Predicting the Exhaustion of Unemployment Compensation
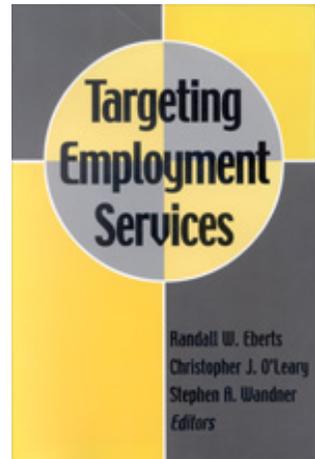
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It has been seven years since the Unemployment Compensation Amendments of 1993 (Public Law 103-152) spawned the Worker Profiling and Reemployment Services (WPRS) system. In that time, the U.S. Department of Labor (DOL) and the states have designed and implemented the WPRS system, which uses the unemployment insurance (UI) system to target reemployment services to permanently displaced workers early in their unemployment spells. The method of targeting used in most states is a two-step process called the worker profiling model. The model is intended to identify permanently separated workers who are likely to exhaust their UI benefits. The likelihood of benefit exhaustion is determined based on a statistical model of the relationship between worker characteristics, which are referred to as the explanatory variables in the model, and benefit exhaustion, which is the dependent variable in the model. As new claimants enter the UI system, they are assigned a probability of exhaustion based on their characteristics. Those claimants with the highest probabilities of exhaustion are referred to mandatory services under WPRS.

In this chapter, we examine the profiling models that states have constructed under WPRS, and we consider the efficacy of these models in targeting services to UI claimants who are most in need of services. In the first section of this chapter, we describe the details of the profiling models used in a sample of states. We focus particularly on the ways in which states have extended their profiling models beyond the prototype model that was developed by DOL. In the second section, we assess the predictive ability of the type of statistical model of benefit exhaustion that many states use. Our assessment is based on comparing the benefit exhaustion rates between claimants who are targeted for WPRS services and claimants who are not. In the third section, we consider whether states can update their statistical models without losing the capacity to identify claimants with high exhaustion probabilities.

WORKER PROFILING MODELS IN THE WPRS SYSTEM

WPRS attempts to identify UI claimants with a high potential for exhausting their benefits and provide them with reemployment services. Prior to WPRS, no objective or equitable mechanism existed for allocating reemployment services to those who needed them most. WPRS is a tool that facilitates both the identification of needy claimants and the allocation of services, such that those claimants most likely to exhaust their benefits receive highest priority in receiving available reemployment services.

In identifying likely exhaustees, states may use either characteristic screens or statistical models. Each method identifies characteristics common to recent exhaustees and targets current claimants who share these characteristics. Although neither method can target exhaustees with complete accuracy, both screens and models have been found to be more accurate than less systematic processes, such as random selection. Most states have chosen to implement statistical models since they offer greater accuracy and procedural flexibility than characteristic screens, and DOL has recommended that states adopt a statistical approach. A few states without sufficient historical data to develop a statistical model have chosen to implement screening methodologies and have taken steps to collect data necessary to develop models in the future.

With either method, the target population specified in the WPRS legislation is claimants who are "likely to exhaust." While the specific make-up of this population differs among states, the ultimate goal is to identify claimants whose job search skills are no longer sufficient to obtain suitable employment in their most recent line of work. Identifying these potential exhaustees is complicated for a number of reasons. First, the availability and integrity of historical data is poor in many states. Data from separate intake systems must often be merged, and these merges face logistical obstacles. Second, some readily available data on personal characteristics (such as ethnicity) have been determined to be discriminatory under federal equal opportunity legislation and thus cannot be used in profiling. Third, and perhaps most importantly, some key influences on benefit exhaustion, such as motivation and networking skills, are not quantifiable. These influences affect whether or not a claimant exhausts his/her benefits but cannot be measured and factored into a profiling model. Given these problems, it is difficult to develop a profiling model that accurately predicts exhaustion.

Although predicting exhaustion is an inexact science, states have been able to develop models that considerably reduce prediction errors relative to less rigorous methods. Most have either directly adopted the model initially developed by DOL in 1993 or have used it as a benchmark in developing state-specific models for identifying likely exhaustees. The DOL model consists of two initial screens, recall status and union hiring hall; a set of variables capturing the claimant's education, job tenure, industry, occupation, and the local unemployment rate. Originally developed from national data, the DOL model was first applied to state-level data in the test state of Maryland.

The national analysis demonstrated that education, job tenure, industry, occupation, and the local unemployment are all statistically related to UI benefit exhaustion. The Maryland test state project showed further that an operational state system could be readily developed from the national model. A number of states followed Maryland's lead in developing their own profiling models using very similar sets of variables. Such models, when applied to out-of-sample historical data (i.e., data not used to develop the model), are able to identify a higher percentage of exhaustees than the alternatives of random selection and characteristic screening. We further examine the predictive power of

the profiling model in the section "Accuracy in Identifying Likely Exhaustees."

Since considerable diversity exists among states, it is not surprising that several states have found that alternative specifications are needed to effectively model their populations. Because state data systems often retain a great deal more information than just these five variables from the national model, several states have expanded upon that model by testing additional variables in an effort to increase predictive ability. These states retained the variables from the national model and added those additional variables found helpful in identifying exhaustees.

The Dependent Variable in Worker Profiling Models

Since the inception of WPRS, benefit exhaustion has been the focal point in targeting those who are eligible. Public Law 103-152 requires states to "identify which claimants will be likely to exhaust regular compensation." Therefore, the law focuses on a binary outcome: a claimant either exhausts regular unemployment insurance compensation or (s)he does not. The dependent variable in the national model was coded as "1" for exhaustees and as "0" for non-exhaustees. The output of the model is the predicted probability that each claimant will exhaust benefits. Both the national and Maryland versions of the DOL model use logistic regression to model benefit exhaustion. A few states have correctly noted that this approach discards information; a claimant who almost exhausted is not distinguished from a claimant who came nowhere near exhausting, although the near-exhaustee may experience a greater need for reemployment assistance. Also, since benefits in most states are subject to variable potential duration, referrals of likely exhaustees may include some claimants with very low potential duration among those referred to reemployment services.

As a result, some states have experimented with alternatives to a binary dependent variable representing exhaustion of unemployment compensation. Some states have tested different dependent variables, such as UI duration and the ratio of benefits drawn to benefit entitlement, and estimated these profiling models via ordinary least squares (OLS). While these states typically found that these models targeted exhaustees no more accurately than the logistic model predicting the binary exhaustion variable, the OLS estimation used to test these mod-

els ignores the fact that the alternative dependent variables are "censored." UI duration cannot exceed some maximum (usually 26 weeks), and the benefit ratio must be between zero and 1. Maximum likelihood techniques exist to accommodate censored dependent variables, and evidence suggests that combining these techniques with dependent variables that use differences between short-term claimants and near-exhaustees can improve the targeting of profiling models (Berger et al. 1997).

Modeling the binary exhaustion variable still allows several options for defining what constitutes "exhaustion." In the DOL model, claimants are coded as exhaustees if they draw 100 percent of their entitlement and are otherwise coded as non-exhaustees. Some states have expanded the scope of the exhaustion variable by using a more general definition. For example, some states code claimants who depleted at least 90 percent of benefits as exhaustees. A related variation is to code claimants who exhaust a high percentage of benefits within a given time frame as exhaustees (e.g., 80 percent within six months of their benefit year begin [BYB] date). This variation would also expand the definition to include both exhaustees and near-exhaustees, and it would also shorten the lag time for discerning exhaustion outcomes. Finally, exhaustion has also been redefined to automatically include claimants collecting extended unemployment compensation, since they had, by definition, exhausted regular benefits.

Other states have narrowed the scope of the exhaustion variable. For example, some states have determined that claimants who take a full calendar year to exhaust 26 weeks of benefits are not truly in need of reemployment services; they may simply be collecting UI benefits between intervening spells of employment. To compensate, a time limit has been set (for example, eight months from BYB date) after which historic claimants would not be coded as exhaustees. Weeks of potential duration have also been used as a criterion for narrowing the scope of the dependent variable. Variable duration complicates the use of exhaustion as the dependent variable because, *ceteris paribus*, claimants with shorter potential durations have higher likelihoods of exhaustion but may not need reemployment assistance. To compensate, some states have set a minimum potential duration below which historical claimants cannot be coded as exhaustees. Narrowing the definition of exhaustion using potential duration has been most useful for states that

find that many short-duration—and perhaps seasonal—exhaustees pass all of the initial screens (e.g., recall, union hiring hall) yet are not truly in need of reemployment services.

Explanatory Variables in Worker Profiling Models

While a few alternative definitions of the dependent variable have been tested, most experimentation has involved the explanatory variables. The national model includes the following five variables: education, occupation, industry, tenure, and unemployment rate. Some states, such as Maryland, adopted only these five variables into their own models and estimated state-specific parameters. Others included additional variables in their models. Most states collect education, occupation, and tenure through their job service registration. Industry information (as well as other, noncore variables) typically come through information gathered during the qualification process for unemployment benefits. The unemployment rate and information on declining industries and occupations often come from a labor market information unit.

Education

Education is often measured as the number of years completed and is then categorized into intervals for inclusion in the model. When education data are accurate and variation exists within the population, profiling models often identify a strong inverse relationship between education and exhaustion. However, in areas where skill levels and educational backgrounds are fairly homogenous, education is not a very effective predictor of exhaustion.

Job tenure

Like education, job tenure is measured in years and categorized into intervals, which are included in the profiling model. There are reasons to believe that job tenure and exhaustion should be positively related. Claimants with long pre-unemployment job tenure are likely to have outdated skills or be unfamiliar with current job search strategies. The evidence suggests that exhaustion is positively associated with years of job tenure.

Occupation

The occupation of a claimant's pre-unemployment job may contain valuable information about the likelihood that the claimant will exhaust UI benefits. Unfortunately, occupational coding is a significant obstacle to including occupations in profiling models. In general, most problems with occupational coding involve either incomplete data or multiple coding schemes. Few states have been able to incorporate meaningful occupational effects into their WPRS systems. Because occupational information would likely be valuable in predicting long-term unemployment, the development of reliable methods for coding claimants' occupations could be very helpful to state WPRS systems.

Industry

Because states are legally required to use either industry or occupation in their WPRS systems, and because creating reliable occupation variables is difficult, most states have included industry variables in their profiling models. Data on industries tend to be fairly reliable because they are typically captured from UI wage records. Industry information is included in some profiling models as a categorical variable indicating employment in a particular industry, and in other models as a measure of the employment change in the industry. Regardless of how industry information is captured, almost all states have partially collapsed the Standard Industrial Classification codes from the four-digit levels in which they are typically recorded because four-digit industries are typically too small to reflect the labor markets faced by claimants.

Unemployment rate

In their profiling models, most states account for regional differences that may affect UI exhaustion. Even the smallest states exhibit a great deal of regional diversity. Therefore, it should not be surprising that regional indicators are usually strong predictors of exhaustion. Because exhaustion is likely higher in areas with high unemployment, most states include unemployment rates from the Local Area Unemployment Statistics program in their models. In states where unemployment and exhaustion are not closely correlated, regional indicator variables are used to control for regional differences in exhaustion. Although these regional variables do not vary across claimants within

particular regions, the inclusion of regional information may produce a more accurate profiling model.

Other variables

While some states have used only the five variables from the national model, others have used them as a benchmark for building a model with a more extensive list of explanatory variables. Development and testing of additional variables is encouraged by DOL, provided either industry or occupation is included and all discriminatory variables are excluded. Several states have done a considerable amount of research, yielding the additional variables described in the remainder of this section.

The variable "pre-unemployment earnings" contains information about the claimant's job skills and reservation wage, i.e., the lowest wage offer that the claimant would accept. Job skills are difficult to measure directly, but to the extent that workers are paid according to their productivity, higher wages are associated with higher skills. Furthermore, because claimants will not work for wages below their reservation wages, pre-unemployment earnings provides information about the minimum earnings that would be required for them to leave unemployment for work. Therefore, some states include pre-unemployment earnings in their profiling models. Other states use it to compute the UI replacement rate and then include the replacement rate in their models.

A claimant's weekly benefit amount (WBA) may contain information about his or her likelihood of exhausting benefits. WBA can be used to compute UI's "wage replacement rate," which equals WBA divided by pre-unemployment weekly earnings. Because this rate is inversely related to the financial hardship from remaining unemployed, we would expect a positive relationship between the wage replacement rate and exhaustion. This expectation is confirmed by the estimates from state profiling models. However, at least one state found that the replacement rate primarily identifies exhaustees with low potential duration because they worked less during the base period.

Some states have included the potential duration of UI benefits as an explanatory variable in their profiling models. Claimants with a short potential duration are much more likely to exhaust their benefits but are unlikely to be "dislocated workers," i.e., the target population

for WPRS services. Therefore, we may want to think of two different groups of variables that help to explain exhaustion: those that explain exhaustion because they indicate "dislocation" (such as job tenure) versus those that explain exhaustion for programmatic and other reasons (such as potential duration). To target WPRS services toward dislocated workers, it may be reasonable to use all of these variables in estimating the profiling model, but to use only those that signal worker dislocation to assign claimants to mandatory WPRS services.

A measure of the delay in filing for unemployment compensation has also been included by some states as a predictor of exhaustion.[1] This delay is captured by either a single variable measuring number of days, or by several variables indicating different ranges for the number of days. Claimants who do not expect to have reemployment difficulty may not immediately file for UI benefits. Four states (of the 13 sampled) were impressed enough with the ability of delay variables to predict exhaustion that they included them in their profiling models. The delay variable appears to be more effective at predicting exhaustion in urban areas than in rural areas. Among rural workers, difficulty in accessing a UI (field) local office may be the primary reason for delays in filing for benefits.

The ratio of highest quarterly earnings to the earnings in the base year is also used as an explanatory variable in their profiling models. Large values of this ratio may identify intermittent workers, workers with difficulties in holding a steady job, or perhaps workers in seasonal industries. While states have found a strong positive relationship between this ratio and exhaustion, the type of workers identified by high ratios are probably not the dislocated workers targeted by WPRS. Therefore, it may be sensible to include this variable in the profiling model but to exclude it in selecting workers for mandatory WPRS services.

A claimant with many employers in the base year may have either worked multiple jobs at the same time, suggesting a strong preference for or need to work, or switched employers, suggesting recent experience with the process of searching for a job. Either scenario suggests a low exhaustion probability. Estimates of state profiling models support this prediction: controlling for the other explanatory variables, exhaustion is negatively correlated with the number of employers in the base

year. However, because it is unclear whether this variable helps to identify displaced workers, the use of this variable in worker profiling deserves further consideration.[2]

Whether or not states include certain explanatory variables in the statistical model may depend on their philosophy with respect to WPRS targeting as well as the predictive power of the variable. Claimants may be likely to exhaust their benefits either because they face barriers to reemployment or because they are reluctant to return to work quickly. Variables that help predict exhaustion may be related to either of these factors. Most of the variables in the DOL prototype profiling model were intended to identify claimants who were likely to exhaust their benefits because they faced barriers to reemployment. Some variables that states have considered adding to the model are more closely related to the incentives claimants face to return to work quickly. For example, higher WBAs are probably positively related to exhaustion because the financial incentive to return to work quickly is lower for claimants with higher WBAs, other things being equal. In deciding whether to include WBA in the profiling model, states need to decide whether they want to target reemployment services to such claimants. Although these claimants do not necessarily face barriers to reemployment, the mandatory nature of WPRS may still bring about a significant reduction in their UI spells.

ACCURACY IN IDENTIFYING LIKELY EXHAUSTEES

The two-step profiling model is designed to identify UI claimants likely to exhaust their benefits and refer them to services. If the approach is at least partially successful, we would expect that in the absence of services, the claimants targeted for services would collect more benefits and exhaust their benefits at a higher rate than claimants not targeted. To investigate the success of the profiling model, we compare claimants targeted for services to other claimants on the basis of exhaustion and benefits collected. However, simply comparing claimants referred to services with claimants not referred will not provide a valid comparison if services have an impact on outcomes. If, for example, services substantially reduce UI receipt, the claimants re-

ferred to services may exhaust benefits at a lower rate than nonreferred claimants, even though services were targeted to claimants with high expected probabilities of exhaustion.

Ideally, to conduct a test of the profiling model, we would like data on a group of nonreferred claimants and a group of referred claimants who were not actually offered services. Fortunately, data from two recent UI experiments sponsored by the U.S. Department of Labor provide just such a group. In the Job Search Assistance Demonstration, which was conducted in Washington, D.C., and Florida from 1995 to 1996 (prior to implementation of WPRS), claimants were profiled using the two-step profiling model, and those claimants identified as likely to exhaust their benefits were randomly assigned to one of three treatment groups or a control group. Claimants assigned to a treatment group were offered special, mandatory reemployment services, while those assigned to the control group were offered only the existing services offered to all UI claimants (pre-WPRS) and were not offered the mandatory services.[3] The control group therefore provided a representative group of claimants targeted for extra services based on the profiling model who were not actually offered extra services—therefore, they were on a "level playing field" with nonreferred claimants in terms of available services. Hence, Decker, Freeman, and Klepinger (1999) were able to make comparisons between the control group and the nonreferred claimants that are attributable to profiling and not to the services linked to profiling.

Another recent UI experiment, the New Jersey UI Reemployment Demonstration Project, also offered an opportunity to test the profiling model. In their long-run follow-up study of the data from the New Jersey project, Corson and Haimson (1996) used the control group and the ineligible claimants to construct and estimate a two-step profiling model. They then applied the model to the same group, simulating the selection of a group to be referred to services and a group not referred to services. Since none of the claimants used in the exercise were offered services, the differences in outcomes for the simulated groups can be attributed to the profiling model.[4]

In this section we present findings from the Job Search Assistance (JSA) and New Jersey demonstrations on the effectiveness of the profiling model in targeting claimants who are likely to experience long spells of UI receipt and exhaust their benefits. Our analysis is based on

three conceptual groups of profiled claimants, which are shown in Figure 2.1. The first group (group A) consists of claimants who did not pass the initial eligibility screens. The claimants who passed the screens are divided into two groups. One group (group B) consists of claimants who passed the initial screening criteria but whose predicted probabilities of benefit exhaustion were below the threshold used to identify claimants to be referred to services. The other group (group C) consists of control group members who passed the screens and whose predicted exhaustion probabilities were above the threshold. This group is representative of all claimants who were referred to demonstration services based on having high exhaustion probabilities.

We examine the effects of both steps in the profiling model by comparing mean outcomes among the three groups defined above. Our comparisons are conducted in two stages in order to examine separately the effect of each step in the profiling model. In the first stage, we compare outcomes for claimants who were excluded by the initial screens (group A) with outcomes for claimants who passed the screens (groups B and C combined). Outcomes for these claimants are shown in Table 2.1. In the second stage, we focus just on claimants who

Figure 2.1 Profiled UI Claimants: Three Conceptual Outcomes
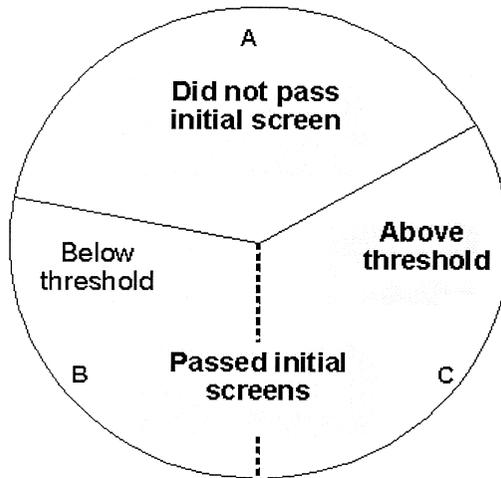
Table 2.1 Mean UI and Employment Outcomes by Initial Screening Status

Outcome	Washington, D.C.		Florida		New Jersey[a]	
	Did not pass initial screens	Passed initial screens	Did not pass initial screens	Passed initial screens	Did not pass initial screens	Passed initial screens
Exhausted UI benefits (%)	43.9	54.6[b]	37.7	43.3[b]	29.7	44.1
Weeks of UI benefits	18.5	19.6	13.6	15.2	ND[c]	ND
Earnings in first quarter[d] ($)	1,819	1,543[b]	2,370	1,933[b]	ND	ND
Earnings in fourth quarter[d] ($)	1,837	1,785	2,658	2,953[b]	ND	ND
Employed with same employer (%)	61.2	50.6[b]	44.4	29.1[b]	ND	ND

[a] Significance tests were not run on the New Jersey outcomes.
[b] Mean outcome for group that passed initial screens is significantly different than the mean outcome for group that did not pass at the 95% confidence level.
[c] ND = no data available.
[d] The first and fourth calendar quarters after the benefit year begin date.

passed the initial screens. For this group, we compare outcomes of claimants above the probability threshold (group C) with those below the threshold (group B). Outcomes for these claimants are shown in Table 2.2.

The primary outcome of interest is the rate of benefit exhaustion, because the second stage of the profiling model assigns a predicted probability of exhaustion to each claimant. We expected the targeted group—the group above the threshold—to have a higher rate of benefit exhaustion than the group below the threshold or the group not passing the initial screens.[5] We also expected claimants above the threshold to have longer UI spells, higher earnings, and to return to their previous employers at a lower rate, since the initial screens are related to employer attachment.

Our findings confirm that the profiling model identified claimants who were likely to spend a long time on UI, and each step of the model appears to contribute to this identification. Although the initial screens used in the first step of the profiling model were not designed specifically to exclude claimants with short spells, they appear to have done so. Claimants who passed the initial screens had higher exhaustion rates and longer UI spells than those who did not pass, as shown in Table 2.3. In Washington, D.C., the claimants who passed the screens had a benefit exhaustion rate of 54.6 percent, compared with 43.9 percent for those who did not pass the screens. Similar differences were found for Florida and New Jersey, although the differences between the groups are somewhat smaller in Florida than in either of the other two states.

Comparisons of the average UI spells yield similar findings. In Washington, D.C., the claimants who passed the screens had average UI spells that were about a week longer than the average for claimants excluded by the screens: 19.6 for those passing compared with 18.5 for those not passing. In Florida, the difference between the groups is a bit greater than one week: 15.2 for those passing compared with 13.6 for those not passing.

Not surprisingly, given the findings on UI benefits, the use of the initial screens also tended to target claimants with low earnings early in their benefit year. In both Washington, D.C. and Florida, claimants passing the screens had substantially lower earnings in the first quarter after their BYB date than those not passing. However, this difference

Table 2.2 Mean UI and Employment Outcomes by Probability Threshold Status

Outcome	Washington, D.C.		Florida		New Jersey[a]	
	Below threshold	Above threshold	Below threshold	Above threshold	Below threshold	Above threshold
Exhausted UI benefits (%)	47.9	58.8[b]	40.0	45.0[b]	40.5	52.5
Weeks of UI benefits	18.6	20.1[b]	14.1	15.8[b]	ND[c]	ND
Earnings in first quarter[d] ($)	1,739	1,422[b]	2,232	1,772[b]	ND	ND
Earnings in fourth quarter[d] ($)	2,118	1,580[b]	3,462	2,679[b]	ND	ND
Employed with same employer (%)	49.1	51.4	27.6	29.9	ND	ND

[a] Significance tests were not run on the New Jersey outcomes.
[b] Mean outcome for group that passed initial screens is significantly different than the mean outcome for group that did not pass at the 95% confidence level.
[c] ND = no data available.
[d] The first and fourth calendar quarters after the benefit year begin date.

Table 2.3 Contamination in Worker Profiling

	Uncontaminated profiling model[a]	
Contaminated profiling model[b]	Below threshold	Above threshold
25% Threshold for eligibility		
Below threshold	66.2	8.8
Above threshold	8.8	16.2
50% Threshold for eligibility		
Below threshold	36.5	13.5
Above threshold	13.5	36.6

[a] The workers used to estimate the uncontaminated profiling model include ineligibles and workers who were assigned to the control group. Explicitly excluded are workers assigned to Structured Job Search Assistance, IJSA, or IJSA+.
[b] The workers used to estimate the contaminated profiling model include ineligibles and workers who were assigned either to Individualized Job Search Assistance (IJSA) or to Individualized Job Search Assistance Plus Training (IJSA+).

disappeared or reversed late in the benefit year. In the fourth quarter after the BYB date, earnings were similar for the two groups in Washington, D.C., and in Florida the claimants who passed the screens had higher earnings than those not passing. The findings suggest that the initial screens tended to exclude claimants who quickly returned to work but who also did not have high earnings once back on the job.

As expected, the initial screens excluded claimants who were more likely to return to their previous employer. Of the claimants in Washington, D.C., who were excluded by the screens and reemployed in the first quarter, 61.2 percent returned to their previous employer. This exceeds the 50.6 percent of Washington, D.C., claimants who passed the screens and returned to their previous employer. The difference between these groups is probably attributable to the screen that excluded claimants who reported that they expected to be recalled by their previous employer on a particular date.

The second step in the profiling model—the application of the exhaustion probability threshold—further directed services to a group of claimants with high exhaustion probabilities and long UI spells. Table 2.1 shows that in Washington, D.C., 58.8 percent of claimants above the threshold ultimately exhausted their benefits compared with 47.9

percent of those below the threshold. The difference between the groups was somewhat smaller in Florida, where there was a 45.0 percent exhaustion rate for those above the threshold compared with 40.0 percent for those below. The pattern of these differences also holds for New Jersey, where claimants above the threshold had an exhaustion rate of 52.5 percent compared with 40.5 percent for those below.

The findings for the other outcomes are consistent with those for exhaustion. Claimants above the threshold in Washington, D.C., and Florida had longer UI spells and lower earnings throughout the benefit year. It is interesting to note that claimants above and below the threshold did not differ greatly in their likelihood of being recalled to their previous employer. In each state, the recall rate is slightly higher for the group above the threshold, but the difference is not statistically significant. Since the probability threshold (unlike the initial screens) is not directly tied to the date of recall, these findings are not surprising.

Overall, our findings demonstrate that the profiling model achieves the objective of targeting claimants who are likely to have long UI spells and exhaust their benefits, and both steps of the model contribute to this achievement. However, the targeting effect of the profiling model is limited. The models do not separate claimants into one group in which nearly everybody exhausts and another group in which practically nobody exhausts. Our estimates for Florida demonstrate this clearly. The claimants who were targeted for services because they were above the probability threshold had a benefit exhaustion rate that was a relatively modest 5 percentage points higher than those below the threshold (45 percent compared with 40 percent). The differences were somewhat larger in the other two states, but never greater than 12 percentage points. This is a reflection of the difficulty in predicting UI outcomes, especially a binary outcome like whether benefits are exhausted, based on the characteristics and work experience of individual claimants at the time they filed their initial claim. Even after accounting for the characteristics included in the statistical model, a substantial part of the variation in exhaustion and UI spells remains unexplained by the models.

The analysis in this section has provided only a first step in evaluating the efficacy of the profiling model. Our findings suggest that the model targets services to workers who appear to be most in need of services. But we may also be interested in whether the profiling model

targets services to claimants who will benefit most from the services. To answer this question, we would need to be able to estimate and compare the impacts of services for referred and nonreferred claimants. Although we do not have the data necessary to address this question directly, we can at least use the data from our evaluation of the JSA demonstration to evaluate how service impacts vary as the probability threshold is increased. Findings on this point have been presented in the final report on the JSA demonstration.

CONTAMINATION IN ESTIMATING THE WPRS MODEL

The worker profiling model used to determine eligibility among UI claimants in Florida was estimated from data collected in the JSA demonstration in 1995–1996. However, as the economic environment changes, the effectiveness of this profiling model in identifying UI claimants likely to exhaust their benefits is likely to decline. Therefore, Florida and other states should consider updating their profiling models as economic conditions change.

Given the implementation of the WPRS system, new estimates of these profiling models will be "contaminated" because eligible UI claimants are required to participate in WPRS. Worker profiling is designed to identify UI claimants who would likely exhaust their benefits if they were not required to participate in WPRS. However, those identified as likely exhaustees are required to participate in WPRS, and whether they subsequently exhaust their benefits is influenced by WPRS participation if the program is effective. Therefore, profiling models estimated from UI data that are collected after the implementation of WPRS and used in WPRS models will provide biased estimates of the exhaustion probabilities if targeted workers were not required to participate in WPRS.

Fortunately, data from the JSA demonstration in Florida can be used to measure the size of this contamination. This demonstration included a control group of UI claimants who passed the state screens (and were thereby deemed eligible by the state), who exceeded the threshold probability of exhaustion, but who were *not* assigned to a mandatory treatment group with requirements similar to those in

WPRS. We can combine the control group with the claimants determined to be ineligible for the demonstration to construct a claimant sample that is representative of the claimant population. Since none of these claimants were required to participate in demonstration services, this sample can be used to estimate and test an "uncontaminated" profiling model.[6]

Because the current WPRS system is very similar to two of the three treatments in the JSA demonstration—Individualized Job Search Assistance (IJSA) and Individualized Job Search Assistance with Training (IJSA+)—we can use claimants assigned to these two treatments, along with demonstration-ineligible claimants, to represent the UI population under WPRS. Only those claimants deemed likely to exhaust their benefits were required to participate in either IJSA or IJSA+. From this sample of participants and ineligible nonparticipants, we estimate and test a "contaminated" profiling model.[7]

In this section, profiling results from the contaminated model are compared to profiling results from the uncontaminated model in Florida. Each model is used to predict exhaustion and to select claimants to be referred to services on the basis of two different eligibility criteria (described later). To measure the impact of contamination, we address the following three questions:

1) Does the contaminated profiling model target services to a different group of claimants than the uncontaminated model? (And to what extent?)

2) Does the contaminated profiling model target services to claimants who are less likely to exhaust their benefits than the uncontaminated model? (i.e., does contamination lead to less effective targeting of services to claimants likely to exhaust their UI benefits? And to what extent?)

3) Does the contaminated profiling model target services to claimants whose characteristics are different from the characteristics of claimants targeted by the uncontaminated model? (And to what extent?)

To address the first question, we measure the degree of overlap between the claimants targeted for services by the uncontaminated profiling model and the claimants targeted for services by the contaminated model under two possible targeting rules. Under the first targeting

rule, claimants in the top 25 percent of all profiling scores are referred to services; the 75th percentile in the profiling score distribution defines the profiling score threshold above which claimants are assigned to services. Under the second targeting rule, claimants in the top 50 percent of all profiling scores are referred to services. Because the contaminated and uncontaminated models produce different profiling scores, the group of claimants referred to services under any targeting rule might depend on which model was used to compute profiling scores. For the two targeting rules, Table 2.3 presents the percent of claimants who would be referred to services based on 1) both the uncontaminated model and the contaminated model; 2) the uncontaminated model only; 3) the contaminated model only; and 4) neither model. If both models targeted the same group of claimants for services, we would expect those percents to be 25 percent, 0 percent, 0 percent, and 75 percent, respectively, for the first targeting rule, and 50 percent, 0 percent, 0 percent, and 50 percent, respectively, for the second targeting rule.

Table 2.3 shows that there is a high degree of consistency between the claimants who would be referred to services based on the two profiling models. For the 25 percent threshold, 16.2 percent of claimants are targeted by both models, versus the 25 percent that we would expect if the two models were perfectly consistent. For the 50 percent threshold, 36.6 percent of claimants are targeted for services by both models, versus the 50 percent that we would expect if the two models were perfectly consistent. The two models are highly if not perfectly consistent because they predict high exhaustion probabilities for many of the same UI claimants.

However, contamination may still be a serious issue if the claimants targeted by the contaminated model have much lower exhaustion rates (in the absence of IJSA and IJSA+) than the claimants deemed eligible by the uncontaminated model (question 2). To answer this question, we compare the two models with respect to exhaustion rates. The sample for this comparison excludes those used in estimating the two models and excludes those assigned to one of the demonstration treatments, which may influence exhaustion. Table 2.4 provides exhaustion rates separately for those targeted for services according to each of the two models.

Table 2.4 UI Exhaustion Rate by Profiling Status (%)

Threshold/model	Below threshold	Above threshold
25% Threshold for eligibility		
Uncontaminated profiling model[a]	41.3	48.9
Contaminated profiling model[b]	41.7	47.7
50% Threshold for eligibility		
Uncontaminated profiling model[a]	40.2	46.2
Contaminated profiling model[b]	39.8	46.6

[a] The workers used to estimate the uncontaminated profiling model include PTS ineligibles and workers who were assigned to the control group. Explicitly excluded are workers assigned to Structured Job Search Assistance, IJSA, or IJSA+.

[b] The workers used to estimate the contaminated profiling model include PTS ineligibles and workers who were assigned either to Individualized Job Search Assistance (IJSA) or to Individualized Job Search Assistance Plus Training (IJSA+).

Before addressing the implications of Table 2.4 for contamination, consider the targeting effectiveness of the uncontaminated model. A perfect model deems only those claimants who would subsequently exhaust their benefits in the absence of mandatory services as eligible. Those predicted by a perfect model to be above the threshold should exhaust at a rate of 100 percent, versus 0 percent for those below the threshold. While the model falls far short of this ideal, it performs better than a process that selects eligibles randomly. Random selection would lead to exhaustion rates that are nearly identical for those above and those below the threshold. However, Table 2.4 indicates that those above the 25 percent threshold exhaust at a rate of 48.9 percent, versus 41.3 percent for those below the 25 percent threshold. Therefore, the uncontaminated model helps to target mandatory services to those more likely to exhaust their benefits.

Does the contaminated model target those with high exhaustion probabilities as effectively as the uncontaminated model? The answer appears to be yes. For both eligibility thresholds, the difference between the exhaustion rates of those above and those below the thresh-

old—a measure of targeting effectiveness—is nearly the same for the contaminated model as for the uncontaminated model. Therefore, contamination from IJSA and IJSA+ does not appear to reduce the targeting effectiveness of Florida's profiling model.

Lastly, we may want to know whether the characteristics of eligibles selected by the contaminated model differ from the characteristics of eligibles selected by the uncontaminated model (question 3). Table 2.5 contains the mean characteristics for the following four groups from the sample:

1) All of those above the 25 percent threshold (i.e., deemed eligible) according to the uncontaminated model.
2) All of those above the 25 percent threshold according to the contaminated model.
3) All of those above the 25 percent threshold according to the uncontaminated model, but below the threshold according to the contaminated model.
4) All of those above the 25 percent threshold according to the contaminated model, but below the threshold according to the uncontaminated model.

The difference in the mean characteristics between those deemed eligible by the uncontaminated and contaminated models (group 1 vs. 2) is driven by two factors. First, as shown in Table 2.2, the two models do not select exactly the same set of eligibles. Second, those selected only by the uncontaminated model may differ from those selected only by the contaminated model (3 vs. 4). Therefore, the differences between groups 3 and 4 will be larger than and partially responsible for the differences between groups 1 and 2. Table 2.5 provides the means needed to make these comparisons for a subset of the variables used in profiling: the unemployment rate, job tenure, and education.

Table 2.5 reveals that the mean characteristics differ considerably between those deemed eligible by the contaminated model and those deemed eligible by the uncontaminated model. These differences result from differences in the estimated logit coefficients between the contaminated and uncontaminated models. However, because both profiling models are imprecisely estimated (perhaps because of small sample sizes), the differences in the estimated coefficients and there-

Table 2.5 Mean Characteristics of Workers above the 25% Threshold by the Profiling Model (Uncontaminated or Contaminated)

Variable	All uncontaminated	All contaminated	Only uncontaminated	Only contaminated
Predicted exhaustion (PTS)	0.520	0.512	0.528	0.505
Unemployment rate	7.962	7.501	7.733	6.419
Job tenure (yr.)				
0–3	0.556	0.615	0.533	0.702
3–6	0.162	0.075	0.272	0.025
6–10	0.142	0.105	0.150	0.043
10+	0.140	0.205	0.044	0.230
Education				
High school dropout	0.446	0.477	0.261	0.350
High school graduate	0.364	0.429	0.374	0.561
Associate's degree	0.104	0.038	0.206	0.017
Bachelor's degree	0.073	0.043	0.135	0.048
Master's/doctoral degree	0.013	0.013	0.024	0.023
N (unweighted)	2,658	2,629	950	921
N (weighted)	22,734	22,724	7,979	7,969

fore in the characteristics of the eligibles selected may largely be attrib-
utable to sampling error. We believe that additional studies are re-
quired to determine whether the differences revealed in this table are
robust. Furthermore, despite the differences in mean characteristics,
the difference in the mean exhaustion probabilities used to determine
eligibility in the JSA demonstration is very small. This suggests that
the mean differences in characteristics used to predict exhaustion are
off-setting. Both the actual exhaustion rates (Table 2.4) and those pre-
dicted by the JSA demonstration (Table 2.5) are comparable between
those deemed eligible by the contaminated model and those deemed el-
igible by the uncontaminated model.

Tables 2.3, 2.4, and 2.5 suggest that the degree of contamination in
estimating exhaustion probabilities from data that include workers re-
quired to participate in Florida's JSA demonstration is very small. If
these results are proven robust across states and years, states planning
to reestimate their worker profiling models should not be concerned
about contamination from mandatory service provision through WPRS.
This conclusion is consistent with previous research that measures fair-
ly 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.

However, results not shown here suggest that states with more in-
tensive programs may face greater contamination from the effect of
WPRS on exhaustion rates. Florida's JSA demonstration included a
program, Structured Job Search Assistance (SJSA), that provided more
intensive services than the existing WPRS program in Florida. There-
fore, workers randomly assigned to SJSA can be used to estimate the
amount of contamination that might occur in states with more intensive
WPRS programs than Florida's. Results from an analysis of this group
suggest that the contamination of Florida's profiling model by manda-
tory SJSA services reduces our measure of targeting efficiency—the
difference between the exhaustion rates of those above and those below
the threshold—by 35 percent (if half of the claimants are eligible).
Therefore, more intensive services with a greater impact on exhaustion
rates may diminish the effectiveness of updated profiling models in
predicting which UI claimants would exhaust their benefits without
these services.

CONCLUDING REMARKS

The goal of the WPRS system is to provide reemployment services to displaced workers, and different states take different approaches to selecting claimants for these services. However, most states use some form of statistical model to predict whether or not claimants will exhaust their benefits in the absence of mandatory WPRS services. Furthermore, most states using statistical models use those variables selected for the national model—education, occupation, industry, job tenure, and the unemployment rate—and perhaps include some additional variables described in the first section of this chapter.

The evidence suggests that the states' efforts in developing profiling models that target likely exhaustees have not been in vain. The profiling models appear to perform better at such targeting than random selection. Both the benefit exhaustion rate and the duration of UI benefits were higher for targeted claimants (who were not assigned to mandatory treatment services) than for other claimants.

However, the targeting power of the profiling models is modest. While the gain in targeting may well produce benefits that exceed the costs of the program (an issue not addressed in this chapter), profiling models fall far short of perfect targeting. In Washington, D.C., for example, even those not targeted for reemployment services had an exhaustion rate of 47.9 percent (versus 58.8 percent for targeted claimants). Exhaustion seems to be very difficult to predict accurately with available demographic and labor market data.

Perhaps more interesting than how well profiling models targeted exhaustees in the past is how well they will target exhaustees in the future. Changes in the economy suggest the need for states to update their profiling models. However, given the legal requirements of WPRS, it is no longer possible to observe whether claimants would have exhausted their benefits in the absence of WPRS because the most likely exhaustees are required to participate in the system. Furthermore, if the program is effective in decreasing unemployment duration, the effect of the program contaminates the exhaustion data and the profiling models estimated from these data.

However, our results suggest that contamination from assignment

to WPRS is very small, at least in Florida. This result is consistent with the evidence suggesting modest effects of mandatory reemployment services. WPRS systems that are modestly effective in reducing exhaustion rates can probably update their profiling models with minimal concern about the contamination issue addressed in this chapter.

Notes

1. This variable is calculated as the difference between the "separation" and "claim filed" dates.
2. It is worth noting that one contribution of this variable is to lower the predicted exhaustion probability of claimants without demonstrated capacity to maintain long-term jobs.
3. Three different packages of services were tested. These packages look broadly similar to services currently provided by states through the WPRS systems.
4. The findings from Washington, D.C., and Florida are generated by a process that is much closer to the way that WPRS actually operates than the findings from New Jersey. However, the findings among all states are similar enough to lead us to the same conclusions.
5. The initial screens used in the first step of the profiling model, specifically permanent layoff and union hiring hall attachment, were not designed to target claimants with long UI spells. Rather, these were intended to exclude claimants for whom WPRS services are inappropriate because they may still be employer attached. Regardless, some of these screens may contribute to the identification of claimants likely to exhaust their benefits.
6. Half of the sample is used in estimating the model. The other half is reserved for comparing it to the "contaminated" model described in the next paragraph.
7. Half of the sample is used in estimating the model. The other half is reserved for comparing it to the "uncontaminated" model.

References

Berger, Mark C., Dan A. Black, Amitabh Chandra, and Steven N. Allen. 1997. "Kentucky's Statistical Model of Worker Profiling for Unemployment Insurance." *The Kentucky Journal of Economics and Business* 16:1–18.

Corson, Walter, and Joshua Haimson. 1996. *The New Jersey Unemployment Insurance Reemployment Demonstration Project: Six-Year Follow-Up and*

Summary Report (revised edition). UI Occasional Paper no. 96-2, U.S. Department of Labor, Employment and Training Administration, Washington, D.C.

Decker, Paul T., Lance Freeman, and Daniel H. Klepinger. 1999. "Assisting Unemployment Insurance Claimants: The One-Year Impacts of the Job Search Assistance Demonstration." Report prepared for the U.S. Department of Labor, Employment and Training Administration.

Comments on Chapter 2

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The chapter "Predicting the Exhaustion of Unemployment Compensation" has two distinct purposes: to provide an overview of profiling models among states and to report reestimation results using demonstration projects from Washington, D.C., Florida, and New Jersey. The summary among states is important, both to provide information on what other states have done and what might be successful in other programs. The reestimation work is also important, especially if the results on contamination bias are similar in other settings. Overall, this chapter may become an important reference for policymakers and technical specialists as states update their profiling models and as profiling is extended into other policy areas.

OVERVIEW OF PROFILING MODELS

In reviewing models used in other states, the authors discuss the dependent variables used, the estimation methods, and the set of explanatory variables included in the model. The authors point out that both the national and Maryland versions of the Department of Labor model use a binary dependent variable indicating exhaustion and a logistic estimation technique. They state that alternative dependent variables such as number of weeks or fraction of benefits exhausted have been tested in some states.

At the Center for Business and Economic Research at the University of Kentucky, we do the modeling, estimation, and operation for the Kentucky Profiling Model.[1] We use the fraction of benefits exhausted

as our dependent variable. There is a fair amount of variation in the distribution of completed spells that cannot be exploited using a simple binary exhaustion variable, but that can be picked up by a variable such as the fraction of benefits exhausted.

We have considered a series of estimation techniques and dependent variables. We tested the predictive power of each (probit, logit, ordinary least squares, Cox model, and double limit tobit) along with random assignment of claimants for profiling services using 10 percent of our sample that was held out from the original estimation. The double limit tobit model consistently came out on top in these exercises.

In discussing explanatory variables, the authors make the point that some states use only the five variables included in the original national model: education, occupation, industry, tenure, and the unemployment rate. In Kentucky, we found that there were many more accessible variables that significantly affected exhaustion and were included in the profiling model. While these variables add to the data collection exercise, they also enhance the model and help insure that the "right" individuals are selected for services. The collection of these additional variables has not been overly burdensome. The key is setting up a system for collection and sticking with it.

The authors also discuss substate indicators, either local unemployment rates or local categorical variables. Regional variables can be used to separate regions and to allow for different effects of personal characteristics across regions. In Kentucky, we defined eight regions across the state based on similar economic circumstances. Thus, region indicators are in essence interacted with other characteristics to produce unique effects of the various characteristics by region.

REESTIMATION RESULTS USING DEMONSTRATION PROJECTS

The authors have embarked on an extensive reestimation exercise in order to assess the effects of "contamination" of the program itself on the estimation process. The idea is that we should not necessarily use the experiences of those receiving services to predict the exhaustion of new claimants in the absence of extra services. They use

demonstration project data from Florida to estimate "contaminated" and "uncontaminated" models.

The "uncontaminated" model uses the control group and those who passed the threshold but did not receive extra services in a Job Search Assistance 1995–1996 demonstration. The "contaminated" model uses those assigned to treatment and program ineligibles from the same demonstration. One-half of each sample was held out for comparisons using the two sets of estimates. The authors find that there is significant overlap in those chosen for services in the two models. Thus, contamination bias may not be a big problem. They also find that the two models are similarly effective at targeting exhaustees. This again points to the possibility that contamination is not a large issue. The result of small contamination effects is consistent with what we have been finding in our reestimation efforts in Kentucky.

This reestimation work is important, although much more work should be done on the robustness of the contamination findings and appropriate estimation techniques. More work needs to be done on how the contaminated observations should be appropriately incorporated into the estimation process. Should we just ignore the treatment or somehow model it? The latter seems preferable.

In the end, perhaps we should not be surprised that contamination bias is not a big problem. The treatments that claimants receive are not extensive, and the effects of profiling on labor market outcomes appear modest.[2] The net effect may be that estimates of profiling models and, more importantly, the predicted rank ordering of claimants by profiling scores are not influenced to any great extent by the use of contaminated data. If this reasoning is correct and if the Florida results are robust, it would be good news to states confronted with the task of reestimating their profiling models.

Notes

1. For a description of the Kentucky model, see Berger et al. (1997).
2. For experimental evidence on the effects of profiling on labor market outcomes in Kentucky, see Black et al. (2002).

References

Berger, Mark C., Dan A. Black, Amitabh Chandra, and Steven N. Allen. 1997. "Profiling Workers for Unemployment Insurance in Kentucky." *The Kentucky Journal of Economics and Business* 16: 1–18.

Black, Dan A., Jeffrey A. Smith, Mark C. Berger, and Brett J. Noel. 2001. "Is the Threat of Reemployment Services More Effective than the Services Themselves? Experimental Evidence from the UI System." National Bureau of Economic Research Working paper no. W8825, March.

Targeting Employment Services

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