9
Targeting Job Retention Services for Welfare Recipients

Anu Rangarajan, Peter Schochet, and Dexter Chu
Mathematica Policy Research

The Personal Responsibility and Work Opportunity Reconciliation Act of 1996 (PRWORA) terminated the welfare program known as Aid to Families with Dependent Children (AFDC). The federal government now provides states with block grants to provide cash assistance under the Temporary Assistance for Needy Families (TANF) program. States have wide discretion to structure TANF eligibility, but federal law imposes a lifetime limit of 60 months on benefit receipt and imposes work requirements on adult recipients after a maximum of two years of benefit receipt.

These changes mean that welfare recipients must now find jobs and stay employed. To help welfare recipients reach these goals, many state welfare agencies are setting up (or are considering setting up) job retention programs. However, because large numbers of welfare recipients are moving into the workforce, states may not have sufficient resources to provide job retention and advancement services to all welfare recipients who become employed. Therefore, states may want to target job retention services to those groups of newly employed welfare recipients who are at high risk of losing their jobs and who can most benefit from these services.

This chapter examines the feasibility of targeting clients for job retention services. In particular, we give states and programs some guidance on how they can identify welfare recipients for job retention services. We do not address what specific services should be offered or targeted, rather, we provide a general statistical framework that can be used to rank clients by their likelihood of having poor labor market outcomes. States can then use these rankings to target clients who are in need of services and who can benefit from them.

This chapter is in two sections. First, we provide a framework for agencies that may want to develop targeting mechanisms and discuss the key steps they must take to target clients. Then, using data from the National Longitudinal Survey of Youth (NLSY), we present a targeting strategy that can serve as a useful guide for programs that want to use it to target clients or to conduct their own targeting analysis.[1]

Using the NLSY data, we find that it is feasible to successfully identify clients who are at high risk of having labor market problems so they may be targeted for more intensive job retention services. This is because we observe diversity in the characteristics of welfare recipients and the types of jobs they find, diversity in their employment patterns over a longer period, and some association between these individual and job characteristics and long-term employment outcomes. These modest associations allow us to predict which cases are likely to have poor employment outcomes and are in particular need of job retention services. It is worth emphasizing that initial job characteristics are good predictors of job retention, and using these characteristics largely accounts for the success of our targeting analysis.

The remainder of the chapter is organized as follows. The first section describes the data and sample used in our empirical application. Next, we discuss our methodological approach to targeting and provide a framework for agencies that want to develop their own targeting mechanisms. We lay out, in six steps, how agencies or programs can conduct their own targeting. In the third section, we use the NLSY data to illustrate our approach to targeting. The data or resources to develop targeting mechanisms may not be currently available in some states or local areas, so the targeting strategy based on the NLSY data can serve as a useful guide for programs that may want to attempt to target clients before conducting their own analysis. The last section provides some concluding comments.

DATA AND SAMPLES

Our targeting analysis attempts to identify cases at high risk of adverse labor market outcomes and provide decision rules for programs to select these individuals for services. This analysis uses data from the 1979–1994 NLSY.[2] The NLSY selected a nationally representative sample of youths who were between the ages of 14 and 22 in 1979 and followed the sample members for the next 15 years, until they reached ages 29 to 37.[3] The data include detailed information on sample members' program participation, labor force participation, and other sociodemographic and economic variables.

Our sample includes 601 young women who, at some point during the panel period, started a job either while receiving AFDC or within three months after ending an AFDC spell. To observe employment experiences over the long run, the sample also includes only those welfare recipients for whom we have five years of follow-up data after initial job start.

The welfare recipients in our sample are fairly disadvantaged, although there is some diversity in their demographic characteristics. Our sample members were on average about 23 years old at the time their jobs started (Table 9.1); however, over 17 percent were teenage mothers. About 64 percent had an infant or toddler less than two years of age. About one-third of sample members did not have a high school credential. In addition, more than 50 percent scored in the bottom 25 percent of those taking the Armed Forces Qualifying Test (AFQT), although more than 15 percent scored in the upper half of test takers nationally.[4]

In general, our sample members found fairly unstable, entry-level jobs that provided low pay, offered few fringe benefits, and had high turnover. Sample members earned an average of $6.60 per hour (in 1997 dollars), and about 33 percent held jobs that paid less than $5.50 per hour; only about 20 percent found jobs that paid $8.00 or more per hour (Table 9.2). Just under half of the sample held full-time jobs (defined as jobs with 35 or more hours of work per week). In addition, just under half reported working in jobs that offered paid vacation, and about 42 percent had jobs that offered some health insurance. Finally, about 48 percent worked in evening or variable-shift jobs.

Job retention was a problem for most welfare recipients in our sample. Nearly 45 percent ended their initial employment spells within four months, and more than 75 percent ended them within one year (not shown). However, many of those who lost their jobs found new ones. For example, about 60 percent found another job within one year.

We find that because of the cycling in and out of employment, there is some diversity in the employment experiences of our sample mem-

Table 9.1 Characteristics of the Sample

Characteristic	All welfare recipients who find jobs (%)	Averages
Age at start of job (yr.)		
Less than 20	17.4	
20–24	57.1	
30 or more	2.6	
Average age		22.5
Age of youngest child (yr.)		
0–2	63.8	
3–5	28.6	
6 or older	7.6	
Average age		2.2
Child care arrangement		
Relative care	47.1	
Nonrelative care	22.5	
Center-based care	15.3	
Other arrangements	14.1	
Lives with mother/partner	55.9	
Degree attained		
High school diploma	53.6	
GED	13.0	
AFQT scores (percentile)		
Less than 10	23.9	
11–25	28.7	
26–50	31.6	
More than 50	15.8	
Average score		28.7
Has a valid driver's license	71.0	
Health limitations	6.1	
Sample size 601		

NOTE: All estimates are weighted using the 1979 sample weights. Data pertain to the start of the first observed employment spell while case was on welfare or within three months after case left welfare. Sample includes those for whom we have a five-year follow-up period.
SOURCE: Data from the 1979–1994 NLSY Surveys.

Table 9.2 Characteristics of Initial Jobs Obtained by Sample Members

Characteristic	All welfare recipients who find jobs (%)	Averages
Hourly wages (1997 $)		
Less than $4.50	21.1	
$4.50–$5.49	11.9	
$5.50–$6.49	24.2	
$6.50–$7.99	22.0	
$8 or more	20.8	
Average wages		6.59
Hours worked per week		
1–19	20.3	
20–29	16.0	
30–34	11.5	
35–39	10.1	
40–more	42.1	
Average hours worked		31.2
Weekly earnings (1997 $)		
Less than $100	21.2	
$100–$174	21.5	
$175–$249	25.1	
$250–$324	17.6	
$325 or more	14.5	
Average earnings		214.09
Fringe benefits available		
Health insurance	41.9	
Life insurance	29.1	
Paid vacation	47.1	
Shift workload		
Regular day shift	52.3	
Evening shift	31.5	
Variable shift	16.2	
Occupation		
Manager/professional/technical	7.1	
Sales	4.2	
Clerical	24.6	
Operators	12.6	
Service	36.8	

Table 9.2 (Continued)

Characteristic	All welfare recipients who find jobs (%)	Averages
Occupation (continued)		
Private household	10.1	
Other	4.5	
Sample size 601		

NOTE: All estimates are weighted using the 1979 sample weights. Data pertain to the start of the first observed employment spell while case was on welfare or within three months after case left welfare. Sample includes those for whom we have a five-year follow-up period.
SOURCE: Data from the 1979–1994 NLSY Surveys.

bers during the five-year period after they found their initial jobs. For example, as seen in Table 9.3, about 25 percent of the sample were employed in less than 25 percent of the weeks over the five-year period after initial job start, whereas about 30 percent worked more than three-quarters of the weeks during the five-year period.

Because our analysis uses data obtained before the passage of PRWORA, some of these findings should be viewed with caution. For example, the work requirements and time limits imposed by the new law may affect the number of people who enter the labor force, as well as their employment patterns. However, while the law may affect individuals' employment experiences, we do not believe that it will affect the more fundamental relationships between individual or job characteristics and employment experiences, which lie at the core of the targeting analysis.

METHODOLOGICAL APPROACH: KEY STEPS FOR MAKING TARGETING DECISIONS

Step 1: Identify Individual Characteristics

Targeting involves identifying key individual characteristics that programs can use to determine who will receive certain services. In se-

Table 9.3 Employment Experiences during the Five-Year Period after the Start of the First Employment Spell

Variable	Sample members (%)	Averages
% of total weeks employed		
Less than 25	25.8	
25–50	22.1	
50–75	22.8	
More than 75	29.3	
Average pecentage of weeks employed		52.5
Number of employment spells		
1	16.1	
2	29.9	
3	20.9	
4 or more	33.2	
Average number of spells		3.0
Sample size 601		

NOTE: Figures pertain to the percentage of sample members in the specified categories. For example, 25.8 percent of sample members worked fewer than 25 percent of weeks during the five-year period after job start.
SOURCE: Data from the 1979–1994 NLSY Surveys.

lecting characteristics, agencies must choose those perceived to be good predictors of labor market outcomes. The choices can be made on the basis of past research or on the experience of the program staff in working with clients, as well as their perceptions of who succeeds and who does not. It is important to select characteristics that can be easily identified at low cost, are readily available to program staff, and are perceived as fair. Programs might consider such characteristics as educational attainment, presence of young children, presence of supportive adults, available transportation and time to commute to a job, as well as job characteristics. In contrast, programs might want to avoid using such characteristics as test scores even if they predict outcomes well, because obtaining them on a systematic basis for all might be difficult. It is also important to minimize the number of data items that program staff will have to consider.

Step 2: Define Outcomes and Goals That Describe Risk Status

Agencies must make decisions on what they consider adverse outcomes, to define the group they intend to target for specialized services. For instance, our study shows considerable diversity among welfare recipients who find jobs. Some recipients are able to maintain their jobs more or less continuously or with only short breaks in employment. Others cycle in and out of low-paying jobs, whereas others lose their jobs and have difficulty obtaining other ones. The risk criteria that state and local agency staff use may be related to the proportion of time welfare recipients are employed during a given period, the number of jobs they hold during a given period, the proportion of time they receive welfare after job start, or other outcomes considered important for targeting of services.

Step 3: Select among Potential Characteristics

Agencies will have to choose from the list of potential characteristics for targeting, as not all identified characteristics will be good predictors of outcomes. Characteristics should only be used if they can effectively distinguish between persons with a high risk of job loss (those more likely to benefit from specialized services) and those with a low risk of job loss.

Efficiency is a key criterion for assessing whether a characteristic is a good predictor of outcomes. An efficient targeting characteristic is one that describes many high-risk cases and only a few low-risk ones. Therefore, programs that target using this variable will ensure that few resources are spent on those who are unlikely to need services. As an example, consider people who have health problems. If most people who have health problems are likely to have poor labor market outcomes, this would be an efficient characteristic on which to target. However, if many with health problems do well in the labor market, targeting on this variable may not be an efficient use of resources.

An efficient characteristic is also one that enables a program to serve a higher proportion of needy clients than would be the case if services were allocated randomly. For example, suppose that two-thirds of all welfare recipients who obtain employment were high-risk cases who likely would lose their jobs quickly. If programs randomly selected 100 clients for services, 67 (two-thirds of the 100) would be high-risk cases who may benefit from additional services. Thus, in this case, a characteristic should be selected only if more than two-thirds of those targeted for services on the basis of the characteristic were high-risk cases. Otherwise, programs could do just as well by randomly serving clients.

It is important to keep in mind that the targeting strategies we discuss here do not address the issue of effectiveness of services in promoting job retention. In selecting characteristics, programs may want to consider whether targeting on the specific characteristic has promise and whether the kinds of intervention that can be implemented for the targeted group have the potential to improve outcomes.

Step 4: Decide Whether to Use Single or Multiple Characteristics

Programs can target people for services on the basis of a single characteristic or a combination of characteristics. Under the single-characteristic approach, an agency would examine each characteristic in isolation and then would use the methods described in Step 3 to select efficient characteristics. The multiple-characteristic approach considers combinations of characteristics that individuals possess and determines how these combinations relate to the risk of adverse outcomes.[5] Programs using the single-characteristic approach would target anyone who has the characteristic for program services. With the multiple-characteristic approach, programs would consider a variety of characteristics and would select those individuals who have one or more of the characteristics, recognizing that those who face multiple barriers are likely to be at higher risk for facing adverse outcomes.

Single-characteristic approach

The main advantage of this approach is that the rules are simple to define and easy to implement. After an agency has identified a characteristic to target, any individual with that characteristic will be selected to receive special services. A second advantage is that, depending on the characteristic selected, the approach may simplify the decision of what services to provide. For example, if people with health limitations are targeted, programs may want to ensure that this group has health insurance or access to medical services.

One of the drawbacks of the single-characteristic approach is that it is less effective than the multiple-characteristic approach in identifying all high-risk cases or in ranking cases according to their need for services. Second, it is somewhat less flexible with respect to enabling programs to select different numbers of clients for possible service receipt. For instance, certain characteristics, such as health limitations, may describe only a small proportion of the overall group of individuals at high risk. Finally, program staff may consider this method unfair because it selects only individuals with certain characteristics for program services.

Multiple-characteristic approach

The main advantage of the multiple-characteristic approach is that it is better able to identify and distinguish those at high-risk for adverse outcomes. If programs make decisions on whom to target for services on a periodic basis after collecting information on a group of clients, this approach also can rank people in order of their risk of having poor outcomes and, consequently, in order of their need for services (see Step 6). This ranking feature allows programs to better select the number and types of individuals who are to receive program services. Finally, program staff may perceive it as a more equitable approach to sharing resources.

The main drawback of this approach is that it is slightly more complex than the single-characteristic approach to implement. For each individual, program staff will have to determine the combination of characteristics he or she possesses, and whether that individual needs special services.

Step 5: Select the Numbers and Types of Clients to Serve

Programs may want to have the flexibility to choose the numbers and types of clients to serve, as program resources or client needs may dictate these choices. For example, agencies confronting tight resource constraints might have to decide in advance what fraction of clients they will serve. With respect to whom to serve, some agencies may choose to serve the neediest set of individuals. In contrast, other agencies may decide that this approach is not the best use of their resources; they may prefer to spread those resources among a middle group of welfare recipients who may face fewer barriers, but who may be more likely to benefit from services. As discussed previously, because the multiple-characteristic approach allows programs to rank individuals according to their risk of having adverse outcomes, it more readily allows programs to choose the number and types of clients they want to serve.

Step 6: Time the Identification of Clients for Targeting

Program staff also have to determine the timing of targeting decisions. For instance, decisions could be made either on a periodic basis, after information on a group of clients has been collected, or on a case-by-case basis, as soon as each client is ready to receive services. This choice will depend on a number of factors, including caseload size, staff size, how quickly services can be provided, assessments of how quickly clients need services, and how quickly the decision rules can be applied.

The timing choice does not affect the way the single-characteristic approach is applied, but it does affect the way the multiple-characteristic approach is applied. If programs make decisions periodically, clients can be ranked on the basis of their likelihood of being high-risk cases, and programs could use these rankings to select cases for services. The rankings would be constructed by using aggregate "scores" for each person that are based on several characteristics (see the appendix). States use this procedure to profile unemployment insurance (UI) claimants who are likely to exhaust benefits (Wandner and Messenger 1999). Programs that make decisions on a case-by-case basis would not be able to rank cases. Instead, they would provide services to an individual if the person's aggregate score were higher than some predetermined cutoff value (see the appendix).

TARGETING STRATEGY USING NATIONAL DATA

To apply the targeting approach most effectively, each state or local agency should attempt to identify targeting characteristics appropriate to their local areas, and program staff must use local data to determine the most appropriate set of decision rules for their own location. Local area circumstances differ to varying degrees, as do the characteristics of individuals who live in each area. Consequently, agencies can create the best decision rules by using data specific to their own areas and identify the most efficient characteristics for targeting purposes.

In this section, we use data from the NLSY sample to identify targeting characteristics for programs that are considering providing job retention services to welfare recipients who find jobs.[6] This analysis has two purposes. First, for agencies that want to conduct their own targeting analysis, this discussion illustrates how to use the proposed targeting framework discussed in the previous section. Second, for agencies that currently lack the data or tools required to conduct targeting analyses but that may be interested in targeting, the NLSY provides preliminary decision rules.

It is important to recognize that our decision rules are based on national data and on our definition of high-risk cases. Caseload characteristics in any given locality might differ from the characteristics of the individuals in our sample. Moreover, the relationship between individual characteristics and employment outcomes may differ across localities. Program staff who choose to use the rules proposed in this report should consider these findings as broad guidelines, and should adapt them to their local circumstances to the extent possible.

Using the NLSY data, we examined eight potential characteristics that programs could use to select individuals for targeting job retention services:

- was a teenage mother at the time of initial employment;
- was employed less than half the time in the year preceding initial employment;
- has no high school diploma or GED;
- has a preschool child;
- received less than $8 per hour (in 1997 dollars) as starting pay in job;
- receives no fringe benefits on the job;
- does not have a valid driver's license;
- has health limitations.

In defining outcomes, we focus on sustained employment during the five-year period after job start. We defined a high-risk case as one who worked less than 70 percent of the weeks during that period.[7] We now summarize the findings from our analysis.

- It is possible to identify single characteristics by using the univariate procedure to identify and target services to high-risk cases.

Table 9.4 shows the efficiency measures of the eight potential targeting variables. The first column presents the sample means (that is, the percentage of individuals who have each characteristic), and the second shows the proportion in that group who need services (that is, who had poor employment outcomes). We find that three-quarters or more of those in three of the eight groups (age less than 20 years, high school dropout, and health limitations) are high-risk cases. For instance, programs that targeted people younger than 20 years of age at the time of initial employment would serve about 17 percent of all welfare recipients who found employment. However, more than 80 percent of those served would be high-risk cases. Similarly, by targeting those with health limitations, programs would serve only 6 percent of all cases, but about 88 percent who receive services would be high-risk cases. If programs wanted to serve high school dropouts, they would serve about 34 percent of all cases. About three-quarters would need services.[8]

Targeting on most of the other variables individually produced either no better or only slightly better results than would have been obtained if the programs were to serve a random set of individuals who find jobs. This finding is driven in part by the fact that a high fraction of the sample members have these characteristics. For instance, more than 90 percent have a preschool child. However, according to our definition of high risk, only two-thirds of the full sample are likely to need services. Therefore, by targeting this group, programs will serve many more cases than need services, which will lead to inefficient use of resources.

- Programs can do better by using a combination of characteristics and applying the multiple-characteristic procedure for targeting.

By using the same set of eight characteristics, the multiple-characteristic or multivariate procedure produced decision rules that were

Table 9.4 Selecting Individual Characteristics for Targeting Purposes Using the Univariate Procedure

Characteristic	% of sample with characteristic	% with characteristic that needs services[a]	% of all high-risk cases receiving services
Age younger than 20 yr.	17.4	80.6	21.7
Employed less than half the time in year prior to job start	79.2	66.6	83.0
No high school diploma/GED	34.2	74.8	39.3
Presence of preschool child	92.4	64.4	93.6
Wage less than $8 in 1997 dollars	79.2	65.6	83.2
No fringe benefits	81.1	70.0	87.8
No valid driver's license	29.0	71.8	32.6
Has health limitations	6.1	88.1	8.3

NOTE: Characteristics are defined at the start of the initial employment spells.
[a] Refers to those in the group who are at high risk for adverse employment outcomes.
SOURCE: Data from the 1979–1994 NLSY Surveys.

able to distinguish between high- and low-risk cases reasonably accurately. Table 9.5 displays findings on how well the multivariate method performed for different fractions of overall caseloads that programs might want to serve.[9] From Columns 1 and 2, we see that if programs serve 10 percent of their caseloads, more than 90 percent of those served will need services (assuming that programs serve the cases at highest risk for negative employment outcomes). Similarly, if they choose to serve 50 percent of their caseloads, more than 80 percent of those served will be high-risk cases who may benefit from services. The values in Column 2 suggest that as programs become more selective with respect to the numbers to serve, they are better able to identify the highest-risk cases.[10]

Compared with the single-characteristic decision rule, the multiple-characteristic decision rule will serve a greater proportion of high-risk

Table 9.5 Efficiency of the Multiple-Characteristic Approach for Targeting Purposes Using the Multivariate Procedure

Fraction of cases served, ranked according to highest level of risk (%)	% that need services[a]	% of all high-risk cases
10	91.1	12.6
20	90.2	27.3
30	87.8	39.2
40	84.6	50.0
50	82.1	60.8
60	79.9	72.7
70	77.9	80.8
80	74.4	88.2
90	71.5	95.1

[a] Refers to those in the group served who are at high risk for adverse employment outcomes.

SOURCE: Data from the 1979–1994 NLSY Surveys.

cases for the same total number of people served. For example, programs that want to serve about 20 percent of their cases could choose to serve teenage mothers (see Table 9.4), or they could use the multivariate method to choose the 20 percent with the highest probability of poor outcomes. By targeting the single characteristic, 80 percent of those served will be high-risk cases; according to the multivariate methods, more than 90 percent will be high-risk cases (Tables 9.4 and 9.5).

- Implementing decision rules is straightforward. However, programs must take into account their own goals and area characteristics when applying these rules.

If programs choose to use the single-characteristic decision rules, implementation is straightforward. Program staff would identify cases with a particular characteristic and would provide services only to those cases.

Program staff could implement the multivariate decision rule in two stages. In the first stage, program staff would calculate an aggregate score for each individual based on the characteristics the individual possesses. The weights attached to each characteristic, displayed in Table 9.6, would be used to construct these aggregate scores.[11] For example, a high school dropout who has a wage of $6 per hour and no fringe benefits, but none of the other characteristics listed in Table 9.6, would receive an aggregate score of 10 (3 + 2 + 5). Individuals with higher aggregate scores are more likely to be high-risk cases than are those with lower scores.

In the second stage, programs would use the aggregate scores to identify cases requiring special services. If program staff decide to make targeting decisions periodically, after collecting information on a group of clients, they would rank all these clients on the basis of their aggregate scores and would select those with the highest scores. However, if program staff decide to make targeting decisions sequentially, on a case-by-case basis, they would have to measure an individual's aggregate score against a cutoff value and provide services if the aggregate score were higher than that cutoff value. The cutoff values are dis-

Table 9.6 Checklist for Multivariate Targeting

Barriers	Weight	Check characteristic	Associated points
Age younger than 20	✓✓	□	—
Employed less than half the time in year prior to job start	✓✓	□	—
No high school diploma/GED	✓✓✓	□	—
Presence of preschool child	✓✓	□	—
Wage less than $8 in 1997 dollars	✓✓	□	—
No fringe benefits	✓✓✓✓✓	□	—
No valid driver's license	✓✓	□	—
Has health limitations	✓✓✓✓✓	□	—
		Total score	________

NOTE: Discussion of the calculation of the weights is contained in the appendix.
SOURCE: Data from the 1979–1994 NLSY Surveys.

Table 9.7 Cutoff Scores for Multivariate Targeting

Fraction served (%)	Cutoff levels
70	10
50	12
30	14
20	15
10	17

NOTE: Discussion of the calculation of the cutoffs is contained in the appendix.
SOURCE: Data from the 1979–1994 NLSY Surveys.

played in Table 9.7 and depend on the fraction of the caseload that the programs want to serve. In particular, the fewer cases a program wants to serve, the higher the cutoff value it will have to use. Thus, if the program had the goal of serving at least 70 percent of cases, a client with an aggregate score of 10 would receive services (because the cutoff value would be 10). If the goal was to serve only 50 percent of cases, this person would not receive services (because the cutoff value would be 12).

As we have mentioned, the decision rules described here were created using information on a nationally representative sample of youths who received welfare and found a job at some point between 1979 and 1990. The caseload characteristics in any locality might differ from the characteristics of the individuals in our sample. Moreover, the relationship between the characteristics and being a high-risk case may differ among localities. Program staff are encouraged to work with researchers to generate their own set of weights and cutoff values using local data. However, program staff who decide to use our results as guidelines should adjust them based on good-sense judgments of local area characteristics (in the absence of data for analysis). For instance, in urban areas with mass transit, programs may want to ignore whether or not a welfare recipient has a driver's license in calculating weights, as this characteristic is unlikely to form a barrier to work. Furthermore, program staff may want to adjust their cutoff values downward because they are dropping this characteristic from consideration.

CONCLUSIONS

Our analysis has shown that programs can successfully identify high-risk cases using data on individual and job characteristics that are likely to be available to program staff. Programs can use single characteristics (such as age, education levels, or health problems) to identify high-risk cases. Alternatively, they can more accurately identify high-risk cases by targeting on a combination of client characteristics. The decision rules we construct can provide guidance to programs that want to target clients, and the programs can use the framework to develop their own decision rules.[12]

The challenge for program operators as they decide to go ahead with targeting is how to select cases so that resources can be put to the best use. Differences in program goals and resources, local circumstances, and area and client characteristics all determine whom programs might want to target. Because of these differences, each state or local area ideally should conduct its own assessments of the feasibility of targeting and should identify the key characteristics most appropriate for targeting in its local area. Conducting these assessments and formulating targeting decisions at the state or local level will require data, both on the characteristics of welfare recipients and on the outcomes, so that a determination can be made of how characteristics relate to outcomes.

Before attempting to target individuals for job retention services, programs have to consider several factors. First, programs should consider whether there is sufficient diversity among welfare recipients' characteristics, the types of jobs they find, and their employment experiences. For example, if all welfare recipients who find jobs have a hard time holding on to their jobs, targeting would not be very meaningful. However, if some groups of individuals can hold sustained employment on their own, while others cannot, programs may want to know who the latter are so they can focus resources more intensively on those who most need them. A second factor that may determine whether or not a program targets clients for services depends on whether it has resource constraints. If a program has no resource constraints, it can serve all clients. By doing so, it will ensure that everyone who potentially needs services is covered. However, if programs want to use their resources efficiently, they may want to allocate their resources to those who most need services. Finally, the types of services being provided may guide whether targeting makes sense. If a program is considering delivering intensive services that are costly and require extensive outreach, it may be worth considering targeting. However, if a program is considering a more passive approach to service delivery (for example, making available job search assistance or child care subsidies, where service use may be driven by client demand), targeting may be less relevant.

Notes

This research was supported by Department of Health and Human Services Contract Number 282-92-0044 (21). We are grateful to Lawrence Wolf, Nancye Campbell, Howard Rolston, and Kelleen Kaye at DHHS, Stuart Kerachsky, Alan Hershey, and Phil Gleason at Mathematica, and Chris O'Leary and Timothy Bartik from the Upjohn Institute for useful comments. We also thank Tim Novak for skillful programming support, Laura Berenson, and Patricia Ciaccio for skillful editing, and Jennifer Baskwell for exemplary production support.

1. Some government agencies are already profiling clients so they can be targeted for services. For example, since 1994, all states have identified those cases who file for benefits under the Unemployment Insurance (UI) program who are likely to exhaust their UI benefits (Eberts and O'Leary 1996). In this volume, Eberts (see p. 221) discusses the use of profiling to target services in state welfare-to-work programs.
2. To increase sample sizes, the random and supplemental samples were used for the analysis.
3. Our sample excludes the small fraction of older women who receive welfare. For instance, in 1995, about 14 percent of households receiving welfare were headed by individuals over 40 years of age.
4. More detailed information on characteristics of sample members, the jobs they found, and their employment experiences can be found in Rangarajan, Schochet, and Chu (1998).
5. The appendix briefly discusses the methods by which agencies can implement the single- or multiple-characteristic approach.
6. In this section, we focus on targeting welfare recipients who have found jobs for job retention services. The general targeting approach, however, can be used by agencies that may want to consider targeting clients for other types of services.

7. Nearly two-thirds of the NLSY sample members were classified as being at high risk for adverse labor market outcomes. The 70 percent cutoff is based on the results of "cluster analysis" that split the sample into those who had low earnings and intermittent jobs (the high-risk cases that were employed less than 70 percent of the time) and those with higher earnings and more stable employment (the low-risk cases).
8. The third column of Table 9.4 shows the percentage of all high-risk cases who would be served by targeting on each characteristic. For example, by targeting on those people younger than 20 years of age at time of initial employment, programs would serve about 22 percent of all high-risk cases.
9. The purpose of Table 9.5 is to indicate how well the multiple-characteristic approach performs (compared with the single-characteristic approach described in Table 9.4).
10. The multivariate decision rule also gives programs the flexibility to decide whom to serve or the types of services to provide. For example, programs may choose to provide the most intensive services to the top 5 percent of the highest-risk cases and to provide less intensive services to the next 20 or 30 percent of the cases that may benefit from certain types of job retention services.
11. The weights are calculated from a simple regression model and reflect the relative magnitudes of the coefficient estimates from the model. The estimation of the model is described in the appendix.
12. To some extent, programs may already be targeting clients for job retention services, although they may not explicitly call it targeting. For instance, programs may allow clients to "self-select" into programs, or case managers may conduct assessments and then decide who receives what type of assistance. The targeting tool presented in this chapter can help case managers as they decide how to direct clients to appropriate services.

Appendix:

Statistical Methods for the Multivariate Targeting Analysis

The multivariate targeting procedure provides decision rules to target cases for postemployment services on the basis of a combination of their individual and job characteristics. This appendix provides details on the statistical aspects of how this procedure can be implemented by program staff who choose to create multivariate decision rules using their own caseload data. This same procedure was used to create the decision rules using the NLSY data that we describe in this report.

To construct decision rules using the multivariate procedure, programs must first identify individual and job characteristics that potentially can be used for targeting. In addition, programs must decide who the group is that they consider at risk of adverse employment outcomes. Finally, they must collect data on a representative sample of their caseload—the test sample—so that decision rules constructed using this sample will apply to cases they will serve in the future. The data must include information on the targeting variables *and* on employment outcomes so that programs can define which cases in the sample are high-risk cases (using their own definitions of a high-risk case).

The tools necessary to construct decision rules are 1) weights needed to assign to each targeting variable, and 2) cutoff values to determine which cases should be targeted for services. These tools are obtained from a regression model, where the targeting variables are used to predict whether a case in the test sample was a high-risk case. Program staff can then use these tools to determine whether the cases that programs serve in the future should be targeted for specialized postemployment services.

The tools necessary to construct decision rules using the multivariate approach can be obtained in the following three steps.

1) *Estimate a logit regression model.* Using data on the test sample, programs should regress the probability that a case was a high-risk case on the selected targeting variables (such as individual and job characteristics).[1] The parameter estimates from this model represent the effects of each targeting variable on the likelihood that a case should be targeted for services. Many statistical software packages can be used to estimate the model. Targeting variables that have little ability to predict who is a high-risk case (that is, that are statistically

insignificant) should be removed from the model, and the model should be reestimated. The overall predictive power of the final model should be assessed using the criteria presented in this report.[2]

2) *Construct weights to assign to each targeting variable.* The weights are the parameter estimates from the logit model. Program staff may want to scale each of the weights by a fixed factor (for example, 10 or 100) and then round them to make the weights user-friendly.[3]
3) *Construct cutoff values for different assumptions about the proportion of the caseload that programs may want to serve.* To construct the cutoff values, programs first need to construct an "aggregate score" for each case in the test sample. The aggregate score for a particular case is a weighted average of measures of the case's characteristics, where the weights are those constructed in step 2.

   The cutoff values can then be constructed using these aggregate scores. Suppose that a program aims to serve 10 percent of the caseload. The cutoff value for that program is selected so that 10 percent of those in the test sample have an aggregate score greater than the cutoff value, and 90 percent have an aggregate score less than the cutoff value. Similarly, the cutoff value for a program that aims to serve 40 percent of the caseload is that value such that 40 percent of those in the test sample have an aggregate score greater than that value.

Once these weights and cutoff values have been obtained using the test sample, programs can use these tools to target cases in the future for specialized postemployment services. The process of assigning cases, however, will differ depending on how sites choose to time the selection process. Programs may choose to target after collecting information on a large number of cases. In these instances, aggregate scores should be constructed for each case by taking a weighted average of the case's characteristics near the job start date and using the weights constructed in step 2 above. Cases should then be ranked on the basis of their aggregate scores, and programs should select cases with large scores. Alternatively, programs may choose to assign a case in isolation as soon as they have information on the case. In these instances, a case should be targeted for services if the case's aggregate score is above the selected cutoff value (created in step 3 above). The relevant cutoff value to use will depend on the proportion of the caseload the program desires to target.

Appendix Notes

1. For example, the following logit model could be estimated using maximum likelihood methods:

$$\text{Pr(case was high risk)} = \frac{e^{x'\boldsymbol{\beta}}}{1 + e^{x'\boldsymbol{\beta}}}$$

where $\boldsymbol{x}$ is a vector of characteristics for an individual, and $\boldsymbol{\beta}$ is a vector of parameters to be estimated. Alternatively, a probit regression model could be estimated.

2. Specifically, this assessment can be performed in four main steps: 1) predicted probabilities should be constructed for each individual using the equation in the previous footnote based on the estimated parameters; 2) individuals should be sorted on the basis of their predicted probabilities; 3) a prespecified percentage of individuals with the largest predicted probabilities should be "selected" for services; and 4) the proportion of those selected for services who are actually high-risk cases should be calculated. The model has sufficient predictive power if the proportion calculated in step 4 is larger than the proportion that would occur if all cases were randomly assigned to services. The assessment should be performed for various prespecified percentages used in step 3.
3. This procedure was used to create the checklist of weights in Table 12 of Rangarajan, Schochet, and Chu (1998), where the logit model was estimated using data on the NLSY sample.

References

Eberts, Randall W., and Christopher J. O'Leary. 1996. "Design of the Worker Profiling and Reemployment Services System and Evaluation in Michigan." Staff working paper no. 96-41, W.E. Upjohn Institute for Employment Research, Kalamazoo, Michigan.

Rangarajan, Anu, Peter Schochet, and Dexter Chu. 1998. *Employment Experiences of Welfare Recipients Who Find Jobs: Is Targeting Possible?* Volume I. Princeton, New Jersey: Mathematica Policy Research, Inc.

Wandner, Stephen A., and Jon C. Messenger. 1999. *Evaluation of Worker Profiling and Reemployment Services Policy Workgroup: Final Report and Recommendations.* Washington, D.C.: U. S. Department of Labor, Employment and Training Administration.

Comments on Chapter 9

Timothy J. Bartik
W.E. Upjohn Institute for Employment Research

The chapter by Rangarajan, Schochet, and Chu develops a simple model that uses data from the National Longitudinal Survey of Youth (NLSY) to predict whether a welfare recipient who gets a job will be employed less than 70 percent of the weeks during the five years after starting the job. These individuals are considered at risk or in need of services.

The chapter outlines how data on individuals can be used to estimate a single- or multiple-characteristic model that can target who is most likely to be at risk. The multiple-characteristic model does better in predicting who is at risk. The authors estimate a logit model predicting which ex-welfare recipients will have employment retention problems and then restate these logit coefficients as simple weights, which can be used to assign points to each client. This approach could easily be implemented by agencies. An agency would measure each client's characteristics, multiply by the weight on each characteristic to get a certain number of points, and add up all these points to determine which clients are the neediest. In the model estimated here, risk is best predicted by whether the person has health limitations, whether the job lacks fringe benefits, and whether the person lacks a high school diploma or GED. Less importance is estimated for other characteristics, such as the job's wage, the client's age, prior employment, or possession of a driver's license. All these characteristics could easily be measured by a social agency, so it would be straightforward for the agency to predict which clients out of a group of potential clients would be most likely to have employment retention problems.

From my perspective as a social scientist, I would like to see an appendix that gives the actual estimates of the logit model. Of course, agencies don't need the actual point estimates and standard errors to implement the model, as long as they have the weights. But the main issues I want to raise go beyond the authors' model to consider the possible purposes of targeting models. In addition, I want to consider how such purposes might vary between targeting unemployment insurance (UI) services and targeting welfare services.

One purpose of targeting models is to best allocate a limited social program budget among potential clients. Given the shortage of funds, we can't serve everyone who might need services. We would prefer to have some rational basis for targeting services. Targeting based on need is appealing, both politically and morally, and the authors have developed an algorithm for this, for which they are to be commended. Targeting based on need is better than simply flipping a coin.

In addition to moral or political purposes, targeting might have the purpose of maximizing the total "value-added" of social services. Targeting might help social programs maximize their value-added in two ways. First, for a given service, a targeting algorithm might identify those who would gain the greatest value-added from the service. Second, if the program offers several services, targeting algorithms might identify those clients who would most gain from a particular service or mix of services.

Compared with targeting based on client need, targeting to maximize program value-added is much more difficult. Ideally, such targeting would be based on estimates of the effects of program participation on outcomes in a model that allows such effects to vary with the characteristics of the person or job. If we want to target different services to different persons, such a model would need to be estimated separately for program participation in different services. This type of targeting is more difficult than what the authors have tried to do, or what most of the targeting literature has tried to do, because the models needed for such targeting are more difficult to estimate. As is well known, there are generally big issues of selection bias in estimating the effects of program participation, as persons who participate in a program may self-select or be selected by the programs. Without some corrections for this selection bias, the estimated effects of program participation may instead represent the effects of this selection.

If we could predict client need extremely accurately, and some people had zero need for services, obviously there would be some correlation between predicted need and value-added: for those with zero need for services, there can be no value-added of services. But in the authors' research, and in the research of others, our predictions of need are usually quite imperfect. Given this imperfection, it is unclear whether predicted need has any correlation with program value-added.

There are some differences between recipients of UI and welfare that make targeting more difficult for welfare recipients. First, I suspect that there is less of a correlation between need and value-added for welfare recipients than for UI recipients. Some people do fine in the labor market on their own and don't need services. Others, who may be a bit needier could benefit greatly from services. Other people do horribly in the labor market, and the kinds of services we can afford to offer don't help. In other words, I have a triage view of the effectiveness of services in improving clients' labor market outcomes. Among UI recipients, I suspect we mostly have persons from the first and second group: people who don't need services, and somewhat needier people who could benefit from services. Hence, it is intuitively plausible that targeting on need could proxy for targeting on value-added, although one would like studies to confirm this. Among welfare recipients, I suspect we have many recipients who fall into the third group and are very needy, but are perhaps too needy for the services we can offer to really help them. So I suspect targeting based on need is less of a proxy for targeting based on value-added. The authors recognize this possible problem, but they need to discuss it further.

A second difference between UI recipients and welfare recipients is the difference in possible services to offer. For UI, the targeting issue is whom to target for mandatory job search assistance. The evidence suggests that such a service probably helps a wide variety of persons gain employment more quickly. For welfare, there is more uncertainty about what services should be offered and more actual variation in services offered. In my view, the services offered to welfare recipients should differ quite a bit, because welfare recipients are a very needy population. Tolstoy's opening sentence in *Anna Karenina* claimed that "Happy families are all alike; every unhappy family is unhappy in its own way." Perhaps we can adapt this observation to social programs to say that the deeper the problems of a potential client of a social program, the more complex and diverse are their needs for services.

Because different welfare recipients will benefit from different services, the type of targeting we do for welfare recipients should depend on what services we are able to offer. Targeting services based on whether the welfare recipient is disabled makes more sense if we have services that provide support for people with disabilities. If we lack such services, I doubt whether targeting based on disability will improve program value-added. Targeting clients based on whether their job placement has fringe benefits makes sense if we have a postemployment service that can help clients find better jobs, or help clients get the Medicaid benefits to which they are entitled. This suggests another possible use of the authors' estimates, which is to decide what services should be offered, not which clients to target. We should seek to adjust our services to what the clients need, not simply adjust the clients served to what we happen to offer.

For highly needy populations such as welfare recipients, doing targeting right requires much more than a statistical targeting algorithm for choosing clients. Welfare reform is already providing the simple services of mandatory job search and work activities. We have already thrown off welfare most of the welfare recipients who can readily find a job if forced to do so. Those who remain on welfare probably need a very diverse set of intensive services. This requires at least two stages to targeting: first, through some simple targeting algorithms, determining who needs more intensive tests to determine specific service needs, and second, based on these more intensive tests, determining what mix of specific services to provide to each client.

For example, work by Sandra and Sheldon Danziger and their colleagues indicates that many welfare recipients are clinically depressed (Danziger et al. 2000). Some welfare recipients may need antidepressants as much or perhaps more than they need job training, but we can't prescribe antidepressants based on a statistical targeting algorithm or a short intake interview. We can use the targeting algorithms to allocate the scarce resource of expensive diagnostic tests. These more expensive diagnostic tests, such as medical exams, would then be used to target specific services.

In sum, the chapter by Rangarajan, Schochet, and Chu is a well-done first step toward the important goal of being able to target job retention services based on need. But we have much more work to do to accomplish the more important but complex goal of targeting the right services to the right clients in order to maximize program value-added.

References

Danziger, Sandra K., Mary Corcoran, Sheldon Danziger, Colleen Heflin, Ariel Kalil, Judith Levine, Daniel Rosen, Kristin Seefeldt, Kristine Siefert, and Richard Tolman. 2000. "Barriers to the Employment of Welfare Recipients." In *Prosperity for All? The Economic Boom and African Americans*, R. Cherry and W. Rodgers, eds. New York: Russell Sage Foundation, pp. 239–277.

Tolstoy, Leo. 1878. *Anna Karenina*. Available on-line at http://www.literature.org/authors/tolstoy-leo/anna-karenina/part-01/chapter-01.html; last accessed December 2001.

Comments on Chapters 8 and 9

Don Oellerich
U.S. Department of Health and Human Services

These chapters are quite timely and important. They address an issue for welfare that has received limited attention—the profiling and targeting of employment-related services to recipients of cash assistance. While not new to the welfare world, the emphasis on work began in the late 1960s with the Work Incentive program and was further emphasized in the 1984 amendments, which created the Job Opportunities in the Business Sector program. Welfare reform of 1996 and the creation of the Temporary Assistance for Needy Families (TANF) marked a giant step in welfare by placing an increased emphasis on work. Both chapters focus on targeting a defined at-risk group for services, moving systematically from the greater welfare population to a smaller group of needy recipients.

Peter Schochet commented that the U.S. Department of Health and Human Services (HHS) is relatively new to reemployment services. While this is true, we have been involved in a large number of random-assignment welfare-to-work experiments since the 1980s. While neither targeting nor profiling was a focus of these experiments, identifying who would benefit from a given set of services has been part of the agenda. Program administrators need to be able to target different types of programs and services to those clients most in need and most likely to benefit. This is particularly true for high-cost services and differentially targeting very disadvantaged and long-term recipients. An example of an early targeting approach was a model employed in Riverside, California. The initial placement into either job search or basic needs training was made based on objective assessment of the applicant's education level—if she had a high school diploma, she was referred to job search. For those with high school degrees, their success or failure in the labor market was the screener for the need for training. This model has become known as the Work First model and has gained wide acceptance with states in operating their TANF programs. Work First has proven to be effective in moving welfare recipients to work very quickly.

Both of the previous chapters take positive steps in moving forward the idea that we can make valid predictions for welfare recipients and identify those who are likely or not likely to succeed in the labor force. Chapter 8, by Eberts, focused on Work First, which in my mind is the dominant model used by states for the treatment of welfare recipients, particularly as they enter the program. Chapter 9, by Rangarajan, Schochet, and Chu, deals with the other end. That is, how to maintain employment for those welfare recipients who manage to get a job, and how to help them leave welfare. Both chapters make the case that targeting could provide a useful tool for defining who might be in need of services, or who is at risk of failing. I don't think the authors go far enough. We need to extend this work to not only identify those at risk but also to identify points of intervention; that is, identify the service needs of clients and identify the strengths that clients bring with them. This is a lot to ask from such models.

HHS is very interested in targeting services, and it is developing several new projects in that direction. These projects are looking at both welfare-to-work strategies for entering and current recipients (the focus of Chapter 8) and job retention and advancement (the focus of the Chapter 9). Hopefully we will learn more over the coming years. An example of a project focused on the former is one jointly sponsored by the Office of the Assistant Secretary for Planning and Evaluation and the Administration for Children and Families (ACF). This project has two components. The first is to get a broad sweep of what is currently going on in the welfare world in terms of identifying disadvantaged clients and targeting them for services. The second piece of this project is more in depth; we will go to 8 to 10 states and observe what the localities are doing. A second project is in the area of retention and advancement; here again, targeting and profiling will come in handy. In the past, the approach has been for those who leave welfare for work to be terminated from the program with little or no employment related services. Today, retention and advancement is an important part of our agenda for ensuring the success of welfare reform. If you start off in a job that is not great or even one that is just okay, we want to provide a set of services that will help you advance in that job, earn a higher wage, and move to a new and better job if that is what is needed. The track record thus far for advancement and retention services is not very positive. ACF, as a first phase in furthering our understanding, is currently awarding planning grants to 13 states to work on retention strategies. From these 13 states it is hoped that we can secure at least several random assignment sites for evaluation purposes of the various strategies that are developed.

A last project I want to mention is one being carried out in Maryland, sponsored by ACF. In this project, they are examining the implementation of assessment practices by line workers at client intake. The aim is to document the information that line workers have for supporting decision making and to find out what changes in this information base would make line workers more effective.

A key point, which has already been mentioned, is that welfare reform has made fundamental changes in the way welfare operates. Eligibility determination and check-writing used to be the main job of line workers. Tools were developed so they could do that job right, and they did it very well. Now they have a new role. Not only do they have to work on eligibility, they have to work on being a job coach, an employment counselor, a needs assessor, and a referral person to direct clients into the right services. Front-line staff need a whole new set of tools that are not yet in welfare offices.

Part of the reason for the increased focus on work is the Personal Responsibility and Work Opportunity Reconciliation Act (PRWORA) of 1996. People who are on welfare have to go to work to maintain their benefits, and there is pressure on the states to get people to work. The initial target is to have 25 percent of the caseload in work-related activities, with this target rising to 50 percent of the caseload in 2002 and thereafter; that is, half the people on the welfare roles have to be in work activities. Also, the hours that these people must be participating has gone up, along with the participation rate. The requirement started at 20 hours and is now at 25, and it will soon go up to 30 hours a week. Part-time work will no longer help meet performance targets. The pressure is on the line worker to make decisions about who needs what, and when to move them to the right place.

There are some additional incentives for states to do the right things. Our financial incentives for high performance total \$200 million per year. These payments reward work outcomes, job placement, and success in the labor force. Success in the labor force has two components: job retention and wage growth. Again, there is an incentive to provide what we call postemployment services. You want to get people into work and move them along. A targeting strategy that would help us to identify those people in need and what they need would come in very handy. Models such as the one demonstrated by Eberts or one that could be developed based on the results of Rangarajan, Schochet, and Chu may help to fill this need.

Peter Schochet raised some good questions. Do the associations between the variables estimated in the models still hold, or have they changed? I believe that the associations have changed, and one of the things that I heard through the day is the need to develop the models and periodically update them so they are in tune with what is happening.

Welfare recipients always went to work. There was always a portion of the caseload that left very quickly, went to work, but unfortunately came back. So the data from the analysis show about half of the people leaving welfare, with about half of those leaving for work and half of them coming back onto public assistance within a year. Preliminary data on trends since PRWORA was enacted in 1996 suggest that things are changing. People are still leaving for work, but in higher proportions: instead of half, about 60 to 65 percent are getting jobs at exit. That is as high as anything that we have seen in any of the welfare-to-work experiments. It is just phenomenal as far we are concerned.

Equally important is the fact that people who leave are much less likely to come back onto the welfare rolls. Previously, half of the people would return within a year. In some states, the fraction has now dropped to 20 percent. People are going out, finding, and keeping a job. How well are they doing? We are studying that in 13 or 14 different locations. A number of states are also doing their own evaluations. We have what we call the "welfare leavers" studies, because the first question that was asked after welfare reform is, what is happening to all of these people leaving? The caseload in late 1998 was 44 percent lower than it was in 1993. There were about 2.2 million fewer families on in December 1998 compared with January 1993.

Not only is work effort up for people who are leaving welfare rolls, but it is up for the people still receiving assistance. It used to be that in any month, about 8 percent of the caseload was engaged in work. The recent data indicate that this fraction is up to 18 percent. Beyond PRWORA, we believe that these results are due to a combination of a strong economy and changes in the way that states figure earnings disregards. The old rules likely discouraged work. Newer policies such as Michigan's, where they are allowed to keep the first $200 plus 20 percent of anything beyond, encourage work. So we are seeing more work happening all of the time.

We would like to target people for additional services while they are on the caseload so they can increase their labor supply and move on. Many welfare recipients have characteristics that would classify them as at-risk. Schochet said that in his data, two-thirds of his sample could be considered at-risk. The question that needs to be addressed is, what are the service needs of this large group of at-risk clients?

Tim Bartik mentioned, and I know Sheldon Danziger talks about this fact, that people with mental disabilities, mental health problems, and learning disabilities are a very large share of the welfare caseload. People with cognitive impairments, developmental disabilities, substance abuse problems, and victims of domestic violence are all clients. About half of the caseload can be considered long-term, meaning that they have received assistance for 30 months or more. People who have been on welfare for 30 months or more don't do a lot of working. They don't have a strong labor force attachment. About 45 percent of this group have neither a GED nor a high school diploma. Reading and math skills are an employment barrier for between 40 and 50 percent, physical disability hinders 20 to 35 percent, about 15 percent have debilitating substance abuse problems, and domestic violence affects 20 to 30 percent of the caseload in any given year.

As Schochet pointed out, if there is no variability in the caseload, you cannot target services. As caseloads decline, I expect that the variability in client types will diminish on the welfare rolls and that remaining clients will be increasingly harder to serve. In terms of observable characteristics, the trends observed for entry cohorts from 1988 to 1997 are the age of the mother at entrance, the age of the mother at first birth, and education of the mother and youngest child. There had been no change in program entrance, but the caseload itself is changing slightly, meaning that there is a distinct population of those leaving.

State-by-state variation in client populations is quite large: some states have had caseload reductions of 90 percent. That is, they have 10 percent of their former caseload from just 1993 to 1998. Other states may have seen caseload reductions of 11 percent. The big states of California and New York have reduced caseloads by about 25 percent.

We will certainly have variation among the states, rather than one size fits all. I like the idea of the Upjohn Institute model, where it could be adapted to other states and reestimated because it uses information that is readily available. When I look at Eberts's model, I noticed that it only explained about 10 percent of the variation. What that tells me is that 90 percent of the variation is still left unexplained by the set of variables. So there is a lot of randomness in this selection process, even when your probability is spread. Additional variables might help reduce this unexplained variation. I liked the implementation plan. It was simple and straightforward.

I think that the model Eberts presented with the personal computer-based operating system is really nice and slick. For a line worker to have something like that at their disposal to help direct clients would be a great help. It's a great advance over what is currently done. On the welfare side, we clearly have a tendency to ask, what do clients need? That requires a systematic plan for assessment and referral.

I conclude with two final thoughts. One concern I have is the time required for assessment; the distribution appears to be bimodal. Clients appear to require either 2 hours or 20 hours for assessment. Is it the case that those requiring 20 hours have more risk factors? I was unclear about what's going on in the assessment box. It would be helpful if you tell us about that. Also, it would be helpful to know how the reemployment probability correlates to the time required for assessment.

Part III

Canadian Approaches for Targeting Employment Services

Targeting Employment Services

Randall W. Eberts
Christopher J. O'Leary
Stephen A. Wandner
Editors

2002

W.E. Upjohn Institute for Employment Research
Kalamazoo, Michigan

Library of Congress Cataloging-in-Publication Data

Targeting employment services / Randall W. Eberts, Christopher
J. O'Leary, Stephen A. Wandner, editors.
p. cm.
Proceedings from a conference held on April 29 to May 1,
1999 in Kalamazoo, Michigan.
Includes bibliographical references and index.
ISBN 0-88099-244-1 (cloth : alk. paper) — ISBN 0-88099-243-3
(pbk. : alk. paper)
1. Unemployed—Services for—Government policy—United
States—Congresses. 2. Employment agencies—United States
—Management—Congresses. 3. Manpower policy—United States
—Congresses. I. Eberts, Randall W. II. O'Leary, Christopher
J. III. Wandner, Stephen A.
HD5875.T37 2002
362.85′84′0973—dc21

2002024572

W.E. Upjohn Institute for Employment Research
300 S. Westnedge Avenue
Kalamazoo, Michigan 49007-4686

The facts presented in this study and the observations and viewpoints expressed are the sole responsibility of the authors. They do not necessarily represent positions of the W.E. Upjohn Institute for Employment Research.

Cover design by Jan Underhill.
Index prepared by Nancy Humphreys.
Printed in the United States of America.