2001	-0.00771	0.00524	1.47
byb040101	BYB = 04-01-2001	0.00815	0.00408	2.00
byb041501	BYB = 04-15-2001	0.00345	0.00516	0.67
byb042201	BYB = 04-22-2001	0.00390	0.00502	0.78
byb042901	BYB = 04-29-2001	0.01930	0.00482	4.01
byb050601	BYB = 05-06-2001	0.01925	0.00514	3.74
byb051301	BYB = 05-13-2001	0.02951	0.00516	5.72
byb052001	BYB = 05-20-2001	0.00191	0.00525	0.36
byb052701	BYB = 05-27-2001	0.02749	0.00591	4.65
byb060301	BYB = 06-03-2001	0.00765	0.00476	1.61
byb061001	BYB = 06-10-2001	0.00763	0.00536	1.42
byb061701	BYB = 06-17-2001	0.01715	0.00504	3.40
byb062401	BYB = 06-24-2001	0.02013	0.00539	3.74
byb070101	BYB = 07-01-2001	-0.04975	0.00297	16.76
byb070801	BYB = 07-08-2001	-0.01992	0.00423	4.71
byb071501	BYB = 07-15-2001	0.00822	0.00503	1.63
byb072201	BYB = 07-22-2001	0.02763	0.00551	5.01
byb072901	BYB = 07-29-2001	0.02699	0.00533	5.07
byb080501	BYB = 08-05-2001	0.02072	0.00522	3.97
byb081901	BYB = 08-19-2001	0.02729	0.00567	4.81
byb082601	BYB = 08-26-2001	0.04851	0.00553	8.77
byb090201	BYB = 09-02-2001	0.03652	0.00533	6.85
byb090901	BYB = 09-09-2001	0.05575	0.00540	10.32
byb091601	BYB = 09-16-2001	0.03247	0.00503	6.46
byb092301	BYB = 09-23-2001	0.02178	0.00436	5.00
byb093001	BYB = 09-30-2001	0.03719	0.00408	9.12
	Education Restriction	1.994e-09		
	Separation Reason Restriction	2.631e-09		
	Occupation Restriction	9.731e-10		
	Industry Restriction	1.316e-09		
	WIA Area Restriction	1.411e-09		
	BYB Restriction	1.666e-09		
	Adjusted R-Square: 0.0394			

Table 9 Means of the Validation Sample; Client Inflow: October 1, 2000–September 30, 2001

Variable	Description	Means	Standard Deviation
tenure	Tenure at Last Employer (Years)	3.584	5.866
tenure2	Tenure Squared	47.257	161.710
educ1	Education, less than high school	0.135	0.342
educ2	Education, High School Graduate	0.529	0.499
educ3	Education, Some College	0.217	0.412
educ4	Education, College Graduate	0.090	0.286
educ5	Education, Advanced	0.037	0.189
exhaust_prior	Exhausted Recent Prior Unemployment Claim	0.174	0.379
base_wages	Base Period Wages ($1000)	29.415	22.620
entitle	Entitlement Length (Weeks)	24.689	2.902
orient_ref	Referred to Orientation	0.064	0.245
sep_reason1	Separation Reason, lack of work	0.765	0.424
sep_reason2	Separation Reason, Quit/Fired	0.220	0.414
sep_reason3	Separation Reason, Still Employed	0.003	0.055
sep_reason4	Separation Reason, Other	0.011	0.106
soc1113	Occup (SOC), Management, Business, Financial	0.085	0.279
soc1529	Occup (SOC), Professional and Related Occ	0.112	0.316
soc3139	Occup (SOC), Services	0.042	0.200
soc41	Occup (SOC), Sales and Related Occ	0.037	0.189
soc43	Occup (SOC), Office, Administrative Support	0.125	0.331
soc45	Occup (SOC), Farming, Fishing and Forestry	0.025	0.159
soc47	Occup (SOC), Construction and Extraction	0.066	0.248
soc49	Occup (SOC), Installation, Maintenance, Repair	0.021	0.142
soc51	Occup (SOC), Production	0.356	0.479
soc53	Occup (SOC), Trans and Material Moving	0.130	0.336
indnaics1	Ind (NAICS): Agric., Forestry, Fishing	0.008	0.090
indnaics2	Ind (NAICS): Mining	0.001	0.033
indnaics3	Ind (NAICS): Utilities	0.001	0.028
indnaics4	Ind (NAICS): Construction	0.098	0.297
indnaics5	Ind(NAICS): Production	0.320	0.466
indnaics6	Ind (NAICS): Wholesale Trade	0.052	0.222
indnaics7	Ind (NAICS): Retail Trade	0.097	0.295
indnaics8	Ind (NAICS): Transportation, Warehousing	0.033	0.179
indnaics9	Ind (NAICS): Information	0.020	0.141
indnaics10	Ind (NAICS): Finance and Insurance	0.030	0.170
indnaics11	Ind (NAICS): Real Estate, Rental, Leasing	0.014	0.117
indnaics12	Ind (NAICS): Prof, Scientific, Technical	0.067	0.250
indnaics13	Ind (NAICS): Company/Enterprise Management	0.003	0.053
indnaics14	Ind (NAICS): Admin, Support and Waste Mgmt	0.113	0.316
indnaics15	Ind (NAICS): Educational Services	0.010	0.100
indnaics16	Ind (NAICS): Health Care/Social Assistance	0.05	0.21
indnaics17	Ind (NAICS): Art, Entertainment, Recreation	0.016	0.125
indnaics18	Ind (NAICS): Accommodation and Food Services	0.038	0.191
indnaics19	Ind (NAICS): Other Services (Except Pub Admin)	0.025	0.156
indnaics20	Ind (NAICS): Public Administration	0.010	0.099

Table 10 Costs of Misclassification of Claimants

<table>
<tr><td colspan="2" rowspan="2"></td><td colspan="2">Actual Event (=1)</td></tr>
<tr><td>0</td><td>1</td></tr>
<tr><td rowspan="2">Predicted Event (=1)</td><td>0</td><td>True Negative</td><td>False Negative
Cost/benefit year:
2.2 more weeks of UI
$143 more in benefits
$1054 lost in earnings</td></tr>
<tr><td>1</td><td>False Positive
Cost/benefit year:
Use services that could have been used by those who need it
Forego job search</td><td>True Positive</td></tr>
</table>

Table 11 Distribution of Profiling Scores and Actual Exhaustion for Models A and B

Percentile Group		Model A (Exhaust)		Model B (Fraction of Benefits)		
	Number in Group	Cumulative Number Actually Exhausting	% Exhausting	Cumulative Number Actually Exhausting	% Exhausting	Difference in Number Exhausting (Model A - Model B)
20	1000	759	75.9	761	76.1	-2
19	1000	1427	66.8	1437	67.6	-10
18	1000	2074	64.7	2064	62.7	10
17	1000	2731	65.7	2715	65.1	16
16	1000	3356	62.5	3318	60.3	38

Table 12 Deciles of the Profiling Score within the 17th Percentile for Model A

	Profiling Score			
Decile	Lower Cutoff Values	Upper Cutoff Values	Proportion Exhausting	Number Referred
10	0.659	0.662	0.680	100
9	0.656	0.659	0.624	100
8	0.652	0.656	0.662	100
7	0.649	0.652	0.747	100
6	0.646	0.649	0.626	100
5	0.643	0.646	0.592	100
4	0.640	0.643	0.653	100
3	0.637	0.640	0.640	100
2	0.635	0.637	0.586	100
1	0.632	0.635	0.671	100

Table 13 Comparison of Rankings from Model A and Model B

	Percentiles of Profiling Scores from Model B								
	Percentiles	13	14	15	16	17	18	19	20
Percentiles of Profiling Scores From Model A	13	226	64	46	38	35	17	3	0
		22.55	6.37	4.64	3.81	3.45	1.72	0.27	0
	14	242	227	90	36	29	29	29	0
		24.17	22.71	9.03	3.59	2.92	2.92	2.92	0
	15	112	130	261	100	43	51	41	3
		11.16	13	26.1	9.96	4.25	5.05	4.12	0.27
	16	49	33	277	284	92	66	62	19
		4.91	3.32	27.72	28.38	9.15	6.63	6.23	1.86
	17	0	0	118	293	332	102	106	24
		0	0	11.82	29.28	33.2	10.23	10.62	2.39
	18	0	0	25	127	316	349	115	68
		0	0	2.52	12.73	31.56	34.88	11.54	6.76
	19	0	0	0	7	102	338	401	153
		0	0	0	0.66	10.21	33.82	40.05	15.25
	20	0	0	0	0	0	27	239	735
		0	0	0	0	0	2.65	23.87	73.47

Figure 1. TEUC and TEUC-X Entitlement

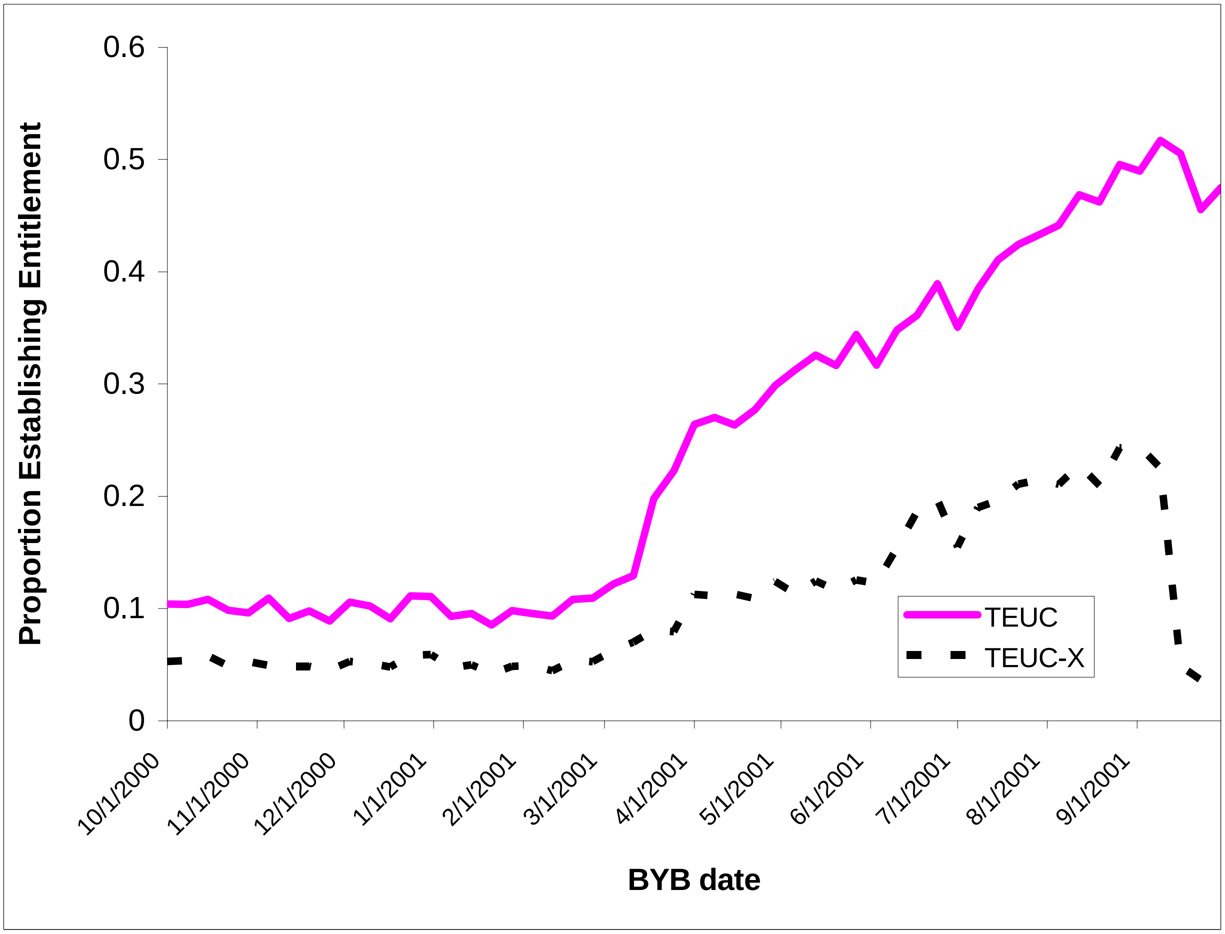

Figure 2. Prior Exhaustion vs. Predicted Exhaustion

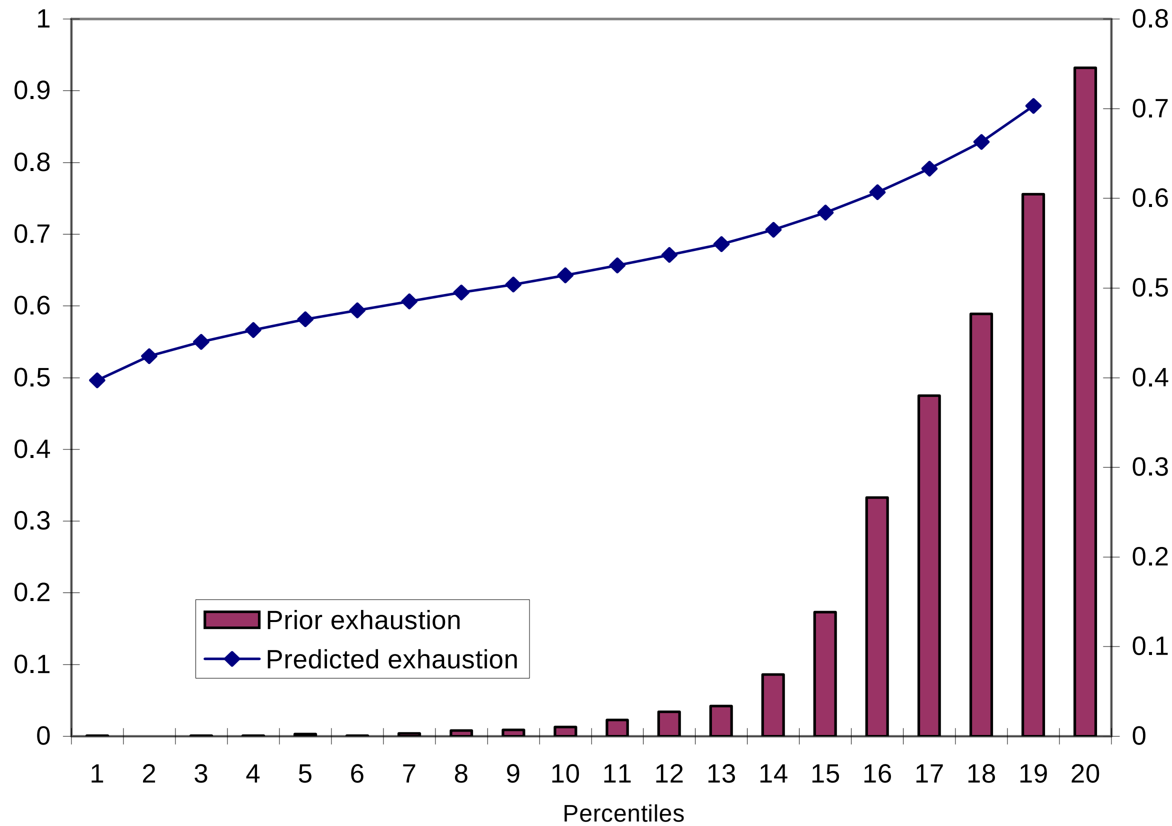

Figure 3. College Graduate vs. Predicted Exhaustion

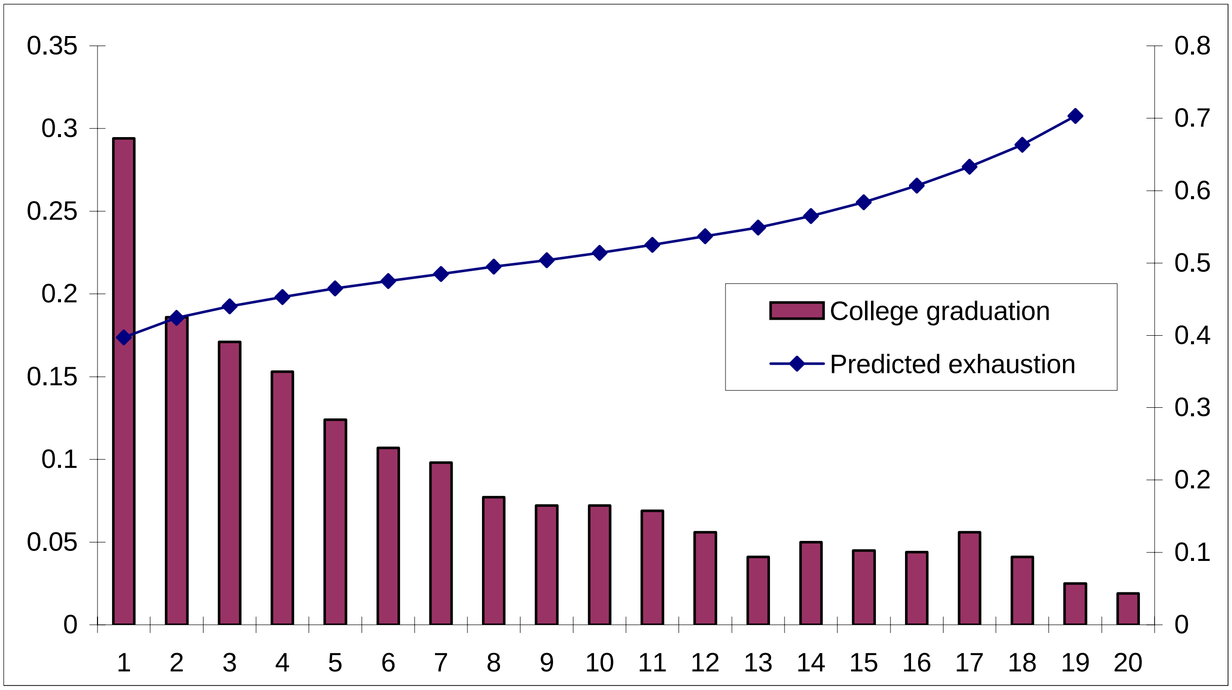

Figure 4. Distribution of Predicted Exhaustion Using Model A

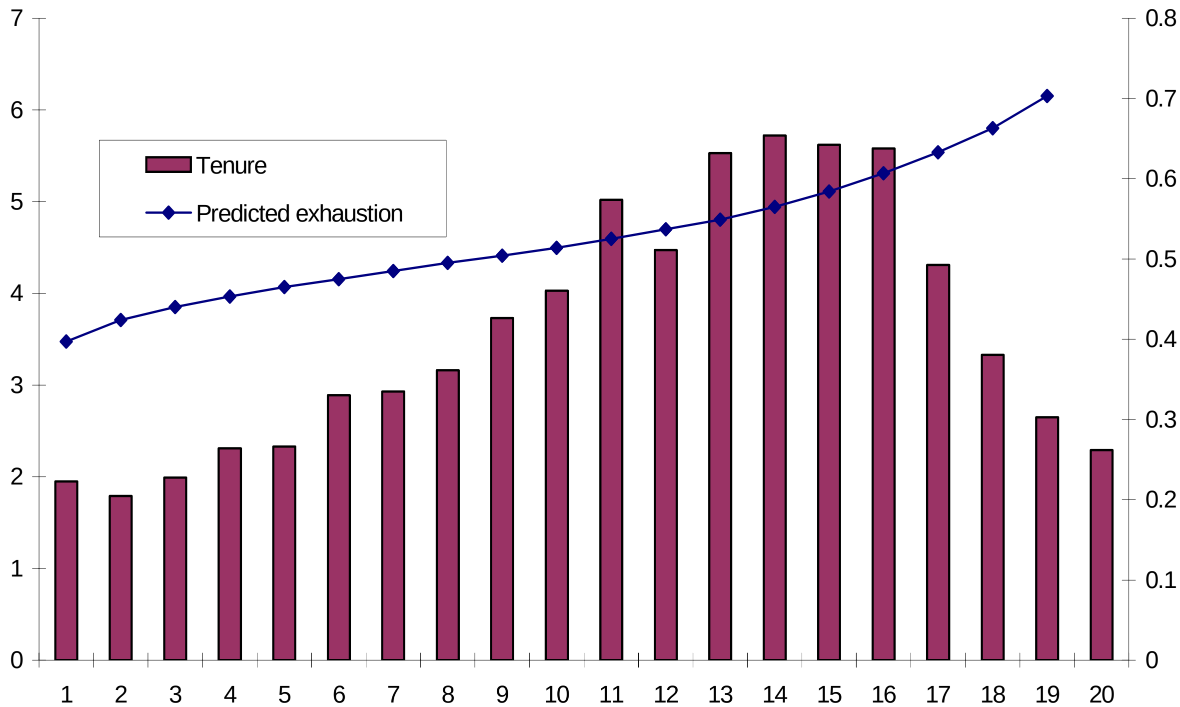

Figure 5 Distribution of Predicted Exhaustion Using Model A

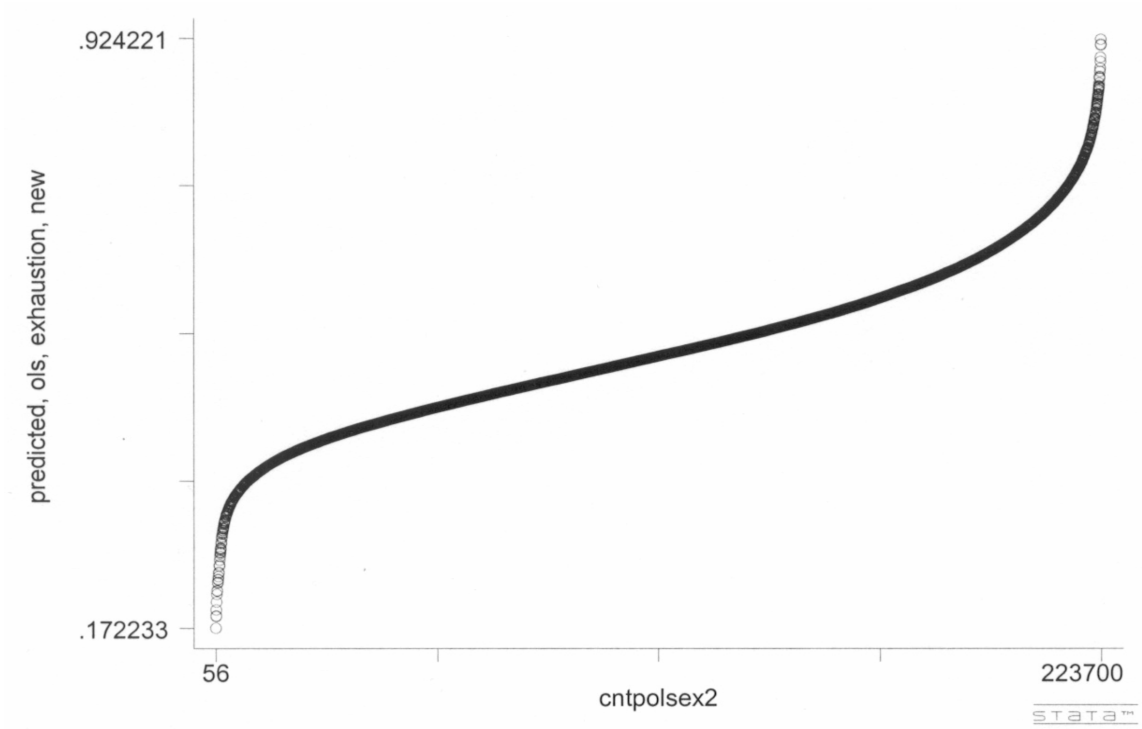

Figure 6 Distribution of Predicted Fraction of Benefits

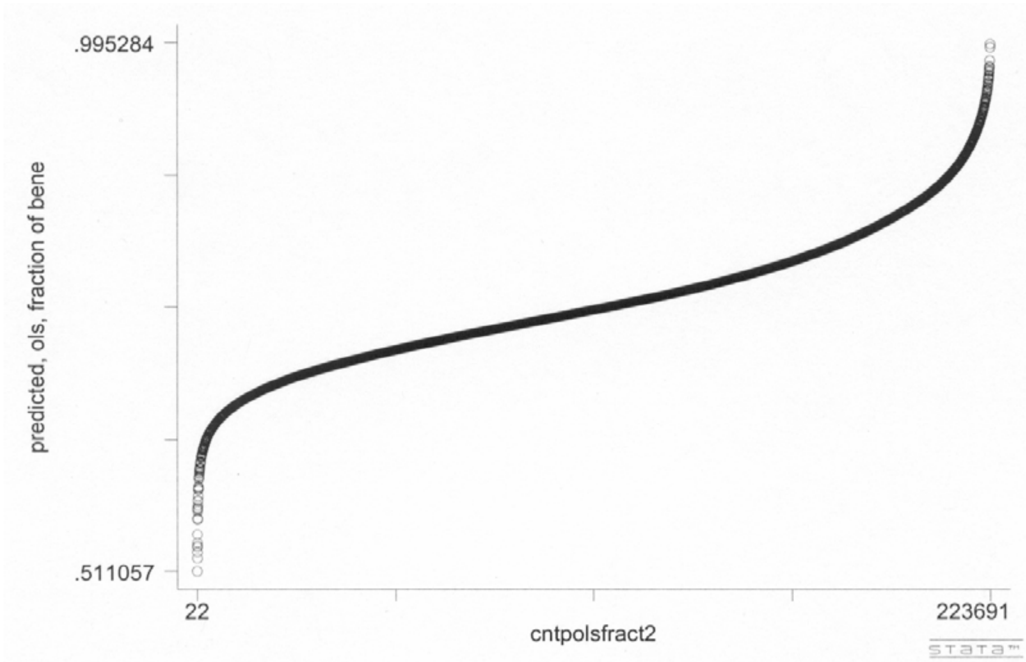

Figure 7 Distribution of Exhaustion Rate vs. Fraction of Benefits

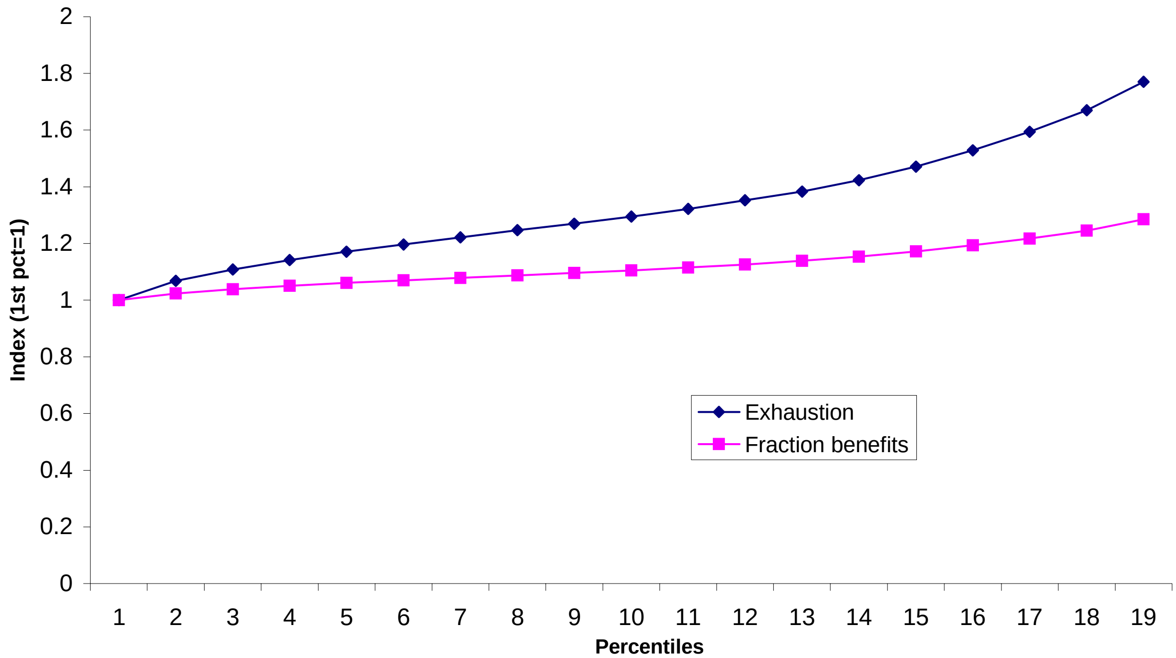

Figure 8. Fitness Test for Model Accuracy, Model A

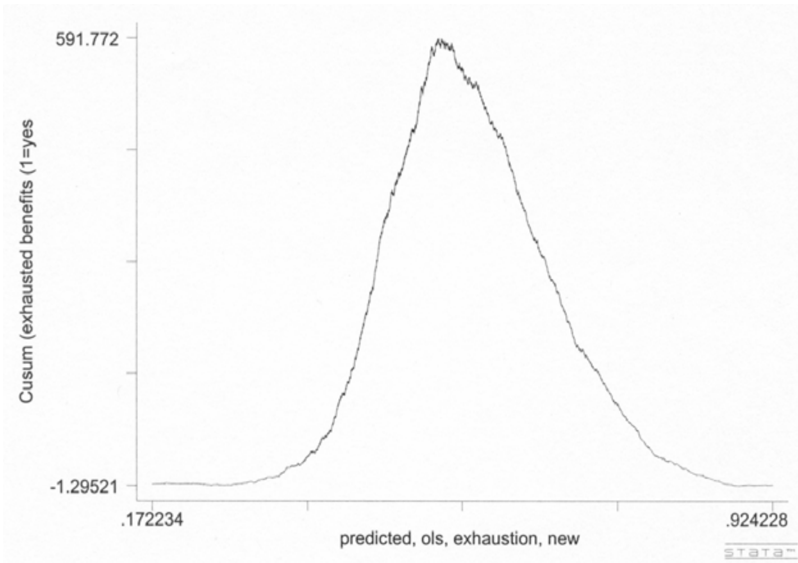

Figure 9. Fitness Test for Model Accuracy, Model B

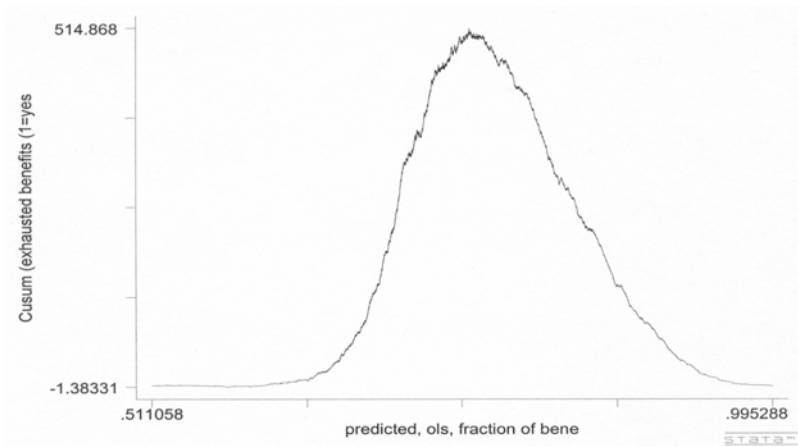

Figure 10. Fitness Test for Model Accuracy, Model A Upper 25% of Distribution

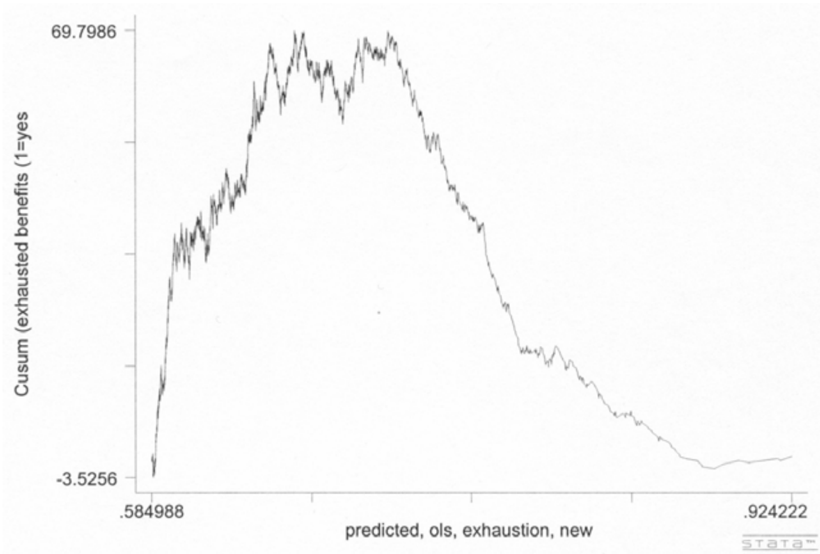

Figure 11. Fitness Test for Model Accuracy, Model B Upper 25% of Distribution

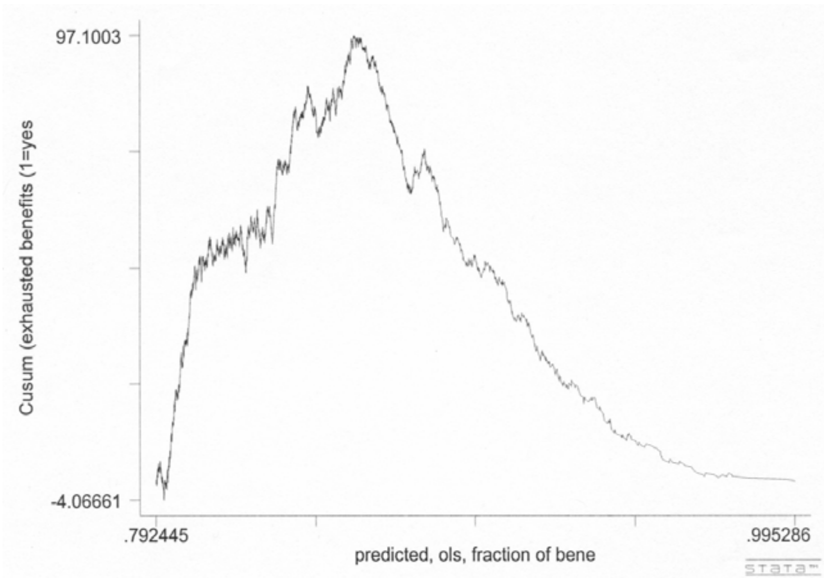

Figure 12. Exhaustion Rates using Percentiles Derived from Predicted Values of the Old and New Models