Chapter 9

Targeting Job Retention Services for Welfare Recipients

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I. INTRODUCTION

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 paper 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 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. In this paper, we do not address what specific services should be offered or targeted.
This paper 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 rest of this paper is organized as follows. In Section II, we describe the data and sample used in our empirical application. In Section III, we discuss our methodological approach to targeting and we provide a framework for agencies that want to develop their own targeting mechanisms and lay out, in six steps, how agencies or programs can conduct their own targeting. In Section IV, we use the NLSY data to illustrate our approach to targeting. The data or resources to develop targeting mechanisms may not be

¹Some 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). Eberts (1997) discusses the use of profiling to target services in state welfare-to-work programs.
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. Finally, in Section V, we provide some concluding comments.

II. 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 to 1994 NLSY. 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. 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. So that we can 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.

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2To increase sample sizes, the random and supplemental samples were used for the analysis.

3Our 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.
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 1). Over 17 percent, however, 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.  

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 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.

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).
We find that, because of the cycling in and out of employment, there is some diversity in the employment experiences of our sample members during the five year period after they found their initial jobs. For example, as seen in Table 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 weeks over 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 numbers 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.

III. METHODOLOGICAL APPROACH: KEY STEPS FOR MAKING TARGETING DECISIONS

Agencies making targeting decisions must take six steps, which we discuss here.

Step 1: Identify Individual Characteristics That Potentially Can Be Used for Targeting

Targeting involves identifying key individual characteristics that programs can use to determine who receives certain services. In selecting 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 program staffs’ experience in working with clients and 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 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 as 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 on 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, then this would be an efficient characteristic to target on. 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, then 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 a Single Characteristic 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. Programs using the single-characteristic approach would target for program services anyone who has the characteristic. 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, then 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.

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5 Appendix A briefly discusses the methods by which agencies can implement the single-characteristic or multiple-characteristic approach.
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 then 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 either be made 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, then 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 Appendix A). States use this procedure to profile 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 Appendix A).

IV. 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. This analysis has two purposes. First, for agencies that want to conduct their own targeting analysis, this discussion illustrates

6In 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.
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:

1. Was a teenage mother at the time of initial employment

2. Was employed less than half the time in the year preceding initial employment

3. Has no high school diploma or GED

4. Has a preschool child

5. Received less than $8 per hour (in 1997 dollars) as starting pay in job

6. Receives no fringe benefits on the job
7. Does not have a valid driver’s license

8. 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.

\(^7\)Nearly two-thirds of the NLSY sample members was 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).
• It is possible to identify single characteristics by using the univariate procedure to identify and target services to high-risk cases.

Table 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

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8The third column 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.
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 able to distinguish between high- and low-risk cases reasonably accurately. Table 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, then 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, then more than 80 percent of those served will be high-risk cases who may benefit from services. The figures 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.\(^{10}\)

\(^9\)The purpose of Table 5 is to indicate how well the multiple-characteristic approach performs (compared with the single-characteristic approach described in Table 4). Implementing the multiple-characteristic approach is discussed in the next bullet point.

\(^{10}\)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 five percent of the highest-risk cases, and provide less intensive services to the next 20 or 30 percent of the cases that may benefit from certain types of job retention services.
Compared with the single-characteristic decision rule, the multiple-characteristic decision rule will serve a greater proportion of high-risk 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 4) or 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 4 and 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, then 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 6, would be used to construct these aggregate scores. 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 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.

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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 Appendix A.
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, then 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, then 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 displayed in Table 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, then 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, then 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 across 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 licence 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.

V. 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.\(^\text{12}\)

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

\(^\text{12}\)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 paper can help case managers as they decide how to direct clients to appropriate services.
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, then 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, then 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.
TABLE 1

CHARACTERISTICS OF THE SAMPLE
(Percentages)

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
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</tbody>
</table>
TABLE 2
CHARACTERISTICS OF INITIAL JOBS OBTAINED BY SAMPLE MEMBERS
(Percentages)

<table>
<thead>
<tr>
<th>All Welfare Recipients Who</th>
</tr>
</thead>
</table>

<table>
<thead>
<tr>
<th>Percentage of Total Weeks Employed</th>
<th>Five-Year Period</th>
</tr>
</thead>
<tbody>
<tr>
<td>Less than 25</td>
<td>25.8</td>
</tr>
<tr>
<td>25 to 50</td>
<td>22.1</td>
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<tr>
<td>50 to 75</td>
<td>22.8</td>
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<tr>
<td>More than 75</td>
<td>29.3</td>
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<tr>
<td>(Average percent of weeks employed)</td>
<td>(52.5)</td>
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</table>

<table>
<thead>
<tr>
<th>Number of Employment Spells</th>
<th>Five-Year Period</th>
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</thead>
<tbody>
<tr>
<td>1</td>
<td>16.1</td>
</tr>
<tr>
<td>2</td>
<td>29.9</td>
</tr>
<tr>
<td>3</td>
<td>20.9</td>
</tr>
<tr>
<td>4 or more</td>
<td>33.2</td>
</tr>
<tr>
<td>(Average number of spells)</td>
<td>(3.0)</td>
</tr>
</tbody>
</table>

**Sample Size**  
601

**Source:** Data from the 1979 to 1994 NLSY Surveys.

**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.
<table>
<thead>
<tr>
<th>Characteristic</th>
<th>Percentage of Sample with Characteristic (1)</th>
<th>Percentage with Characteristic That Needs Services(^a) (2)</th>
<th>Percentage of All High-Risk Cases Receiving Services (3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age younger than 20 years</td>
<td>17.4</td>
<td>80.6</td>
<td>21.7</td>
</tr>
<tr>
<td>Employed less than half the time in year prior to job start</td>
<td>79.2</td>
<td>66.6</td>
<td>83.0</td>
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<td>No high school diploma/GED</td>
<td>34.2</td>
<td>74.8</td>
<td>39.3</td>
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<tr>
<td>Presence of preschool child</td>
<td>92.4</td>
<td>64.4</td>
<td>93.6</td>
</tr>
<tr>
<td>Wage less than $8 (in 1997 dollars)</td>
<td>79.2</td>
<td>65.6</td>
<td>83.2</td>
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<tr>
<td>No fringe benefits</td>
<td>81.1</td>
<td>70.0</td>
<td>87.8</td>
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<td>No valid driver’s license</td>
<td>29.0</td>
<td>71.8</td>
<td>32.6</td>
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<tr>
<td>Has health limitations</td>
<td>6.1</td>
<td>88.1</td>
<td>8.3</td>
</tr>
</tbody>
</table>

**Source:** Data from the 1979 to 1994 NLSY Surveys.

**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.
### TABLE 5

EFFICIENCY OF THE MULTIPLE-CHARACTERISTIC APPROACH FOR TARGETING PURPOSES, USING THE MULTIVARIATE PROCEDURE

<table>
<thead>
<tr>
<th>Fraction of Cases Served Ranked According to Highest Level of Risk (Percent)</th>
<th>Percentage That Need Services&lt;sup&gt;a&lt;/sup&gt;</th>
<th>Percentage of All High-Risk Cases</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>91.1</td>
<td>12.6</td>
</tr>
<tr>
<td>20</td>
<td>90.2</td>
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<tr>
<td>30</td>
<td>87.8</td>
<td>39.2</td>
</tr>
<tr>
<td>40</td>
<td>84.6</td>
<td>50.0</td>
</tr>
<tr>
<td>50</td>
<td>82.1</td>
<td>60.8</td>
</tr>
<tr>
<td>60</td>
<td>79.9</td>
<td>72.7</td>
</tr>
<tr>
<td>70</td>
<td>77.9</td>
<td>80.8</td>
</tr>
<tr>
<td>80</td>
<td>74.4</td>
<td>88.2</td>
</tr>
<tr>
<td>90</td>
<td>71.5</td>
<td>95.1</td>
</tr>
</tbody>
</table>

<sup>a</sup>Refers to those in the group served who are at high risk for adverse employment outcomes.

**SOURCE:** Data from the 1979 to 1994 NLSY Surveys.
### TABLE 6

**CHECKLIST FOR MULTIVARIATE TARGETING**

<table>
<thead>
<tr>
<th>Barriers</th>
<th>Weight</th>
<th>Check Characteristic</th>
<th>Associated Points</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age younger than 20</td>
<td>✅✅</td>
<td>☐</td>
<td>--</td>
</tr>
<tr>
<td>Employed less than half the time in year prior to job start</td>
<td>✅✅</td>
<td>☐</td>
<td>--</td>
</tr>
<tr>
<td>No high school diploma/GED</td>
<td>✅✅✅</td>
<td>☐</td>
<td>--</td>
</tr>
<tr>
<td>Presence of preschool child</td>
<td>✅✅</td>
<td>☐</td>
<td>--</td>
</tr>
<tr>
<td>Wage less than $8 (in 1997 dollars)</td>
<td>✅✅✅✅</td>
<td>☐</td>
<td>--</td>
</tr>
<tr>
<td>No fringe benefits</td>
<td>✅✅</td>
<td>☐</td>
<td>--</td>
</tr>
<tr>
<td>No valid driver’s license</td>
<td>✅✅</td>
<td>☐</td>
<td>--</td>
</tr>
<tr>
<td>Has health limitations</td>
<td>✅✅✅✅</td>
<td>☐</td>
<td>--</td>
</tr>
</tbody>
</table>

Total Score ________

**SOURCE:** Data from the 1979 to 1994 NLSY Surveys.

**NOTE:** Discussion of the calculation of the weights is contained in Appendix A.
### TABLE 7

CUTOFF SCORES FOR MULTIVARIATE TARGETING

<table>
<thead>
<tr>
<th>Fraction Served (Percent)</th>
<th>Cutoff Levels</th>
</tr>
</thead>
<tbody>
<tr>
<td>70</td>
<td>10</td>
</tr>
<tr>
<td>50</td>
<td>12</td>
</tr>
<tr>
<td>30</td>
<td>14</td>
</tr>
<tr>
<td>20</td>
<td>15</td>
</tr>
<tr>
<td>10</td>
<td>17</td>
</tr>
</tbody>
</table>

**SOURCE:** Data from the 1979 to 1994 NLSY Surveys.

**NOTE:** Discussion of the calculation of the cutoffs is contained in Appendix A.
REFERENCES


APPENDIX A

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 cases 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 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). 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 (for example SAS, SPSS, and S+) 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 re-estimated. The overall predictive power of the final model should be assessed using the criteria presented in this report.

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

\[
Pr(\text{Case was High Risk}) = \frac{e^{X\beta}}{1 + e^{X\beta}},
\]

where \(X\) is a vector of characteristics for an individual, and \(\beta\) is a vector of parameters to be estimated. Alternatively, a probit regression model could be estimated.

Specifically, this assessment can be performed in four main steps: (1) predicted probabilities should be constructed for each individual using equation (i) 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.
8. **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.\textsuperscript{15}

9. **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. Then, 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 3 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 4).

\[\text{This procedure was used to create the checklist of weights in Table 12 of the report, where the logit model was estimated using data on the NLSY sample.}\]
above). The relevant cutoff value to use will depend on the proportion of the caseload the program desires to target.