

U. S. Department of Labor

Employment and Training Administration
Washington, D.C. 20210

CLASSIFICATION

UIS

CORRESPONDENCE SYMBOL

TEUMC

DATE

January 5, 1994

DIRECTIVE: UIS INFORMATION BULLETIN NO. 4-94

TO: ALL REGIONAL ADMINISTRATORS

FROM: MARY ANN WYRSCH *Mary Ann Wyrusch*
Director
Unemployment Insurance Service

SUBJECT: Profiling Model Paper - Profiling Dislocated Workers for Early Referral to Reemployment Services

Attached is a copy of the final version of the above report. The report describes an econometric model that serves to identify those unemployment insurance (UI) claimants who are dislocated workers and in need of reemployment services.

This model is the basis for much of the discussion contained in Unemployment Insurance Program Letter (UIPL) No. 45-93, Profiling of Unemployment Insurance (UI) Claimants. Its basis was research performed on national level survey data, which would have to be adjusted for use by individual States.

The information contained in this report should be useful to all State Employment Security Agencies (SESAs) in developing UI claimant profiling systems in accordance with the provisions of Public Law 103-152, The Unemployment Compensation Amendments of 1993. Information contained in this paper should also be useful to Regional Office staff in providing assistance to SESAs on profiling implementation issues.

A copy of the paper should be provided to the individual in the SESA responsible for developing the SESA's profiling system. Please contact either Wayne Zajac on 202-219-5616 or Ingrid Evans on 202-219-5922 concerning this report.

Attachment

RESCISSIONS None	EXPIRATION DATE
---------------------	-----------------

PROFILING DISLOCATED WORKERS FOR EARLY REFERRAL
TO REEMPLOYMENT SERVICES

Kelleen Worden

October 6, 1993

EXECUTIVE SUMMARY

BACKGROUND Changes in technology and international trade have lead to changes in the U.S. economy and, consequently, changes in the labor market. Workers who held jobs in a plant that has closed, or who possess skills that are no longer in demand may find themselves permanently separated from their employers, with no similar jobs available. Many of these "dislocated workers" could face great difficulties in finding new employment and may exhaust their unemployment benefits. Services such as job search assistance have been shown to significantly help dislocated workers make the transition to a new job.

Policy makers believe such services would be even more effective if provided earlier in the worker's unemployment spell. As a result, the Clinton Administration proposed and the Congress approved Section 4 of P.L. 103-6, which provides for assistance to state UI agencies in profiling new UI claimants. One of the primary goals of profiling will be to identify, early in their unemployment spells, those permanently separated workers who are likely to experience reemployment difficulty. Once identified, these workers can be referred to additional job search assistance and/or training. A profiling model must also narrow the target group to a size that can be effectively served. Profiling would allow for more timely provision of services to dislocated workers likely to experience long durations of unemployment. This paper describes the analysis used to develop a profiling model based on worker characteristics.

MODEL OVERVIEW Various academic studies have already documented strong relationships between reemployment difficulty and characteristics such as schooling or job tenure, but this paper summarizes further analysis which is the basis for a profiling model (hereafter referred to as "the model") that addresses the specific policy issues of this profiling initiative. Most importantly, the model proposed in this report is simple and straightforward. In addition, although the model is based on a

single national algorithm, it is sensitive to changes in the labor market across states and over time. It also contains a mechanism to adjust the size of the targeted population. Finally, the model contains only variables that are statistically justified as well as intuitively sensible. The model provides a more comprehensive assessment of the worker's needs compared to earlier profiling attempts, leading to a measurable improvement in the accuracy of targeting.

The proposed model encompasses a two-step approach. As mentioned above, the model is designed to target those unemployed workers who are permanently separated and whose characteristics make them more likely to suffer long jobless spells. Determining permanent separation will be done in the first step. Workers will be asked if they are on recall, and whether they have a union hiring hall agreement. It is not the intent of profiling to disrupt a worker's existing attachment to an employer or labor union, and those unemployed workers who are on recall or have a union hiring hall agreement will be excluded from the target group. The model would then be used to assess the reemployment difficulty of the permanently separated workers, based on a combination of several characteristics.

It is important to note that once the permanently separated workers have been identified, there is no single characteristic that acts as a "screen" to include or exclude workers from the target group. Rather, individual workers will be included or excluded based on their overall combination of characteristics. Those workers whose estimated probability of reemployment difficulty is sufficiently high will be targeted for reemployment services.

ADDITIONAL DETAILS Many characteristics were statistically shown to be related to reemployment difficulty, but only the seven variables found to be most important were included in the proposed model. As mentioned above, the two required data items in the first step are recall status and union hiring hall status. The

five data items used in the second step to predict reemployment difficulty are: employment change in the worker's pre-UI industry and occupation, years of schooling, years of tenure on pre-UI job, and state unemployment rates.

The analysis used historic data to measure the effects of these seven characteristics on reemployment difficulty, and to develop a model that estimates an unemployed worker's likelihood of a long unemployment spell associated with those characteristics.

Schooling and tenure are characteristics that describe the individual worker. The worker's predicted probability of reemployment difficulty decreases with the worker's level of education and increases with the worker's years of tenure. This model is consistent with many studies that show workers with no high school diploma have significantly more trouble finding new employment. Tenure is positively related to reemployment difficulty because it measures job specific human capital, a finding also reported in several other studies.¹

Three additional variables, the state's total unemployment rate and the decline or growth in the worker's industry and occupation, assess the overall employment environment in which the worker is searching for a job. These variables build into the model sensitivity to varying labor market conditions, particularly at the state level. Earlier studies based estimation of reemployment difficulty on particular industry screens, shown to be troubled at the national level at that point in time. But industry composition varies greatly across states and over time. Applying nationally determined industry screens at the state level could lead to some industry screens that are not sensitive enough to differences in state labor markets, or that become outdated over time.

¹ It is important to remember that this analysis focuses on those workers already unemployed. Workers with higher tenure are usually less likely to lose their jobs, but among those already unemployed, longer tenured workers suffer greater reemployment difficulties.

Rather than estimating the reemployment difficulty associated with being from a particular industry, the estimate is based on the employment change in the worker's industry for his or her state, whatever that industry is. Because employment change by industry is measured at the state level, the model is sensitive to each state's growing and declining industries.

Due to data limitations, the impact of declining occupations could only be measured at the national level.² While the model will not capture variations in occupational employment across states, it will capture changes in nationally declining industries over time. The recent recession has shown that dislocation is no longer strictly a blue-collar phenomenon, making this sensitivity to changes in declining industries and occupations particularly important.

The state's total unemployment rate also increases the model's sensitivity to varying state economic conditions. While an unemployed worker with given characteristics may have little trouble in a state with low unemployment, that same worker might have much greater difficulty in a state with high unemployment. The model will target a greater proportion of unemployed workers as a state's unemployment rate rises.

The model gives policy makers flexibility in setting the size of the targeted population. Choosing the threshold for predicted probabilities directly determines the number of workers included in the target group. Including only those workers with a very high predicted probability of difficulty leads to very few referrals, while lowering that threshold increases the number of referrals. In applying this model, states could have discretion to set that threshold within a range determined by the model. This is another aspect of the model that is sensitive to states' needs. As

² BLS staff indicated that state level occupation data could only be obtained by contacting individual states, which was not feasible given the scheduling of the profiling initiative. State level occupation data may be available for future re-estimations of the profiling model.

mentioned above, for a given threshold, the state unemployment variable will adjust the size of the targeted population as the state's economy changes. The addition of state unemployment rates will enable the model to help states make more informed decisions as to the appropriate size of the targeted population.

EVALUATION OF MODEL Preliminary results based on historic data show the model is significantly more accurate compared to earlier profiling efforts. The goal of profiling is to narrow the target group to a size that can be effectively served, while including as many permanently separated workers with serious reemployment difficulty as possible. Historic data indicate that the model would target a group of claimants equal to 30 percent of the total UI population, while including 53 to 60 percent of all UI recipients with serious reemployment difficulties.

Naturally, not all of the workers targeted by the model will actually experience serious reemployment difficulty, and it is also important to look at the composition of the target group. The group of workers targeted by the model has a much higher concentration of dislocated workers than in the UI population at large. Within the group of UI recipients targeted by the model, 55 percent were permanently separated and experienced jobless spells of over six months. This compares to only 30 percent who were permanently separated and unemployed over six months in the UI population at large.³

These results are significantly better than for a more simplified profiling effort based solely on a permanent separation screen. Based on current estimates, this single screen would place fully 75 percent of the total UI population in the target group. It would not be feasible for State Employment Security Agencies to effectively serve a target group this large. Using a tenure screen in addition to the separation screen would only lower the sample to

³ Note that these measures are intended as indicators of potential outcomes, not statistical fit.

approximately 42 percent, and the composition of the targeted group would be less accurate than the group targeted by the model; only 45 percent of the group identified by the separation and tenure screens were unemployed over six months, compared to 55 percent of the group targeted by the model.

CONCLUSION An operational profiling model for state UI agency use that is based solely on permanent separation and/or tenure screens alone would not build in sensitivity to state employment conditions or flexibility regarding program size. Given the goal of profiling, to target dislocated workers for early referral while narrowing the target group to a feasible size, the model described above provides a more flexible, accurate and statistically justified method to accomplish this.

INTRODUCTION

Changes in technology and international trade have lead to changes in the U.S. economy and, consequently, changes in the labor market. Workers who held jobs in a plant that has closed, or who possess skills that are no longer in demand may find themselves permanently separated from their employers, with no similar jobs available. These workers are typically referred to as dislocated workers. There are several definitions of a dislocated worker. The most general definition includes all workers who are permanently separated from their employers. The Bureau of Labor Statistics (BLS) definition includes only those permanently separated workers with at least 3 years of tenure on their pre-layoff job. Other policy makers view dislocated workers as all workers who are permanently separated and experience measurable difficulty in securing reemployment, whether evidenced by long unemployment durations or significant earnings reductions.

Increases in worker dislocation is a primary concern of the Clinton Administration, and is the basis for the Profiling initiative. This initiative seeks to help state Unemployment Insurance (UI) agencies identify and assist dislocated workers early in their spells of unemployment. The proposal was enacted on March 4, 1993 as section 4 of P.L. 103-6.

Although total unemployment rates experienced during the recession of 1990 to 1991 were significantly lower than those during recessions of the 1970s and 1980s, these aggregate unemployment rates understate the severity of the early 1990s recession. The increase in permanent job loss or worker dislocation during this recession approached the post-war high experienced in the 1981 to 1982 recession. The average duration of total unemployment during the early 1990s was 14 weeks.

The 1990s recession is also unique in that more workers in white collar occupations lost their jobs compared to workers in blue collar occupations.⁴ The changing nature of structural

⁴ See Mishel and Bernstein, 1992.

unemployment poses additional challenges to the profiling initiative.

Many of these permanently separated workers could face great difficulties in finding new employment and may exhaust their unemployment insurance (UI) benefits. Services such as job search assistance have been shown to significantly help dislocated workers make the transition to a new job. Policy makers believe such services would be even more effective if provided earlier in the worker's unemployment spell. In New Jersey, for example, early referral to job search assistance (JSA) programs reduced targeted claimants' spells on UI an average of three quarters of a week. This program was found to provide net benefits to the claimant, U.S. Department of Labor agencies, and society as a whole.⁵

One of the primary goals of the profiling initiative is to identify, early in their unemployment spells, those permanently separated new claimants whose characteristics strongly increase their likelihood of reemployment difficulty. Profiling would allow for more timely and accurate provision of services to dislocated workers likely to experience long durations of unemployment. Profiling is all the more needed given limited program funding, because it helps focus resources on those most likely to need such services in making the transition to a new job. This paper describes the analysis used to determine what worker characteristics should be used to target dislocated workers.

EXISTING STUDIES ON DISLOCATION

Several studies that investigate the relationship between various characteristics and reemployment difficulty are described below. Much of this research is based on data collected by the Bureau of Labor Statistics (BLS) in its Dislocated Workers Survey (DWS). This survey is supplemental to the regular Current Population Survey (CPS) and has been conducted every two years

⁵ See Anderson Et al., 1991

since 1984. Interviewees who respond that they have been dislocated in the last five years are asked an additional 25 questions regarding their pre- and post-dislocation work history.

Ross and Smith, of the Congressional Budget Office (CBO) compiled the DWS data from 1984 to 1992 for a selected subset of DWS and CPS variables. This data enabled them to study the characteristics of dislocated workers over a ten-year period.⁶ CBO looked at a variety of characteristics including age, schooling, job tenure, gender, ethnicity, reason for job loss, worker's previous industry, whether the worker was blue collar, and state and national unemployment rates at the time of dislocation. CBO found that job tenure, age, and schooling were among the most important characteristics in explaining reemployment difficulty and earnings losses among dislocated workers. They found this relationship to be relatively stable over time, that is these characteristics were associated with reemployment difficulty during economic contractions as well as expansions. Reemployment difficulty was measured both as the probability of reemployment and the duration of unemployment. Earnings loss was measured as the probability of at least a 20 percent reduction in earnings from the pre-UI job to the post-UI job.

CBO points out differences in characteristics between workers who are just permanently separated and those who also have reemployment difficulties. For example, workers with long tenures are less likely to become permanently separated from their jobs. But among workers who are permanently separated, those with long tenures tend to experience the greatest reemployment difficulties. According to this study, women were also less likely to find new jobs.

Over the ten-year period studied CBO found that blue collar workers and workers in goods producing industries were more likely to become permanently separated and more likely to have reemployment difficulties, when compared to white collar workers.

⁶ See Ross and Smith, 1993.

However, the proportion of displacements occurring among white collar or service producing workers is growing. CBO reports that the proportion of dislocation occurring in services producing industries rose from about 40 percent to just over 50 percent between 1981 and 1990. They also note, however, that while the share of dislocation occurring within goods-producing industries is falling, its share of dislocation still equals twice its share of total unemployment.

CBO found that workers who lost their jobs due to plant closing or shift termination were more likely to find new jobs than those unemployed due to slack work. The authors believe this may be because those workers from closed plants or terminated shifts were more certain of their need to search for new jobs than those unemployed because of slack work.

Corson and Dynarski, of Mathematica Policy Research Inc., also investigated reemployment difficulty in their study on UI exhaustees.⁷ They found their results varied significantly by recall status and conducted their analysis separately for workers with specific recall dates, workers who expected to be recalled but had no recall date, and workers who did not expect to be recalled.

They found that workers' recall expectations were fairly accurate indicators of recall outcomes. Only nine percent of workers who did not expect to be recalled returned to work for their previous employer. Approximately 92 percent of workers with definite recall dates were recalled, as were 72 percent of workers with recall expectations but no dates. This indicates it may be best to screen out those workers with a specific recall date as well as those who expect to be recalled but have no date.

Similar to the CBO study, the Mathematica exhaustee study measured reemployment difficulty in terms of duration of unemployment, probability of benefit exhaustion and probability of earnings loss. Mathematica selected a sample of claimants from 20 states, who filed between 1987 and 1988. These claimants were

⁷See Corson and Dynarski, 1990.

interviewed in 1989 regarding their personal characteristics and labor market experience since filing their claim. Mathematica studied more variables than CBO, including not only demographic characteristics and economic indicators, but also UI program parameters and job search activity. Mathematica found the rate of benefit exhaustion was substantially higher among those workers not on recall. For those who did not expect to be recalled, age, tenure, gender, marital status and ethnicity were significant predictors of exhaustion probability. Older workers and workers with longer tenure or union membership were more likely to exhaust, as were minorities and women, particularly women with working spouses.⁸ These characteristics also lead to significantly longer unemployment durations. Being a high school dropout significantly increased the probability of benefit exhaustion, but not unemployment duration. Mathematica did not find that being from the construction or machinist occupations or the manufacturing industry had significant effects on exhaustion probabilities, but did significantly increase unemployment durations. Having regular layoffs in the past did not significantly increase a worker's probability of exhaustion or duration of unemployment.

Higher UI replacement rates were also associated with higher probability of exhaustion. Part of this effect could be due to disincentive effects and part could be due to the correlation between income and skill level. Higher replacement rates are typically associated with lower incomes.

Not surprisingly, increases in potential duration significantly lowered the probability of exhaustion. Increases in potential duration also significantly shortened unemployment duration, a less intuitive result. Mathematica attributes this result to their measure of unemployment duration, measured from the

⁸ While some studies found that women are clearly associated with longer duration or other measures of displacement, Mathematica found the relationships between gender and displacement is more complicated and cannot be examined without considering marital status and working status of spouse.

initial claim date, and the fact that workers with shorter potential durations may delay filing for benefits.

The local total unemployment rate significantly increased the probability of exhaustion. Work search activity was not found to significantly affect exhaustion probability or unemployment duration, nor did participation in current Job Service Activities or training. It is important to note that the sample sizes for this investigation were fairly small, and failing to find significant effects for certain characteristics does not mean such effects do not exist, simply that the effects were not revealed by this particular estimation.

Although Mathematica ran no regression on earnings loss, their analysis showed that 37 percent of exhaustees and 14 percent of nonexhaustees incurred earnings losses of at least 25 percent upon accepting their first post-UI job. Two thirds of this reduction in earnings was shown to be due to a reduction in weekly hours. The reduction in earnings may also be partially explained by significant industry shifts among exhaustees, primarily from the manufacturing industry to retail trade and services.

The CBO and Mathematica studies were two of the primary studies of dislocation sponsored by the government. Many other studies regarding dislocated workers have been published in various journals. Several of these articles are based on the DWS data described above and many of their results were consistent with the CBO findings. Paul Swaim and Michael Podgursky investigated the effects of an additional year of education on dislocation. They found that workers with more schooling had shorter durations of unemployment, greater probabilities of full-time reemployment, and were reemployed at salaries that compared more favorably to their pre-UI earnings. The authors found the effect of schooling on joblessness was stronger for blue-collar workers, but the effect on future earnings was stronger for white-collar workers.⁹

⁹ See Swaim and Podgursky, 1989.

Studies measuring the effect of job tenure on reemployment difficulty were conducted by Kletzer in 1989 and Valletta in 1991. Kletzer looked at the effect of pre-displacement job tenure on post-displacement earnings for workers displaced between 1979 to 1984.¹⁰ The author found that as pre-displacement tenure rose, managerial, professional and technical workers were able to transfer most of the associated increase in earnings to their new jobs. Blue-collar workers, on the other hand, were able to transfer much less of their returns to seniority, indicating that their skills are not as readily transferable as those of some white collar occupations. These findings are consistent with the notion of job specific human capital described earlier.

Valletta uses duration models to measure the effect of job tenure on unemployment duration for workers displaced between 1979 and 1986.¹¹ He finds that years of tenure is positively related to duration of unemployment and that these effects are generally greater for men than for women. Valletta hypothesizes that longer tenure is associated with longer unemployment spells because workers with long tenures have traditionally been paid wages that are greater than the value of their marginal product would be in different job. Workers who are separated from their employers late in their tenure and searching for new jobs therefore have unrealistic reservation wages, leading to longer unemployment spells. Valletta believes the effect of years of tenure may smaller for women, possibly because women have not been rewarded as strongly for long tenures, or that women are more willing to accept jobs paying less than their previous wage.

Studies by Herz investigate the changing nature of the dislocated worker population, especially regarding industrial and occupational distribution.¹² Herz echoes the earlier reported

¹⁰See Kletzer, 1989.

¹¹See Valletta, 1991.

¹²See Herz, 1991 and 1990.

findings of Ross and Smith and Mishel and Bernstein that displacement is no longer strictly a blue-collar or goods-producing phenomenon. While most displacement still occurs in blue-collar professions and manufacturing industries, displacement in services and white collar occupations was growing at a faster rate between 1979 and 1989. The number of displaced workers in manufacturing between 1985 and 1989 was 1.6 million, compared to 2.5 million between 1979 and 1983. The number of displaced workers in trade during these two periods grew from 0.7 million to 0.8 million. The number of displaced workers in services grew from 0.5 million to 0.6 million. Herz also found that about 50 percent of displaced manufacturing workers changed industries upon becoming reemployed.

MODEL OVERVIEW

As mentioned above, reemployment services could be more effective if provided early in a worker's unemployment spell. Profiling dislocated workers for early referral entails identifying permanently separated workers and predicting who among them are more likely to experience difficulty finding a job. The proposed model encompasses a two-step approach. Determining permanent separation will be done in the first step. In the second step, the model would assess the reemployment difficulty of the permanently separated workers, based on a combination of several of the most important characteristics.

The second tier of the model was constructed using historic data and regression analysis to estimate the effects of various worker characteristics on their reemployment difficulty. The final estimated equation calculates each worker's total probability of serious reemployment difficulty, based on those characteristics.

While many studies already provide strong evidence on the relationships between reemployment difficulty and characteristics such as schooling or job tenure, further analysis was needed to develop a model that addresses the specific policy issues of this profiling initiative. Most importantly, the model proposed in this

report is simple and straightforward. Because academic research is done largely for the purpose of learning more about dislocated workers, the models may use complex techniques and long lists of variables to represent the characteristics of dislocated workers as completely as possible. The goal of this research, on the other hand, was to develop a model for operational use by individual states. The focus at every step of this analysis was to create a model that was less complicated, less expensive, and acceptable to the states, while still capturing most of the predictive power of more complicated models. Only variables that were both statistically significant and intuitively sensible were tested, and among those only the seven most important variables in terms of predictive power were included.

It was also important to develop a model that was based on a single national algorithm, but nonetheless was sensitive to changes in the labor market across states and over time. Because the proposed model is based on a single national algorithm, it helps provide comparable treatment of claimants across states and facilitates evaluation of the model and possible improvements in the program. At the same time the model recognizing each state's overall economic climate and unique mixture of growing and declining industries. The model is also sensitive to changes in declining occupations. The recent recession has shown that dislocation is no longer strictly a blue-collar phenomenon, making this sensitivity to changes in declining industries and occupations particularly important.

The model provides a more comprehensive look at the worker's needs compared to earlier profiling attempts, leading to a measurable improvement in the accuracy of targeting. It is important to note that once the permanently separated workers have been identified, there is no single characteristic in this model that acts as a "screen" to include or exclude workers from the target group. Rather, individual workers will be included or excluded based on an assessment of their overall combination of characteristics. For example, there is no single level of tenure

which serves to include or exclude a worker in the target group; rather, the level of difficulty associated with that worker's tenure would be added to his or her overall estimated probability of reemployment difficulty. Those workers whose estimated probability of reemployment difficulty is sufficiently high will be targeted for early referral to reemployment services.

Finally, the model also gives policy makers flexibility in setting the size of the targeted population. Choosing the threshold for predicted probabilities directly determines the number of workers included in the target group. Including only those workers with a very high predicted probability of difficulty leads to very few referrals, while lowering that threshold increases the number of referrals. The states would have discretion to set that threshold within a range specified by the model. This is another aspect of the model that is sensitive to states' needs.

DATA SELECTION

As mentioned above, the estimated relationships between various characteristics and reemployment difficulty were based on historic data. Unfortunately, there is no single data set currently available that contains all the relevant variables for the universe of workers we wish to observe. Several existing data sets have varying strengths and weaknesses, and different data sets were used for various elements of the analysis. The tight schedule of deliverables on the profiling initiative made it necessary to focus on those data sets most readily available. The three data sets used for the analysis were the 1990 and 1992 panels of the DWS/CPS surveys, the CBO data and the Mathematica exhaustee data.

The 1990 and 1992 panels of the DWS/CPS data were simply used to evaluate whether any of the variables excluded from the CBO extract were important to profiling research. Several regression equations estimated with BLS data indicated that no variables excluded from the CBO extract were of use to this study.

The CBO and Mathematica data sets were both considered as candidates for the final estimation. One important issue considered when choosing a data set for the final estimation was the accuracy of reemployment measures. The DWS measures of reemployment outcomes are subject to substantial memory bias, since interviewee's were asked to describe unemployment spells occurring up to five years earlier. CBO eliminates much of this recall bias by discarding observations more than two years in the interviewees' past. Nonetheless, all observations based on memory involve some bias.

Secondly, the universe of the DWS and CBO data sets may be too restricted. The sample only includes observations for those workers who identified themselves as being laid off due to "plant closing, shift elimination, layoff without recall, or other similar reason." Based on this broadly defined and self-identified criterion, it is difficult to tell exactly who is included in the sample.

The Mathematica data, on the other hand, are subject to very little recall bias because the data are based on actual claim status. It is a sample of all UI claimants, and a variable on recall status allows for comparison of those workers who do not expect to be recalled, those who expect to be recalled but have no date, and those with a specific recall date. The recall status variable would allow for a more accurate sample of permanently separated employees. Unfortunately the Mathematica data only include a sample of 20 states and cover only a single year, 1988, when the lowest number of dislocated workers were observed over the past decade. Although the measure of reemployment outcomes was more accurate using this data set, a model developed using 1988 data may not be appropriate for the current economic climate.

The CBO data set was used to evaluate whether using this single year of data for only 20 states would substantially alter the structure of the model. CBO estimation based on only the 20 states covered by the Mathematica data did not differ significantly from estimations based on all 51 jurisdictions. However,

estimations based on 1988 data were significantly different than estimations based on other years of data. Using 1988 data would therefore significantly affect the structure of the model. This may appear to contradict CBO's findings that dislocated workers' characteristics remain fairly stable over time, but it merely reflects a different research focus. CBO is correct to point out that when the model is estimated separately for each year of data, the same general positive and negative relationships between various characteristics and reemployment difficulty are revealed. They note that while the estimated size of some effects may vary from year to year, some of this is due to smaller sample sizes, rather than actual changes in the relationships.

Nonetheless, the focus of this research is not simply to understand the general nature of dislocation, but to develop a model that will be implemented. Although many of these yearly changes in estimated effects are not statistically significant, they imply very different model specifications. Based on these findings, the final equation was developed using CBO data, because it was decided that a predictive equation based on data covering 1981 to 1990 would be more appropriate than a model based solely on data from 1988, when dislocation was at a low point for the decade. The CBO data set covered more variation in economic activity, allowing for better estimations of the coefficients on industry and occupation variables.

As mentioned earlier, there was some concern regarding the accuracy of the self identified sample of permanently separated workers contained in the CBO data. A final analysis was conducted to see if the CBO sample was significantly different than the Mathematica sample. The same equation was run for 1988 observations from both data sets. Unfortunately, these results are inconclusive. Because the resulting sample sizes were so small, many of the coefficients were insignificant, and it was not possible to tell if the CBO estimation was significantly different from the Mathematica estimation. It was still felt that the problems regarding the use of 1988 data were more serious than

problems regarding sample selection, therefore the CBO data was used to develop the final equation. Using a full ten years of data as well as a sample of 51 jurisdictions would make this model more nationally representative.

As discussed below, the Mathematica data was used to help measure how well the model would perform. Since the Mathematica sample was representative of all UI claimants, and was then separated by recall status, it was well-suited to measure the effects of the first and second steps of this model.

There were several data sets considered that were not used. The SIPP data (Survey of Income and Program Participation) appeared to avoid many of the weaknesses described in the above data sets. This nationally representative longitudinal data set has been collected since 1984 and has many variables on demographic characteristics, training participation and labor market history. It does not rely on respondents' ability to remember their recent labor history; rather, the survey tracks their experience every four months over a period of 36 months. However, the record layout of SIPP has changed substantially over the years. The variable identifying recall status was dropped from SIPP after 1984, and no other indicator of permanent separation was included. Permanent separation is an important characteristic for this study, and this data set was dropped from consideration.

Data sets gathered for the purpose of U.I. state demonstration projects also were not used during this analysis. While the reports from these projects provided valuable context to this study, the data analysis required a nationally representative data set. In the future, researchers may also want to consider the longitudinal data collected by Canada's office of Office of Employment and Immigration. While this data set was not available soon enough to be considered for this project, its longitudinal coverage of employment history and program participation could be useful for future research on profiling.

DETAILS OF MODEL SPECIFICATION

As mentioned above, many characteristics were statistically shown to be related to reemployment difficulty, but only the seven variables found to be most important were included in the proposed model. In the first step, workers will be asked if they are on recall, and whether they have a union hiring hall agreement. It is not the intent of profiling to disrupt a worker's existing attachment to an employer or labor union, and those unemployed workers who are on recall or have a union hiring hall agreement will be excluded from the target group.⁹

The five data items used in the second step to predict reemployment difficulty are: employment change in the worker's pre-UI industry and occupation, years of schooling, years of tenure on pre-UI job, and state total unemployment rates. These variables measure worker characteristics, as well as describe the economic environment in which the worker is seeking reemployment.

In measuring the characteristics of workers with reemployment difficulty, this analysis focussed on permanently separated workers unemployed over six months. This does not imply that workers with slightly less than six months of unemployment will somehow be screened out of the target group, simply that the model was estimated using the characteristics of those unemployed over six months. It was felt that permanently separated workers unemployed over six months, many of whom had already exhausted their benefits, were most representative of true reemployment difficulty.¹⁰

⁹ Careful attention should be given to collecting data on recall status. Several policy makers have noted that many claimants on recall tend to deny their recall status, because they mistakenly believe that being on recall reduces their eligibility for UI benefits.

¹⁰ The sample was also restricted to workers who collected UI. It was felt this sample would more closely represented UI applicants than a sample of unemployed workers in general.

For each observation in the CBO historic data, the probability of reemployment difficulty was assigned a value of 1 if the worker was unemployed over six months, zero otherwise. This dependent variable was regressed on several worker characteristics to develop an equation that estimates the probability of reemployment difficulty for each worker. It is important to note that while the dependent variable was coded as a binary variable during estimation, the output of the model will be a continuous variable--the unique probability predicted for each worker based on that worker's characteristics. The equation was estimated using a logit specification in order to constrain the predicted probabilities to lie between zero and one. This specification chooses the coefficients on each characteristic that maximize the likelihood of correctly predicting the zeros and ones assigned to the dependent variable in the historic data. The structural form of the model will be:

$$\text{Prob}(Y_i=1) = \frac{e^{\beta X_i}}{1 + e^{\beta X_i}}$$

In this model, βX_i equals $\beta_1 + \beta_2 X_{21} + \beta_3 X_{31} + \dots + \beta_n X_{n1}$ where each X_{ni} represents a different worker characteristic and each β_n represents the estimated effect of that characteristic on the probability of reemployment difficulty.

Unlike coefficients from a simple linear model, logit model coefficients do not imply a constant effect for each characteristic. The increase in probability for a given characteristic is smaller for workers who already have a very large probability than for workers with probabilities closer to one half. Interpreting the effects of each characteristic on a worker's reemployment difficulty depends on what worker is being analyzed. The effects reported below are based on workers with average characteristics.

Schooling was entered into the equation as a set of categorical dummies rather than as a single variable measured in years. The high school dropout variable was assigned a value of one for each worker represented in the CBO data that did not have

a high school diploma, zero otherwise. Similar variables measured whether the worker had a diploma but no college, some college but no degree, and a college degree or more. This set of variables measured a different effect for each level of schooling. Had years of schooling simply been entered as a single variable, that would imply every additional year of schooling would have the same effect on the probability of being unemployed over six months, and the model would have been less powerful.

The coefficients on education imply the probability of reemployment difficulty would be 8.7 points higher for a person without a high school diploma compared to someone with a diploma. A person with some college would have a probability 9.2 points lower than a person with just a diploma. The total change in probability between a person with no diploma and a person with some college is therefore 17.9 points. The probability of reemployment difficulty is 3.7 points lower for a person with a college degree or more compared to someone with a only a diploma. The effect of having a college degree or more is actually smaller than the effect of having only a few years of college. The finding could reflect the fact that those workers with relatively high education are competing in more narrow job markets. This model is consistent with studies described above that show workers' difficulty in finding a new job increases with lower education levels, particularly for workers with no high school diploma.

A similar set of variables was entered to described workers' tenure. These variables measured whether a worker had less than three years of tenure, three to five years, six to nine years, or ten or more years. As seen in Table 1, not only does additional tenure tend to increase reemployment difficulty, but the size of this effect increases as tenure grows. A worker with three to five years of tenure would have a probability of reemployment difficulty 5.8 points greater than a worker with less than three years of tenure. A worker with six to nine years of tenure would have a probability 8.5 points greater, and a worker with ten or more years would have a probability 12 points greater.

Tenure is positively related to reemployment difficulty because it measures job-specific human capital. Workers who have accumulated most of their qualifications while working for a single firm have developed some skills that are uniquely valuable to that particular company, and may have difficulty finding demand for those skills at other companies. This finding is reported in several studies mentioned earlier.

The state total unemployment rate, and the growth or decline the worker's pre-UI industry and occupation assess the overall economic environment in which the worker is searching for a job. Such variables build into the model sensitivity to varying labor market conditions, particularly at the state level. Earlier studies have used a set of categorical dummies to estimate the reemployment difficulty associated with each industry, and identify which industries had the strongest effects at the national level. While this approach is appropriate for academic research, it is less desirable for a model applied at the state level. Industry composition varies greatly across states and over time. Applying nationally determined industry screens at the state level could lead to some industry screens that are not sensitive enough to differences in state labor markets, or that become outdated over time.

Rather than estimating the reemployment difficulty associated with being from a particular industry, the proposed estimation is based on the percent employment change in the worker's industry for his or her state, whatever that industry is. Industry categories consist of mining; construction; durable manufacturing; nondurables; transportation and public utilities; wholesale trade; retail trade; finance, insurance and real estate; services; and government. This choice of industry detail was based in part on data availability, concerns for future resources needed to collect the data, and concerns for the accuracy of more disaggregated industry data. Because employment change by industry is measured at the state level, the model is sensitive to each state's growing and declining industries.

The model parameters presented in Table 1 imply that a worker's predicted probability of reemployment difficulty will rise by about half a point for every percentage point decline in his or her industry. For example, a 10 percent employment drop in a worker's industry would raise that worker's predicted probability by roughly 4.4 points.

Due to data limitations, the impact of declining occupations could only be measured at the national level.¹¹ Employment change by occupation was measured for managerial and profession specialty; technical, sales, and administrative support; service occupations; precision production, craft and repair; operators, fabricators and laborers; and farming, forestry, and fishing. This level of aggregation was chosen for reasons similar to those described above. This component of the model will be sensitive to yearly changes in declining occupations at the national level and represents an important improvement over the dummy variable approach described above. While the model will not be sensitive to changes in occupation mix across states, the model captures one of the most important sources of state variation--changes in industry mix.

The employment change by occupation is entered as a dummy variable, assigned a value of 1 if the employment change is positive, zero otherwise. This variable was a stronger predictor than the percent change itself. The predicted probability of reemployment difficulty would be 4.2 points higher for a worker from an occupation that is declining.

Because the CBO data only indicated the year of the worker's layoff, and not the month, the most timely measures of employment change by industry and occupation that could be entered were the percent changes during the previous calendar year. Policy makers

¹¹ BLS staff indicated that state level occupation data could only be obtained by contacting individual states, which was not feasible given the scheduling of the profiling initiative. State level occupation data may be available for future estimations of reemployment data.

may choose to update this data more often, but the percent changes should still be based on a full twelve months of data to prevent seasonality.

The state total unemployment rate also increases the model's sensitivity to varying state economic conditions. While an unemployed worker with given characteristics may have little trouble in a state with low unemployment, that same worker might have much greater difficulty in a state with high unemployment. The model will target a greater proportion of unemployed workers as a state's unemployment rate rises. The predicted probabilities assigned to workers from a particular state will rise by 3.6 points for every percentage point increase in the state unemployment rate. As mentioned above, this ability of the model to adjust to varying state economic conditions will allow the state to make more informed decisions as to the appropriate number of dislocated workers to target.

As mentioned above, only variables that are statistically significant are included in the model. The dummy variable for having a college degree was significant at the 10 percent level. All other variables were significant at the five percent level or better. Including the categorical dummies for tenure and schooling, the model contains 11 variables, but it is important to remember that only seven data items need to be collected. The separation of schooling and tenure into categorical dummies will be performed by the model software.

It is also important to remember that this model was constructed as a predictive tool, not as a structural equation. The coefficients on some variables do not correctly measure the effect of that variable due to factors such as omitted variable bias and endogeneity. The goal was to maximize the overall predictive power of the model, while still addressing the policy constraints described earlier.

OTHER CHARACTERISTICS OF STRUCTURAL UNEMPLOYMENT

Several other characteristics were analyzed, even though they were not included in the final model. Some of these characteristics were not found to be strong predictors. Other variables were significant predictors but had inappropriate policy implications.

The columns of Table 2 show the effect of dropping different variables from the equation. The final model is depicted in column five. The first observation evident from Table 2 is that the coefficients are fairly robust, meaning the estimated effects associated with various characteristics are similar for all equation specifications. This fact strengthens their statistical validity. Comparing the Log Likelihood measure indicates the change in statistical significance associated with dropping certain variables. The measure Percent Accurate provides an indication of the size of the effect from a programmatic standpoint¹². In addition, the R^2 from a linear estimation of unemployment duration is reported because some people find this measure of fit more intuitive.

The first column contains most of the variables described earlier, plus variables measuring age, ethnicity, gender, whether the worker's plant closed or job was abolished, and a series of dummy variables representing the year the worker was laid-off. All variables except JOB ABOLISHED, SIC EMP CHNG (NATIONAL), COLLEGE DEGREE, and 1981 through 1987 dummies were statistically significant at the five percent level or better. The next column contains all of these variables except measures of age, ethnicity and gender. The effect of removing these three variables from the equation will be discussed below in a separate section.

¹² This measure shows how many observations would be correctly included or excluded from the target group, assuming everyone with a predicted probability greater than 0.5 would be targeted.

The third column shows the effect of removing the variables Plant Closed and Job Abolished. As evidenced by the CBO study, Plant Closed was significant and negative, indicating that workers from closed plants were more certain of their need to search for new jobs than those unemployed because of slack work. However, the inclusion of these variables in the model would imply targeting those workers from closed plants to a lesser extent, and this is not in the spirit of the profiling initiative. Furthermore, while the improvement in fit associated with these two variables was statistically significant (evidenced by the change in -2 Log Likelihood), the improvement was not large in a programmatic sense. The accuracy dropped from 65.3 percent to 64.9 percent when these variables were excluded. The R^2 associated with the linear estimation dropped by only .002. Therefore these variables were dropped from the model.

A comparison of the third and fourth columns shows the effect of removing the yearly dummy variables from the equation. These yearly dummies measure whether a worker's probability of reemployment difficulty depends on the year in which the layoff occurred, and whether the effect for each year is significantly different from the effect for 1988 (the omitted year).

Not surprisingly, the results show that the probability of reemployment difficulty for a worker laid off in 1990 would be considerably higher than that for a worker laid off in 1988. This is consistent with the results presented earlier regarding data selection. As Table 2 shows, removing these variables caused the most significant drop in -2 Log Likelihood. The findings indicate that there is some source of yearly variation not captured by the model. As mentioned above, given this weakness in the model, it would be more appropriate to use a full ten years of data to estimate the model rather than data from just 1988, the lowest point in structural unemployment.

The final model is presented in column five. In this specification, the measure of SIC employment change at the national level was dropped. The amount of accuracy added by this variable

was not deemed large enough to justify adding it to the model. The dummy variable for growing industries at the state level was replaced with the actual percent change in employment by industry. It was felt that using the actual percent change would be more sensitive to those states with particularly large decreases in various industries. While the R^2 associated with this linear estimation is only .09277, the estimation explains significantly more variance than a specification based solely on tenure. Linear specifications containing only a dummy variable for tenure greater than three years, not shown, generated an R^2 of only .01. This shows that the proposed profiling model would be more accurate than profiling initiatives based solely on permanent separation and a tenure screen.

The final column measures the effect of dropping the measures of declining industries and occupations. The relatively small drop in R^2 associated with dropping these variables indicates that they are not the most statistically significant variables in the model, but they are important because they increase the sensitivity of the model to state economies, and help the model adjust to future trends in structural unemployment that may not have been present in the historic data.

There were other variables, not contained in the CBO data set, that Mathematica found to be significant. In particular, workers without a working spouse or workers with dependents tended to have shorter unemployment durations. This reflects the fact that those workers with greater financial need return to work faster. These variables were statistically significant predictors of reemployment difficulty. However, including such variables would imply targeting workers with greater financial need to a lesser extent, and this is not in the spirit of the profiling initiative.

Finally, an alternative measure of dislocated worker was considered as the dependent variable. The alternative dependent variable was assigned a value of 1 if the worker was unemployed over six months, or suffered an earnings loss of at least 20 percent when taking his or her first post-UI job. This measure

would have included fully 75 percent of the UI population in the target group, nearly double that of the first measure of reemployment difficulty. The coefficients on the tenure variables increased significantly, indicating that many of the additional workers who suffered earnings losses were higher tenured workers, possibly with higher salaries. Given the goal to target a population significantly lower than 75 percent of UI claimants, the probability threshold would have to be set very high if this model were used, straining the accuracy of the model. It was decided that the first measure of reemployment difficulty would remain in the model.

It would have been desirable to include a measure of skill in addition to the schooling variables. Schooling is an important variable in the model because it provides a measure of basic qualifications. Many jobs may require at least a high school diploma or at least a college degree. But there are differences in literacy, math and computer skills not reflected in years of schooling that may also affect a worker's difficulty in finding a new job.

Mamoru Ishikawa reports that literacy scores had a statistically significant impact on hourly wages among UI job seekers. He found that for each one point increase in literacy scores, measured on a scale of one to 500, hourly wages increased by 0.1 percent.¹³ Unfortunately, it would not be possible to measure the literacy of each UI applicant. Ishikawa also studied the determinants of literacy, and it was hoped that the variables used to profile literacy could be incorporated into the dislocated worker profiling model. However, this study included variables on newspaper reading, television watching, and the importance of reading, writing and mathematics at the former workplace. These variables were either inappropriate for the profiling initiative or unavailable in the data sets described above.

¹³ See Ishikawa, 1992.

In addition, various measures of prior earnings and interaction terms for earnings and education were entered into the equation as a proxy for skill level. Mathematica found a dummy variable for low-wage workers without a high school diploma to be significant but small. However, various measures of earnings were not significant in the estimation described above and were not included in the final specification of the profiling model.

THE EFFECTS OF AGE, ETHNICITY, AND GENDER

Particular attention was paid to the effects of age, ethnicity and gender on the probability of reemployment difficulty. It was concluded that using these variables in the estimation was inappropriate; attorneys for the Justice Department concurred and these variables were not included in the model. Nonetheless, it was important to analyze the implications of omitting the variables.

Older workers, minorities and women have been shown to face significantly higher probabilities of reemployment difficulty. There are three ways these variables could be treated. A researcher could include these variables in the equation and include their effects when measuring the total probability of reemployment difficulty. A researcher could also include these variables in the equation as control variables but only measure the probability associated with the other characteristics. Finally, the researcher could exclude these variables from the estimation altogether.

The first treatment implies measuring the effects associated with age, ethnicity and gender and including these effects in the calculated probability. The second treatment implies measuring the effects of these variables and explicitly excluding these effects from the calculated probability. The third treatment, used in the proposed model, implies allowing the effects of age, ethnicity and gender to indirectly affect the calculated probability of reemployment difficulty through omitted variable bias. The bias

introduced by omitting variables is very complex and depends not only on the effects of the omitted variables, but also on the correlations between the omitted variables and the included variables.

Results showed that while the omitted variable bias did affect many groups of people differently, the effects were generally very small. Workers' predicted probabilities were largely the same whether age, ethnicity and gender were included in the equation or not. The change in predicted probability introduced by the bias was less than one point in most cases and greater than five points for only 3.4 percent of the sample.

The omitted variable bias would tend to raise the predicted probabilities of higher tenured workers and older workers, and lower the predicted probabilities of workers with higher education. This is because age has a strong positive correlation with tenure. When age is dropped from the equation, the coefficient on tenure increases substantially to absorb the age effect. This can be seen by comparing the tenure coefficients in columns one and two in Table 2. Omitting gender and ethnicity from the equation biased the coefficients on higher education downward because gender and ethnicity are negatively correlated with higher education.¹⁴ As mentioned above, however, these changes were negligible.

PROGRAM OUTCOME MEASURES

In addition to the measures of statistical fit described earlier, it is important to discuss the likely program outcomes associated with using this model. The model was used to profile workers surveyed in the historic CBO data to see how accurate the model was in targeting workers who were unemployed over six months. Chart 1 compares the outcomes for the proposed model with two other

¹⁴ Omitting gender also biased the coefficient on blue collar occupations downward, a variable from an earlier model, for similar reasons.

profiling methods.

The first bar represents the total UI population. The second bar represents the group targeted by simply excluding those workers on recall. The third bar shows the group that would be targeted as the result of excluding those on recall and those with less than three years of tenure. (This is similar to the profiling method used in the New Jersey demonstration project.) The final bar depicts the group of workers that would be targeted as the result of using the model described above. The shaded portion of each bar represents the portion of targeted workers who actually had serious reemployment difficulty (those workers unemployed over six months.)

This chart shows three important measures of program outcome. The size of the bar for each profiling method measures the size of the selected target group relative to the total UI population. It indicates how effective the profiling methods are in narrowing the target group to a size that is feasible to serve from an operational perspective.

For each profiling method, the ratio of the gray portion to the white portion measures how many workers in the group targeted by the profiling method experienced serious reemployment difficulty. This indicates what portion of the targeted group had serious need of the reemployment services to which they would be referred. These percentages are shown in Chart 1 for easy comparison.

Finally, the size of the gray area for each profiling method compared to the size of the gray area for the total UI population shows what portion of all permanently separated workers unemployed over six months would be served by each method.

As Chart 1 shows, simply screening out those workers who are on recall would include fully 75 percent of the total UI population in the target group. Given that it would not be feasible to effectively serve a target group this large, this method is not a realistic option.

Using the tenure screen in addition to the recall screen narrows the targeted population to 42 percent of the total UI

population. Chart 1 shows that of those workers targeted by this method, 45 percent would be unemployed more than six months. The method would have served 62 percent of all permanently separated UI recipients who were unemployed over six months.

The fourth bar shows the increase in targeting accuracy resulting from the proposed model. The model narrows the target group to 30 percent of the total UI population, while targeting a more accurate sample of workers. Of the group targeted by the model, 55 percent were unemployed over six months. This model would have served 53 percent of all permanently separated UI recipients unemployed over six months.

These figures assume a recall rate of 25 percent, the 1992 rate estimated by BLS. This is the lowest recall rate since 1967. As recall rates increase, permanently separated workers with reemployment difficulty will make up a smaller portion of the total UI population. Using the model to draw a 30 percent sample of the UI population would therefore include a greater portion of the intended target group as the recall rate increases. Using the model to profile workers identified in the 1988 Mathematica survey, when the recall rate was about 49 percent, indicates that about 60 percent of permanently separated workers unemployed over six months would have been targeted by the model.

SETTING THE PROBABILITY THRESHOLD

As described above, the level chosen for the probability threshold directly affects the size of the program. The probability threshold used to target the 30 percent sample described for the CBO data was 0.45. This finding is confirmed by the Mathematica data as well. Setting the threshold below this level would target a sample larger than 30 percent of the total UI population. In addition, as the threshold is lowered, an increasing proportion of the targeted group would be workers without "serious reemployment difficulty" (unemployed less than six weeks). Of the additional workers targeted by lowering the threshold

below 0.40, 60 percent would be unemployed less than six months. It would therefore be best to choose a threshold above 0.40.

The CBO data also indicate it would also be best to choose a threshold below 0.50. This would target a group equal to 20 percent of the UI population. Of the workers excluded by setting the threshold higher than 0.50, over half would be unemployed at least six months. The proper threshold in each state will depend on the desired size of the target group and the state's demographics. It is recommended that the threshold be set between 0.40 and 0.50. As mentioned above, for a given threshold, the state unemployment variable will adjust the size of the targeted population as the state's economy changes. The addition of state unemployment rates will enable the model to help states make more informed decisions as to the appropriate size of the targeted population.

POSSIBLE DATA SOURCES FOR INDUSTRY AND OCCUPATIONAL EMPLOYMENT

Currently it would appear that the best data source for state employment levels by industry would be the Current Establishment Survey, CES 790. This data is collected by SESAs and records SIC employment at the three-digit level. This was the source of SIC employment used for the estimation of the model.

A possible data source for employment by occupation would be the Occupation Employment Survey or OES. This data is also collected by SESAs and measures occupational employment at the three-digit level for Standard Occupation Classifications (SOC). The data would be consistent with the SOC occupation categories used to estimate the model. States that currently classify a claimant's occupation according to DOT codes could continue to do so, as long as they classified the claimant at the two digit level. The claimant's two digit DOT code could then be translated into a one-digit SOC code, allowing the claimant's occupation to be matched to the aggregate employment change by occupation. (This translation from DOT to SOC could easily be done by the computer

program used for the profiling model, so the staff entering the claimant's data would only have to deal with DOT codes.)

CONCLUSION AND CAVEATS

The profiling model basically entails collecting seven pieces of data. The initial claimant will be asked whether he or she is on recall or has a union hiring hall agreement. If the claimant answers no to both questions, he or she will also be asked his or her years of schooling and tenure, and pre-layoff industry and occupation. The staff member would then enter the years for schooling and tenure and SIC and DOT codes into the computer.

The summary data, including state unemployment rates and employment changes by industry and occupation would already reside in the software, and would have to be updated at least once a year, preferable more often. The probability threshold would also reside in the model software, and would be updated at set intervals. The software would then calculate each worker's predicted probability and indicate whether the worker should be referred to job search assistance services.

While this method is somewhat more complex than earlier profiling methods, it provides a more comprehensive assessment of a worker's likelihood of reemployment difficulties. Limiting the profiling approach to the use of permanent separation and/or tenure screens alone would not build in sensitivity to state employment conditions or flexibility regarding program size. Given the goal of profiling, to target dislocated workers for early referral while narrowing the target group to a feasible size, the model described above provides a more accurate, and flexible method to accomplish this. The model has met the criteria for statistical significance, but also has addressed the unique policy constraints facing a model that will be implemented at the state level.

As mentioned above, the model is more accurate than a simple tenure screen, both measured in terms of program outcomes and statistical fit. However, while the model represents an

improvement over earlier profiling methods, it is important to keep this improvement in perspective. There are many factors that affect the outcome of a worker's job-search activity that cannot be easily measured--a worker's attitude, networking skills, personality, and just plain luck to name a few. In addition, the outcome of a worker's job search activity depends on events that have not yet occurred, such as future economic trends during the worker's unemployment spell. The effect of unmeasurable worker characteristics and future events on reemployment outcomes cannot be captured in a statistical model. In fact, prior research has shown that 75 to 89 percent of the variation in reemployment outcomes is due to these unmeasurable factors.¹⁵ For example, a study of reemployment outcomes in Massachusetts, estimated by Benus, Et al., explained only 11 percent of the variance in unemployment duration.

The proposed model only captures the effect of those measurable characteristics found to be most important, and explains about 10 percent of the variation in reemployment outcomes. This means that for some workers, the characteristics measured by the model may indicate a very high probability of reemployment difficulty, while their total combination of measured and unmeasured characteristics may give them a very low probability. The model will target some workers with little need of reemployment services, and fail to target other workers with great need.

Nonetheless, while the proposed model cannot estimate the effect of luck and other unmeasured characteristics, it does capture likelihood of reemployment difficulty attributable to those characteristics most traditionally associated with the concept of structural unemployment, e.g. education, tenure, occupation, industry and state economic conditions. The proposed national model is nearly as accurate as the state-specific estimation for Massachusetts (an R^2 of 0.09 compared to 0.11) while at the same

¹⁵ See, for example, Corson and Dynarski, 1990 and Benus Et al., 1992.

time building in greater sensitivity to policy and program constraints.¹⁶

One possible way to increase the accuracy of the profiling program is to reexamine those initial claimants not targeted by the model. Those workers who are still unemployed, say, four months after their initial claim, could also be referred to job search assistance services. This model could be viewed as one of several outreach mechanisms for dislocated workers.

It is also important to note that the appropriateness of this model depends on several factors. As mentioned earlier, this model is only appropriate given the need to target a population significantly less than half the total UI population. The value of the model also depends on the quality of reemployment services received by the targeted workers, and the supply of jobs available to the dislocated workers.

¹⁶ For example, while the number of dependents was included as an explanatory variable in the Massachusetts estimation, it was excluded from the proposed model because it implied targeting families with more dependents to a lesser extent. In addition, the Massachusetts estimation is based on fixed industry and occupation variables, while the proposed model builds in greater flexibility to changes in declining industries and occupations.

BIBLIOGRAPHY

Anderson, Patricia, Walter Corson and Paul Decker. The New Jersey Unemployment Insurance Reemployment Demonstration Project Follow-Up Report. Unemployment Insurance Occasional Paper 91-1, 1991.

Benus, Jacob M., Et al. "Massachusetts UI Self-Employment Demonstration." Self Employment Programs for Unemployed Workers. Unemployment Insurance Occasional Paper 92-2, 1992.

Corson, Walter and Mark Dynarski. A Study of Unemployment Insurance Recipients and Exhaustees: Findings from a National Survey. Unemployment Insurance Occasional Paper 90-3, 1990.

Herz, Diane E: "Worker Displacement in a Period of Rapid Job Expansion: 1983-87." Monthly Labor Review, May 1990.

Herz, Diane E. "Worker Displacement Still Common in the Late 1980's." Monthly Labor Review, May 1991.

Ishikawa, Mamoru. "Determinants of Literacy," from Workplace Literacy and the Nation's Unemployed Workers. Forthcoming.

Kirsch, Irwin and Ann Jungeblut. Profiling the Literacy Proficiencies of JTPA and ES/UI Populations. Report to Department of Labor, 1992.

Kletzer, Lori Gladstein. "Job Displacement, 1979-86: How Blacks Fared Relative to Whites." Monthly Labor Review, July 1991

Kletzer, Lori Gladstein. "Returns to Seniority After Permanent Job Loss." The American Economic Review, June 1989.

Mishel, Lawrence and Jared Bernstein. "Job Destruction: Worse Than We Thought." Challenge, September-October, 1992.

Podgursky, Michael. "The Industrial Structure of Job Displacement, 1979-89." Monthly Labor Review, September 1992.

Ross, Murray and Ralph Smith. Displaced Workers: Trends in the 1980s and Implications for the Future. Congressional Budget Office, 1993

Swaim, Paul and Michael Podgursky. "Do More-Educated Workers Fare Better Following Job Displacement?" Monthly Labor Review, August 1989.

Valletta, Robert G. "Job Tenure and Joblessness of Displaced Workers." Journal of Human Resources, XXVI 4 1991.

OUTCOME MEASURES FOR PROFILING METHODS

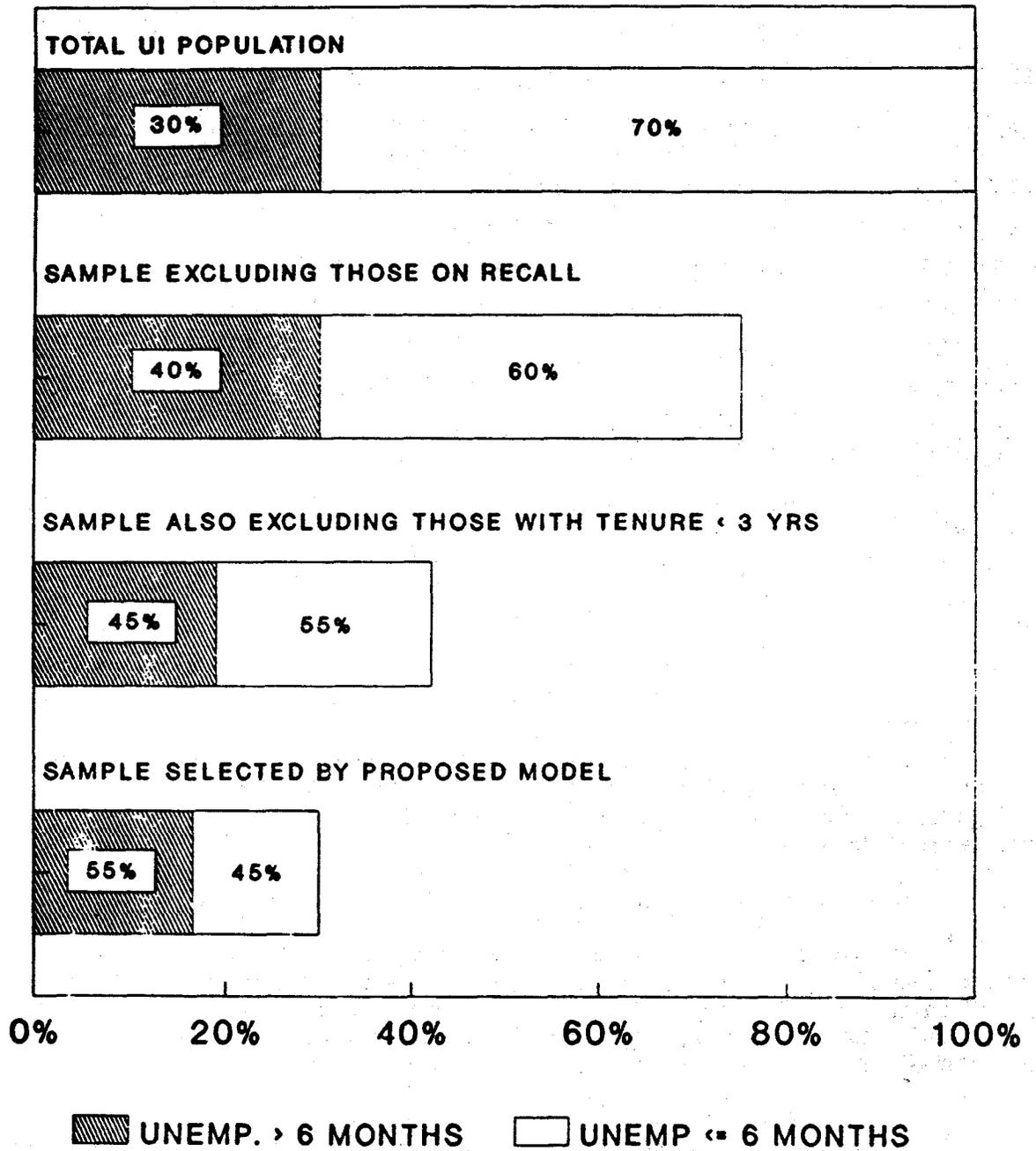


TABLE 1. LOGIT ESTIMATION OF REEMPLOYMENT DIFFICULTY¹

<u>INDEPENDENT VARIABLE</u>	<u>MEAN OF INDEP. VAR.</u>	<u>COEFFICIENT</u>	<u>STANDARD ERROR</u>	<u>CHNG IN PROBABILITY PER UNIT CHANGE OF INDEP.VAR (PERCENTAGE POINTS)²</u>
NO HS DIPLOMA	0.18	0.3465	0.0805	8.66
HS DIPLOMA	0.46	*****	*****	
SOME COLLEGE	0.21	-0.3688	0.0802	-9.22
COLLEGE DEGREE	0.15	-0.1462	0.0910	-3.66
TENURE < 3 YRS	0.45	*****		
TENURE 3-5 YRS	0.18	0.2320	0.0831	5.80
TENURE 6-9 YRS	0.20	0.3413	0.0801	8.53
TENURE 10+ YRS	0.18	0.4814	0.0825	12.04
SIC EMP CHNG % ₃ STATE LEVEL ³	0.42	-0.0175	0.0056	-0.44
GROWING OCC NAT. LEVEL ⁴	0.78	-0.1668	0.0746	-4.17
STATE TUR	7.49	0.1449	0.0123	3.62
CONSTANT		-1.4942	0.1258	

¹ Dependent variable is assigned value of 1 if unemployed at least six months, 0 otherwise. ***** identifies omitted categories for dummy variables. Sample covered 1981 to 1990 and contained 5062 observations.

² Evaluated at mean of independent variable.

³ Percent change in employment by industry, measured at the state level for the following industries: mining; construction; durables; nondurables; public transportation and utilities, wholesale trade; retail trade; finance, insurance and real estate; services; and government. Based on annual change during previous year.

⁴ Variable is assigned value of 1 if national employment change for worker's occupation is positive, 0 if negative. Occupation employment was measured for the following categories: managerial and professional; technical, sales and administrative support; service; precision production, craft and repair; and operators, fabricators and laborers; Based on annual change during previous year as indicated in Employment and Earnings annual summaries.

TABLE 2. ALTERNATIVE LOGIT ESTIMATIONS OF REEMPLOYMENT DIFFICULTY¹

INDEPENDENT VARIABLE	SPECIFICATION					
	1	2	3	4	5	6
NO HS DIPLOMA	0.2462 (.0837)	0.3296 (.0821)	0.3206 (.0820)	0.3364 (.0808)	0.3465 (.0805)	0.35 (.08)
HS DIPLOMA	*****	*****	*****	*****	*****	*****
SOME COLLEGE	-0.3420 (.0823)	-0.3479 (.0817)	-0.3483 (.0816)	-0.3481 (.0806)	-0.3688 (.0802)	-0.3909 (.0799)
COLLEGE DEGREE	-0.1344 (.0955)	-0.1099 (.0943)	-0.0987 (.0929)	-0.1008 (.0916)	-0.1462 (.0910)	-0.1838 (.0902)
TENURE < 3 YRS	*****	*****	*****	*****	*****	*****
TENURE 3-5 YRS	0.2202 (.0853)	0.2568 (.0846)	0.2441 (.0844)	0.2335 (.0833)	0.232 (.0831)	0.2420 (.0829)
TENURE 6-9 YRS	0.3225 (.0835)	0.3936 (.0822)	0.3744 (.0818)	0.3222 (.0806)	0.3413 (.0801)	0.3518 (.0800)
TENURE 10+ YRS	0.4198 (.0938)	0.6056 (.0865)	0.5535 (.0846)	0.4635 (.0828)	0.4814 (.0825)	0.4978 (.0822)
STATE TUR	0.1147 (.0155)	0.1128 (.0154)	0.1144 (.1144)	0.1286 (.0125)	0.1449 (.0123)	0.1606 (.0118)
GROWING IND STATE LEVEL	-0.2662 (.0704)	-0.2495 (.0697)	-0.2563 (.0695)	-0.2422 (.0656)		
SIC EMP CHNG % NAT.LEVEL	-0.0099 (.0083)	-0.0059 (.0082)	0.0067 (.0082)	-0.0335 (.0067)		
SIC EMP CHNG % STATE LEVEL					-0.0175 (.0056)	
GROWING OCC NAT. LEVEL	-0.2456 (.1022)	-0.2156 (.1013)	-0.2294 (.1008)	-0.2062 (.0752)	-0.1668 (.0746)	
1981	0.7871 (.1709)	0.7688 (.1699)	0.7777 (.1695)			
1982	0.8502 (.1708)	0.8457 (.1696)	0.8645 (.1694)			
1983	0.0828 (.1961)	0.1074 (.1948)	0.0914 (.1945)			
1984	0.1629 (.1760)	0.1720 (.1749)	0.1726 (.1746)			
1985	0.0494 (.1681)	0.0426 (.1672)	0.0430 (.1671)			
1986	0.1257 (.1651)	0.1504 (.1642)	0.1614 (.1640)			

¹ Dependent variable is assigned value of 1 if unemployed at least six months, 0 otherwise. ***** identifies omitted categories for dummy variables. Sample covered 1981 to 1990 and contained 5062 observations.

1987	-0.1243 (.1780)	-0.1287 (.1771)	-0.1308 (.1769)			
1988	*****	*****	*****			
1989	0.3187 (.1640)	0.3394 (.1633)	0.3450 (.1631)			
1990	0.5329 (.1569)	0.5566 (.1561)	0.5753 (.1559)			
JOB ABOLISHED	-0.0815 (.0954)	-0.0540 (.0944)				
PLANT CLOSED	-0.239 (.2390)	-0.2059 (.0675)				
AGE 25-34 YRS	*****					
AGE 35-44 YRS	0.2324 (.0762)					
AGE 45-55 YRS	0.3753 (.0946)					
AGE 55-59 YRS	0.6619 (.1408)					
AGE 60+ YRS	0.7361 (.2101)					
MINORITY	0.3595 (.0915)					
FEMALE	0.1424 (.0656)					
CONSTANT	-1.5344 (.1987)	-1.389 (.1959)	-1.4759 (.1937)	-1.2024 (.1343)	-1.4942 (.1258)	-1.7464 (.1059)
-2 LOG LIKELIHOOD	6272	6332	6342	6450	6490	6510
MODEL CHI-SQUARE	579	519	509	401	360	340
PERCENT ACCURATE	65.9	65.3	64.9	64.4	64.2	63.6
\bar{R}^2 FROM LINEAR ESTIMATION OF UNEMPLOYMENT DURATION	.14078	.12596	.12329	.10231	.09277	.08182

² A linear estimation of unemployment duration based only on tenure greater than three years, not shown, had an R^2 of .01.