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2013

Improved Targeting of Social Programs: An Application to a State Job Coaching Program for Adults with Intellectual Disabilities

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November 11, 2013

Abstract

In a climate of flat or shrinking budgets, can programs reallocate existing resources to improve efficiency? We illustrate the potential for gains from redirecting resources using data from a state job coaching program that is designed to increase employment among adults with intellectual disabilities (ID). We model selection into the program and employment outcomes for participants and non-participants allowing for potentially heterogeneous response among observationally equivalent individuals. In our simulations, we find that state ID population employment can be increased from 10.7 percent to an upper bound of 16.7 percent by a program administrator who can allocate the job coaches to those with the most to gain. This is a 56 percent increase in the overall employment rate. While we assume that program administrators know more about individual program participants than we do, we can consider an administrator who has only the information available to the econometrician. In this case, targeting gains based only on observable characteristics would lead to 11.8 percent employment, which is an 11 percent increase in the overall employment rate. Surprisingly, a simple rule that only requires administrators to predict employment success when treated (based on observables) will achieve almost the same results.

JEL Classification: C50; H43; J24

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¶ *The information provided in this manuscript was supported in part by Grant/Cooperative Agreement Number U59/CCU421834 from the Centers for Disease Control and Prevention (CDC). We thank Seminar participants at SEA Annual Meeting and the ASHE biannual meeting, John Gordanier, John Kennan, Kin Blackburn, Scott Gross and Michele Sylvester for their helpful comments and advice. We also would like to thank Jerry Junkins, the director of the job coach program at the South Carolina Department of Developmental Disabilities and Special Needs, for his help. The contents are solely the responsibility of the authors and do not necessarily represent the official views of CDC.*

Key words: Social program evaluation; Discrete-choice models; Policy simulations; Factor structure model

1 Introduction

Social programs are increasingly asked to find more efficient ways to allocate resources, but, practically speaking, how can this be done? Re-allocating resources to improve efficiency requires knowledge of who would benefit most. Economic program evaluations typically focus on estimating the effects of the marginal program dollar, but recent work on estimating the distributional treatment effects allows us to identify who wins and who loses from program participation. In this paper, we go one step further and use this modeling approach to estimate the gains from several counterfactual resource allocations. This kind of analysis can help policy makers identify whether there are feasible ways to make existing program resources go further. In a climate of tightening government budgets, we think this can be a very useful policy tool.

We illustrate the potential for gains from redirecting resources using data from a state job coaching program that is designed to increase employment among adults with intellectual disabilities. Intellectual disabilities are disabilities that originate prior to age 18 which are characterized by significant limitations in both intellectual functioning and adaptive behavior (including everyday social skills and practical skills). Supported employment programs, including job coaching, have been encouraged under federal policy since the Developmental Disabilities Assistance and Bill of Rights Act of 1984 and are present in every state. The goal of job coaching is to help individuals with severe disabilities find stable employment in integrated community settings rather than work environments that employ only people with intellectual disability. Job coaches provide a range of services (from individual skills assessments to on-site job training) to help overcome barriers to community employment. Job coaching programs have been shown to significantly increase employment (Cimera, 2007) even after controlling for potential endogeneity of program participation (McInnes *et al.* 2010), but we do not know how these gains are distributed among current participants and eligible non-participants.

To identify the distribution of treatment effects, we model the uptake of job coaching and employment outcomes. Our model allows for observationally equivalent individuals to have heterogeneous responses to job coaching. Since differences in expected gains from job coaching may also affect the likelihood of participation, we begin with the approach suggested by Aakvik, *et al.* (2005). They develop a model to analyze the effects of a vocational rehabilitation program that allows unobserved gains to affect the likelihood of program participation. This model allows us to estimate the counterfactual outcomes for everyone, as well as the distribution of the potential and realized gains. Using these estimates, we assess the employment effects of possible reallocation of job coaches. The optimal allocation provides job coaches to those who gain the most. Since gains may not be observable to program evaluators, we consider a second best scheme in which the program is assessed based on the employment success of participants. If administrators target employability rather than gains, there can be an unfortunate outcome in which the program appears to be successful because participants are employed but population employment is lower. Our simulations allow us to quantify the costs of using a second best scheme relative to the optimal one. In addition, we consider a well-intentioned policy objective of targeting those who are least employable.

We use a unique data set collected in South Carolina from 1999 to 2005 for all individuals receiving any service from the Department of Disabilities and Special Needs (DDSN). The data includes information on individual characteristics (including IQ, age, gender, race, and an indicator for emotional or behavioral problems), participation in job coaching, and employment outcomes. Because the goal of job coaching is stable employment, our employment measure excludes jobs for short duration (less than 26 weeks) or very low pay (less than $50 per week). The estimates from our model show that while the treatment effects from the job coaching program are positive and significant, they are not maximized. We find that the Average Treatment Effect (ATE) is greater than the Treatment Effect on the Treated (TT). This arises when the program is less likely to reach those with the most to gain from participation. For example, we find that individuals with emotional and behavioral problems are less likely to be employed and coached, but they gain more from coaching (everything else held constant). In our simulations, we estimate that employment can be increased by as much as 56 percent by a program administrator who can perfectly target gains. A more achievable goal of targeting based on observable characteristics is estimated to increase population employment by roughly 11 percent. To put these potential employment gains in perspective, a 50 percent expansion of the program as currently deployed (that is, assuming no change in the way program participants are selected) would achieve a 12 percent increase in population employment.

We begin by describing supported employment and job coaching in Section 2 and then discuss our data and variables in the following section. Section 4 describes the latent variable models of program participation and employment and our estimation strategy. Section 5 reports the estimation results, which are used to conduct the policy simulations described in Section 6. Our conclusions are discussed in the final section.

2 Supported Employment and Job Coaching

Supported employment is a broad term used to describe a set of services that assist individuals with severe disabilities to work in integrated work environments. The primary service of supported employment is job coaching, but it provides other services as well, including transportation and assistive technology and adaptive equipment. People with intellectual disabilities (ID, previously referred to as mental retardation or MR), other developmental disabilities (cerebral palsy, spina bifida, etc.), severe psychiatric disabilities, cognitive disabilities (brain injuries, stroke, etc.) and some other disabilities obtain supported employment services from a variety of service agencies, such as Vocational Rehabilitation and state or private disability service organizations.

The Developmental Disabilities Assistance and Bill of Rights Act of 1984 (re-authorized in 2000, it is referred to as DDA from this point on) encouraged the creation of state-level supported employment programs designed to help individuals with developmental disabilities find and retain paid employment in integrated settings in a community. Intellectual disability is the largest category of developmental disabilities, and it is estimated that about 1.2 percent to 1.5 percent of adults in the United States meet the criteria for having intellectual disabilities as defined in the DDA of 2000 (Yamaki and Fujiura, 2002). By 2006, every state had supported employment programs, with total spending (federal and state) of $709 million, accounting for 21 percent of all individuals participating in education, leisure, and work-related programs offered during the day (Braddock, Hemp, and Rizzolo, 2008). A recent national study finds that on average across states, $1 spent on supported employment returns $1.21, with the savings coming primarily in reduced expenditures on alternative day services (Cimera, 2010). For the SC program we study, McInnes et al. (2010) find that the job coaching services for the average placement cost roughly $7100 but save $10,000 in avoided shelter workshop payments. Employment in an integrated setting in the community is also associated with higher wages and opportunities to expand social networks; however, the majority of individuals with intellectual disabilities remain unemployed, underemployed, or employed in segregated workshops (Jones and Bell, 2003; Yamaki and Fujiura, 2002; Rusch and Braddock, 2004).

There are many barriers that prevent individuals with severe cognitive impairment from finding stable employment in integrated environments. First, because intellectual disabilities vary in type and severity, it is not easy to determine if work in a community setting is suitable. Second, when employment is suitable, individualized skill assessment is required to identify appropriate jobs. Third, longer on-the-job training periods may be required for individuals to acquire the necessary skills to perform a given job. Employers may not be willing or able to provide the required training and may not be aware that these individuals can be reliable and productive employees. Finally, in addition to learning specific job skills, stable employment requires appropriate workplace behavior, some social skills (e.g. table manners), and an ability to adapt as the workplace or job changes. Job coaching can address all of these concerns from identifying jobs to providing on-site training to teach required job-specific, workplace or social skills.

The job coaching program for adults with ID in South Carolina has four components: 1) assessing skills and developing a plan for achieving competitive employment; 2) identifying a job suitable for the individual; 3) placement and job-site training in a competitive community job; 4) follow-up. Once a job has been identified by a job coach, she works with the individual in the natural environment of the job for as long as it is necessary for the individual to learn the job duties. The job coach will be present at the job site initially a few hours a day, fading from the site to maximize independence. On-site coaching typically lasts 6 months, and the client reaches job stabilization when he is able to complete his job duties within the natural environment without support from the job coach. The job coach must maintain contact for at least six months once the customer has reached stabilization. When the customer is stabilized in his employment, the services of the job coach are terminated. While independence and job stability are the goal, retraining and "follow along" may last for a year or more.

In South Carolina, 38 local Disability and Special Needs (DSN) boards provide supported employment services to adults. While the DSN boards try to make job coaches available for everyone who would like one, only a fraction of working age adults served by the board receive job coaching in any year. Some families and individuals opt for non-vocational day services (including recreation and leisure activities) or placement in a sheltered workshop rather than job coaching in the community. The demand for job coaching services at each DSN Board is a function of the number of adults served by the Board, the reputation for success or failure that has developed, and the staff support of the program. Some DSN Boards have a waiting list of 10-20 individuals at any given time while other Boards have a difficult time recruiting participants.

We do not observe whether employment affects disability benefits. Most adults with mental retardation are eligible and do receive Supplemental Security Income (SSI). The SSI program provides cash assistance to aged, blind or disabled individuals who have limited income and resources. Earnings from employment result in lower SSI benefits if the individual's adjusted earnings are sufficiently large. Most working individuals with ID do not reach the substantial gainful activity (SGA) standard, which translates to full-time work (37.5 hours per week) at $6.53 per hour[1]. Thus, individuals with ID who work competitively, with or without a job coach, are usually eligible to maintain their Medicaid benefits which include health insurance and disability related services. Our empirical strategy must also allow for the possibility that there are unobservable individual characteristics that affect both coaching and employment. We discuss this in more detail when we construct our model in Section 4.

3 Data and Variables

We obtain administrative data from South Carolina for all individuals with ID who received any service from the Department of Disabilities and Special Needs (DDSN) at any time between 1999 and 2005. Individuals are active in the DDSN data system if they receive any service from the agency during a calendar year. The most common service is "service coordination" which consists of an annual meeting with the individual, his family or staff and other interested parties. This meeting is intended to review goals and coordinate services. When an individual obtains a competitive job, they often stay in the DDSN system for family support services, recreation, or residential services. The full list of services for adults are given in the Appendix.

[1] For 2004 and 2005, we have additional data that allows us to get a rough assessment of the impact on SSI benefits for these two years. Without considerations of possible exclusions, about 90 percent of all employed and 86 percent of the employed among job-coached are making below the threshold of SGA which was set to be $810 for 2004 and $830 for 2005 for non-blind disabled.

To be included, an individual must be between 21 and 65 years of age (inclusive) during the year and have an IQ score above 26 and below 75. Individuals whose primary diagnosis is autism are excluded, as are those who live in intermediate care facilities (group homes with the highest level of supervision for people with ID) or other institutional settings. Because there are very few individuals whose race is identified as other than African American or white, these individuals are also excluded. We also have employment data collected every year, through a collaboration of the University of South Carolina School of Medicine and DDSN, that reports on every individual with ID who obtained, sustained, or lost a job in the last twelve months. The employment data indicates the job title, place of employment, wages earned, and whether a job coach was provided. The final data set includes only individuals with ID who have a linker number for the DDSN administrative data file so information about the individual can be merged with the employment data. The data from the two sources are de-identified for analysis.

Job coaching typically consists of 6 months of on-site training and at least 6 months of follow-up. Our goal is to see whether coaching enables the individual to continue working after the coach has left the job site (but may still be offering continued support via monthly phone calls or visits). Hence we measure the effect of job coaching in year $t-1$ on the probability of employment in the subsequent year t among the sample of individuals who are unemployed in $t-2$. Because this requires 3 years of observation, we can model employment outcomes for 5 years (2001 to 2005) for all individuals who received any services from DDSN in any year. If the individual has no data from the previous year, then their job coaching variable is set to zero. Of those with incomplete histories, about half of these are individuals who just turned 21 (corresponding to about 3 percent of the observations from each year) and would most likely have been in high school through their 21st birthday. High schools provide some vocational services, but we do not observe this coaching in our data and count them in the not-coached group.

We construct a pooled cross section in which individuals are only included once. We begin with a true cross section which was all individuals for whom we observe employment outcomes in 2001 and job coaching status in 2000 that were unemployed in 1999. We then add in individuals who were not in this group (because they were employed in 1999 or had incomplete histories) but for whom we had 3 consecutive years of data with unemployment observed in the first year. Excluding duplicates prevents over-representing the substantial fraction of the sample who are never employed in our observation period. Hence, the employment status of the long-term unemployed group will be only measured in the first eligible year (2001). The majority of our data comes from the 2001 cross section, but adding in the unique observations from later years allowed us to increase the sample size from 6625 to 9898.

Since job coaching is intended to facilitate stable employment in integrated settings (rather than sheltered workshops), we screen for employment in jobs with very low pay or very short duration. For the purposes of this study, employment is defined as earning at least \$50 per week for 23 weeks or more (see, for example, Howarth, Mann, Zhou, McDermott, & Butkus, 2006; Pierce, McDermott, & Butkus, 2003; Moran, McDermott, & Butkus, 2002). We consider anyone who works for shorter durations and makes less per week as unemployed.[2] Because our data do not differentiate between on-going on-site coaching, follow-up contact, and any re-training that occurs if there are job changes, we utilize a bivariate measure of job coaching (some or none) in year $t-1$.

[2] If individuals are earning less than \$50 per week or employed for fewer than 26 weeks, we do not observe their wages or employment in the data. To gauge sensitivity of the results to the definition of the dependent variable, we increase the cutoff wage to \$60 and find that the results do not change.

Table 1 : Variable Definitions and Descriptive Statistics (N=9898)					
		Mean	Std. Dev.	Min	Max
Job Coached	Job Coaching Program Participation Status in year $t-1$ Dummy =1 if Participant	0.078	0.268	0	1
Employed	Employment Status in year t Dummy =1 if Employed	0.105	0.307	0	1
IQ score	IQ Score	50.87	12.75	26	75
Emotional Beh Prob.	Does Client have any Emotional or Behavioral Problems? Dummy =1 if Yes	0.225	0.417	0	1
Female	Gender of the Client Dummy =1 if Female	0.471	0.499	0	1
African American	Race of the Client Dummy =1 if African American	0.515	0.499	0	1
Age	Age of the Client	35.47	12.049	21	65
Age-squared	Age Squared	1403.31	937.09	441	4225
Supervised housing	Does Client live in Supervised Housing? Dummy =1 if Yes	0.204	0.407	0	1
Unemployment	Unemployment Rate in the County	6.149	1.955	3.6	13.8
Job Coach Avail	Number of Job Coaches Divided by Number of Clients Registered with the Board	0.161	0.075	0	0.400

Variable definitions and descriptive statistics for the sample are shown in Table 1. About half (51 percent) of the sample is African American, and just under half (47.1 percent) of the sample is female. The average age and IQ are, respectively, 35.5 and 50.9. About 23 percent of the sample has some emotional or behavioral problems reported. Finally, 20 percent live in a supervised setting (group homes or supervised apartments), and the remaining 80 percent live with parents or independently.

In Table 2, we stratify our sample by receipt of job coaching services. This table highlights the statistically significant differences between the two groups in terms of observables. On average, the group receiving job coaching consists of individuals who have higher IQ's (53.8 versus 50.6) and who are older (36.7 versus 35.4). Participants are also more likely to be African American (56 percent versus 51 percent) and live in supervised housing (20 percent versus 33 percent). Absolute values of the t-statitics for differences in means are reported in the last column of Table 2.

Table 2 : Descriptive Statistics by Job Coaching Program Participation Status					
	Non-Participant (N=9126)		Participant (N=772)		
Variable	Mean	Std.Dev	Mean	Std.Dev	$\lvert t \rvert$-*statistics*
Employment	0.078	0.268	0.425	0.495	19.240
IQ score	50.619	13.788	53.823	11.953	7.061
Emotional behavioral problems	0.227	0.418	0.202	0.402	1.654
Female	0.472	0.499	0.452	0.498	1.071
African American	0.511	0.499	0.557	0.497	2.469
Age	35.364	12.211	36.72	9.856	3.596
Supervised housing	0.199	0.399	0.328	0.469	7.419
Unemployment	6.15	1.952	6.138	2.001	0.160
Job coach availability	0.158	0.074	0.198	0.073	14.603

Note: Absolute value of the t-statistics for the differences of the means are reported

4 Model and Estimation

4.1 Model

Our conceptual framework begins with the observation that among individuals with ID, those with lower IQ or emotional and behavioral problems are less likely to participate in job coaching. We expect that those characteristics also hinder employment, but job coaches can help to overcome these deficits by providing on-site training, working with employers to help them supervise effectively, teaching social skills, and finding good matches between individual skill sets and employment settings. Thus, we may expect that the relationship between individual characteristics and employment probability will differ for those who are coached and those who are not. We incorporate this possibility into our model by using two separate latent indices for employment outcomes, one for the coached state and one for the non-coached state. Because factors unobserved by us may affect the success in the program, our model also allows for observationally equivalent individuals to have heterogeneous responses to job coaching. If the unobserved factor is correlated with program participation, an instrumental variables (IV) approach is needed to produce unbiased estimates. However, if knowledge of idiosyncratic gains affects the likelihood of being job coached, then we have the condition termed "essential heterogeneity" and IV estimates will be biased. To address this concern, Aakvik, *et al.* (2005) develop a discrete outcome factor structure model to analyze the effects of a vocational rehabilitation program on employment outcome that provides the basis for our econometric approach. If there is no essential heterogeneity, then their model collapses to a standard IV model.

There are three latent indices in our model, one for job coaching (J^*), the other two for employment (E^*). The first index is defined as follows:

$$\begin{aligned} J_i^* &= Z_i\gamma - V_i \\ J_i &= 1 \text{ if } J_i^* \geq 0,\ J_i = 0 \text{ otherwise} \end{aligned} \tag{1}$$

where J_i is the observed participation status, Z_i is a vector of individual characteristics reported in the DDSN record and V_i is an unobserved individual error term. As we discuss above, we do not directly observe the selection process. Our discussion with officials in the program suggests that both self-selection and recruitment play a role. For simplicity in the discussion below and for later use in our policy simulations, we will describe the process in terms of recruitment. However, our model can be interpreted either way.

The employment latent index is allowed to differ by participation status for observationally equivalent individuals. For participants, the employment status is determined by:

$$\begin{aligned} E_{1i}^* &= X_i\beta_1 - U_{1i} \\ E_{1i} &= 1 \text{ if } E_{1i}^* \geq 0,\ E_{1i} = 0 \text{ otherwise,} \end{aligned} \tag{2}$$

where E_{1i} is the employment outcome for individual i given participation in job coaching, X_i is a vector of observed individual characteristics, and U_{1i} is the unobserved shocks for participants. For non-participants, the index is:

$$\begin{aligned} E_{0i}^* &= X_i\beta_0 - U_{0i} \\ E_{0i} &= 1 \text{ if } E_{0i}^* \geq 0,\ E_{0i} = 0 \text{ otherwise,} \end{aligned} \tag{3}$$

where E_{0i} is the employment outcome for individual i given that she is not job coached. The error term U_{0i} is the unobserved shocks for non-participants. In this model, $\Delta_i = E_{1i} - E_{0i}$ is the effect of participation in job coaching on the employment outcome.

In order to identify the unobserved gains from treatment, we model the relationship between the unobserved factors that determine employment and treatment as follows:

$$V_i = -\theta_i + \varepsilon_i \tag{4a}$$

$$U_{1i} = -\alpha_1\theta_i + \varepsilon_{1i} \tag{4b}$$

$$U_{0i} = -\alpha_0\theta_i + \varepsilon_{0i} \tag{4c}$$

where θ_i is the common unobserved factor. If either α_0 or α_1 is non-zero, then we have essential heterogeneity. We assume that θ, ε, $\varepsilon_{1,}\varepsilon_0$ are independently and identically normally distributed error terms.

Due to nonlinearities, the model is identified even without an exclusion restriction. However, we find inclusion of an instrument substantially increases the fit of the model. When choosing our instrument, our strategy is similar to Aakvik, et al. (2005) in seeking a measure of treatment availability that is correlated with participation in the program (vocational rehabilitation in their case), but does not affect employment probability other than through the effect of program participation. Aakvik et al. have a direct measure of the length of the queue for entering the program that they use as their instrument. While we have no way of directly measuring how long individuals have to wait before entering the program, we do have a board-level measure of job coaching availability. This measure is the ratio of individuals receiving job coaching to clients registered at each disability board in each year. We show below in Table 3 that the percent of clients participating in the job coaching program at the board level is a statistically significant predictor of individual participation in job coaching. McInnes et al. (2010) use the same data to model employment outcomes in a panel data analysis and find that this is a valid instrument. We also include two time-varying variables (an indicator for whether the individual resides in supervised housing and the county unemployment rate for year $t-1$) and find both are significant predictors of participation. Given that we control for current values (year t) of these variables in the employment equation, we do not expect the previous period values to have an independent influence on current employment status.

4.2 The Likelihood Function

The likelihood function has the following form

$$L = \prod_{i=1}^{N} \int \Pr(J_i, E_i | X_i, Z_i, \theta) \phi(\theta) d\theta, \tag{5}$$

where

$$\Pr(J_i, E_i | X_i, Z_i, \theta) = \Pr(E_i | X_i, J_i, \theta) \Pr(J_i | Z_i, \theta),$$

and ϕ is the standard normal probability distribution function. Since θ is not observed, we need to integrate it out. We numerically approximate this integration over 100 draws from a standard normal distribution.

5 Estimation results

The parameter estimates of the latent index model are reported in Table 3. First we consider the characteristics that affect the likelihood of being job coached. Males, African Americans, older individuals, and those individuals who live in supervised settings are more likely to participate. Having no emotional and behavioral problems reported and having a higher IQ also significantly increase the probability of participating in job coaching. Our instruments for participation are all strongly statistically significant. The probability of being job coached in t-1 increases with the contemporaneous (that is, the t-1) county unemployment rate, job coaching frequency, and the individual's residence in a supervised setting. Residents in supervised settings may have more access to services, including job coaching, increasing the likelihood of participation.

Next we look at the coefficient estimates for the latent indices that define employment in period t. The characteristics that increase the likelihood of participation also tend to increase the likelihood of employment in the subsequent year whether or not the individual is job coached. However, the effects are generally much smaller and not significant when job coached. Thus, having a job coach helps individuals overcome the labor market losses associated with certain characteristics. This suggests that job coaches are good at finding suitable employment for all types of clients - as long as jobs are available. We do see that living in a county with higher unemployment rates reduces employment probability whether coached or not. We also see that living arrangements affect employment outcomes regardless of job coaching status. Supervised residential settings may offer other employment supports (e.g. transportation) that aid in finding and keeping jobs even without a job coach.[3]

[3]Lagged housing may be directly correlated with employment success in t and also correlated with contemporaneous housing. To gauge sensitivity to this, we estimate with lagged housing in all indices and find the results do not change. We also try excluding housing status from the job coaching equation and find that the results are qualitatively similar.

Table 3: Employment and Job Coaching Program Participation Probability Estimates

	Employment (t)		Job Coaching (t-1)
	Non-participant	Participant	
Constant	-2.609 ***	-0.917	-7.239 ***
	(0.532)	(1.233)	(0.340)
Female	-0.207 ***	-0.091	-0.094 *
	(0.051)	(0.094)	(0.055)
African American	0.176 ***	0.116	0.151 **
	(0.052)	(0.102)	(0.056)
Age/10	0.594 ***	0.474	1.816 ***
	(0.194)	(0.430)	(0.168)
Age-squared/100	-0.080 ***	-0.067	-0.239 ***
	(0.025)	(0.054)	(0.021)
IQ	0.010 ***	0.002	0.018 ***
	(0.003)	(0.004)	(0.002)
Emotional Problems	-0.272 ***	-0.114	-0.318 ***
	(0.070)	(0.125)	(0.068)
Unemployment Rate	-0.061 ***	-0.069 ***	
	(0.013)	(0.025)	
Supervised (t)	0.169 **	0.370 ***	
	(0.082)	(0.134)	
Job Coaching Avail (t-1)	-	-	4.961 ***
	-	-	(0.378)
Supervised (t-1)	-	-	0.613 ***
	-	-	(0.067)
Unemployment Rate (t-1)	-	-	0.048 ***
	-	-	(0.015)
α_0	0.436		
	(0.286)		
α_1	0.126		
	(0.369)		
ATE	0.225		
TT	0.174		
Number of Observations		9898	
Log likelihood		-5422	

Notes:
Model is estimated using Fortran90
Standard errors in parentheses: * significant at 10 percent;
** significant at 5 percent; *** significant at 1 percent

Table 3 also gives the estimates of the factor coefficients α_0 and α_1. Both factors are positive, indicating that the unobservables that make an individual less likely to participate are associated with lower employment probability. We also find $\alpha_0 > \alpha_1$ indicating that the negative effect on employment is greater when not job coached. That is, the person who does not look very employable (based on factors observable to individuals and perhaps policy makers, but not the econometrician) would, if treated, gain in terms of employment probability. However, since neither factor is significantly different than zero, we conclude that there is no significant sorting on unobserved gains in this program as currently deployed. Later in our simulations we will consider the potential benefits were the program to target individuals based on observed and unobserved gains.

The results in Table 3 also show that job coaching works. The average treatment effect (ATE) is estimated to be about 0.23. That is, the probability of employment increases by almost 23 percentage points on average when a randomly chosen person is job coached. If we measure the gains only among those who are actually job coached (TT), the gain is only about 17 percentage points. This indicates that the individuals who are enrolled in the program are not the ones with the most potential to gain. Thus, the program is not reaching its full potential, and program resources can be reallocated to improve total employment.

The estimated correlations between the observable components of the latent indices, shown below in Table 4, also indicate the potential for gains from reallocating job coaches. From the first correlation, we see that the observable factors influencing employment are strongly correlated between the job-coached and non-job-coached individuals. The second and third correlations indicate that the characteristics that are positively associated with job coaching are also positively associated with employment with or without a job coach. The correlation is slightly higher for the non-coached state. From the last correlation, we see that the observable gains in the likelihood of employment due to job coaching are negatively correlated with the probability of being job coached. This reiterates our conclusions from above (e.g ATE > TT) that the program is not reaching those with the most to gain.

Table 4: Correlations Between Latent Indices	
$Corr(X\beta_1, X\beta_0)$	0.7384
$Corr(X\beta_1, Z\gamma)$	0.4979
$Corr(X\beta_0, Z\gamma)$	0.5866
$Corr(X(\beta_1 - \beta_0), Z\gamma)$	-0.2754

The degree to which the treatment effect varies with observable characteristics can be seen from the estimates of the marginal effect of each observable characteristic on the expected gains. Table 5 reports these estimates. We see that marginal gains are largest for females, Caucasians, and those with lower IQ and emotional and behavior problems. Those who live in high unemployment counties and supervised settings also have greater gains.

Table 5: Marginal Effects of Regressors on the Expected Gain from Participation

Regressors	$E_x\left[\frac{\partial E(\triangle \mid X=x)}{\partial x_K}\right]$	std. dev.
Female	0.067	0.022
African American	-0.056	0.023
Age	0.031	0.296
IQ score	-0.004	0.001
Emotional behavioral problems	0.595	0.141
Unemployment	0.061	0.193
Supervised	0.538	0.153

Notes: The marginal effects are calculated as the difference in gains from participation resulting from a one unit change in the covariate value. For dummy variables, the marginal gains are calculated as the difference in gains as the value of the dummy is changed from zero to one. For example, to calculate the marginal effect of being female, we first set the female dummy equal to one for everyone (leaving all other variables unchanged) and calculate the ATE for each individual. We then set it equal to zero, and recalculate the ATEs. Finally we calculate the difference in ATEs and average over the population. To obtain the standard errors, we repeated this with a set of 200 coefficient estimates obtained by bootstrapping

6 Policy Simulations

The purpose of this paper is to see whether job coaching resources can be more efficiently deployed. Our model estimates indicate that there is room for improvement. The advantage of the structural factor model that we employ is that it can be used to develop and assess counterfactual reallocations of program resources. We simulate several different allocations of job coaches to individuals to see whether a more targeted approach would increase the effectiveness of the program and, if so, by how much.

We consider four alternative schemes for allocating job coaches to individuals:

1. Random assignment of job coaches

2. Coach the ones with the highest gains

3. Coach the ones who are the most employable if coached

4. Coach the ones who are the least employable if not job coached

The random lottery assignment serves as a benchmark for measuring the efficiency of the current assignment regime. The calculated ATE and TT above shows us that a random re-assignment of all existing job coaches across DDSN clients will improve outcomes, but by how much? Next we consider the perfect targeting scheme (coach the ones with highest gains) and compare it to two other reallocation schemes that may be more feasible since they require less information. Coaching the most employable if coached is commonly referred to as cream skimming and it is thought to occur in most programs when evaluation is based on the success of participants (Heckman, et al., 2011). Coaching the least employable if not coached can be called bottom scraping. While less efficient than targeting gains, this scheme may serve other social goals. As benchmark for how much can be gained from re-allocating job coaches, we also consider a 50 percent increase in the number of job coaches (using the estimates for the participation model and keeping the distribution of job coaches constant across boards).

To compare the results of the alternative job coaching allocations, we simulate the employment outcomes under each and compare the aggregate probability of employment. Reallocating job coaches may cause aggregate employment to rise or fall, depending on the efficiency of the current allocation system relative to the alternative. To better understand where the relative gains and losses are, we also disaggregate gains from re-assignment to the actual participants and non-participants. An example helps to explain why this matters. In the spirit of Roy's (1951) model of selection, suppose that Bob's marginal benefit from coaching is high but his employment probability if coached is still low. Joe is likely to be employed with or without the program. Now compare the possible outcomes of sorting on employability to sorting on gains. Sorting on employability makes job coaching look very successful: Joe is coached and likely to be employed while Bob is not coached and likely to be unemployed. Sorting on gains will allocate the coach to Bob rather than Joe, and job coaching will not appear to be very successful compared to no job coaching, but the overall employment level will be higher.

Our procedures for the simulations are as follows: for each person in the sample, we replace the unknown stochastic terms with independent random draws from the standard normal distribution. Then we use the fitted values from the model to predict the probability of being employed when job coached and when not job coached. Because the outcomes of each simulation will depend on the outcome of random draws, we create 100 simulated versions of each person and constructed 100 simulated populations and then average the results over these simulated populations.

For the random lottery assignment, we draw a lottery number for each individual from the uniform distribution. We then rank by the lottery number and re-assign the job coaches to those with the highest lottery numbers holding the number of job coaching participants fixed at 772. Note that we allow for reassignment within and across boards, allowing us to capture the employment gains produced by the allocation of coaches by boards and to boards. If the same number of individuals are coached but the assignment is randomized by lottery, the simulated employment rate would rise from 10.7 to 10.8 percent. This result is another illustration of the inefficient assignment of job coaches under the current regime shown by ATE > TT above, but the simulations show that the actual impact in terms of employment is small. With randomized assignment, the treatment effects for the treated and untreated should be roughly the same, and that is what we observe (TU = 0.226 and TT = 0.222).

Next we consider the ideal targeting scheme in which the program is allocated to those who gain the most. Because the program administrators may be able to observe what we cannot, we consider two types of decision makers based on how much information they have relative to the econometrician: 1) The administrator who only observes what we observe in estimating the model; 2) the omniscient administrator who also observes the characteristics that are unobservable to us. An administrator who targets based on only those characteristics available to us would achieve 11.9 percent employment, which represents a 11 percent increase in employment for the overall population with intellectual disabilities. Of course, an omniscient administrator could do even better with knowledge of individual characteristics and unobserved (to us) factors, achieving employment of 16.7%. The difference in effectiveness of these regimes is illustrated by comparing the treatment effects for the treated and untreated. When marginal gains are targeted the TT is greater than the TU (0.31 vs. 0.22) but the difference is much more extreme when the administrator has knowledge of factors unobserved in the model (0.84 vs. 0.17).

We next consider allocating coaches based on an individual's potential for employment if coached. Case workers and job coaches have had opportunity to observe the outcomes of many individual-level coaching "experiments" and may use their experience to guide resources to those who are most likely to attach to the labor force following job coaching. If our administrator targets job coaches based on the probability of employment if treated with knowledge of the unobserved factors which can cause heterogeneous response to treatment, then the overall employment rate would rise to 15.8 percent. Even if the administrator cannot observe these factors, targeting employability based on observables could still improve employment to 11.8 percent. Surprisingly this "second best" targeting scheme (cream skimming) achieves nearly the same success as targeting marginal gains. We also see this when comparing the TT and TU. Targeting employment if coached leads to recruitment of individuals with higher gains so that TT rises above TU and is quite similar to that of the ideal targeting scheme, particularly when the administrator can observe only what is observable in the model. While the employment effects are similar, slightly different groups will be served. The optimal targeting scheme will include a higher percentage of women (46 percent vs. 43 percent among job coached) as well as those with emotional and behavioral problems (24 percent vs. 22 percent) and/or lower IQ (mean IQ of 50 vs. 51.16).

For completeness, we also consider targeting individuals who are the least likely to be employed without a coach. These may be thought of as the individuals who need the program the most. Targeting the "hard" cases would lead to 10.4 percent or 11.1 percent employment rate depending on the information available to the program administrators. Absent knowledge of unobserved factors, the simulations show that "bottom scraping" will result in lower overall employment than the current scheme.

To provide a benchmark for the gains achievable from redirecting resources, we consider how much might be gained by an expansion of the program. While such a change seems unlikely given current budgetary pressures, we consider a 50 percent increase in the number of job coaching hours available. Based on our model, an expansion of the program as currently deployed would increase employment to 12.03% (an increase of 12.7%). This shows that the increase in employment from targeting marginal gains or targeting employment are on par with what could be achieved by a significant increase in resources available to the program.

Table 6: Policy Simulations

	Overall Employment Rate		Average Treatment Effects: Non-Participant(TU)		Average Treatment Effects: Participant (TT)	
Data	10.54%					
Estimate Given Current Program	10.67%	(0.32%)	0.23	(0.003)	0.174	(0.015)
Simulations						
Random Assignment	10.81%	(0.31%)	0.226	(0.003)	0.222	(0.013)
Target Marginal Gains	11.85%	(0.31%)	0.218	(0.003)	0.309	(0.014)
Target Marginal Gains (omniscient administrator)	16.69%	(0.30%)	0.174	(0.003)	0.840	(0.004)
Target Employment Probability if Coached	11.78%	(0.31%)	0.219	(0.003)	0.297	(0.014)
Target Employment Probability if Coached (omniscient administrator)	15.77%	(0.29%)	0.183	(0.003)	0.733	(0.009)
Target Least Employable if Not Coached	10.39%	(0.31%)	0.227	(0.003)	0.209	(0.011)
Target Least Employable if Not Coached (omniscient administrator)	11.08%	(0.32%)	0.216	(0.003)	0.338	(0.010)
50 percent Increase given current participation rule	12.03%	(0.29%)	0.232	(0.004)	0.185	(0.010)

Note: Each policy simulation is performed 100 times. Standard errors are reported in paranthesis and they are the standard deviations for the average participation rates and treatment effects across 100 simulations.

6.1 Limitations

Our interest is in obtaining counterfactual outcomes for individuals so that we can assess winners and losers from participation and experiment with different job coaching assignment rules. Thus, we use a parametric model with assumptions about the relationships between the unobserved factors that affect program participation and employment outcomes. We think our model fits the data reasonably well, but recognize that our conclusions are dependent on the accuracy of structural assumptions. Our broad conclusion that job coaching increases employment is consistent with findings of an earlier paper. In a panel analysis of the same data, McInnes et al. (2010) finds that OLS estimates ignoring unobserved heterogeneity are upwardly biased, but the employment affect remains significant even after IV, FE, or propensity score matching methods are used. Their instrument for job coaching participation, which we also use here, passes conventional tests. Unfortunately, we cannot run the same kinds of instrument validity tests in the model we use here. We also note that the DDSN offers other services and these may affect job preparadness and desire to participate in the labor market. Our policy experiment takes the provision of these services as given, and we cannot seperately identify the effects of these services. We also take the distribution of job coaches as given and recognize that there may be additional gains to be made by matching top quality job coaching programs to those with the most to gain. While reallocating resources within a board may be more politically feasible than reallocating among the boards, it may still be difficult to get individual coaches, boards and families to change intake patterns to the program. Moreover, some of the proposed schemes may be seen as politically incorrect. For example, in Table 5, we see that the females have higher marginal gains (relative to males) while African Americans have lower (relative to whites). Hence, our recommendation is that boards should try to enroll more females and fewer blacks. Even without these concerns, changing habits is hard.

The limitations noted above affects the generalizability of the results; however, the methodology proposed here is more broadly applicable.

7 Conclusion

In this paper, we illustrate the potential for gains from redirecting resources using data from a state job coaching program that is designed to increase employment among adults with intellectual disabilities. Our analysis of the program shows that those who are currently participating benefit greatly from the program. However, we find that participants have characteristics that are favorable in the labor market even without coaching which implies lower marginal benefits from participating. We also find that job coaching is effective in helping overcome the labor market penalties associated with characteristics such as low IQ and having emotional or behavioral problems. These traits are negative and significant predictors of employment without coaching, but when coached, these effects are smaller and not statistically significant. Unfortunately, these characteristics are also negative predictors of participation in job coaching. Redirecting resources to these individuals has the potential to increase program efficiency.

The contribution of this paper is to develop alternative targeting schemes and to compare the resulting gains. We calculate the maximum gains that could be achieved by an omniscient administrator who perfectly targets those who gain the most and then compare that to the gains that could be achieved when information about individuals and their outcomes is limited. When an omniscient administrator enrolls only those with the highest employment probability gains, there is a 56 percent increase in the overall employment rate. Even a naive administrator who observes only the data available to us can achieve an 11 percent increase in employment. Though modest, this is equivalent to the effect of increasing the number of job coaches by 50 percent without changing the targeting scheme. Implementing the ideal targeting system may be difficult, since it requires the program administrator to be able to calculate the marginal gains for each individual. We consider a simple rule that is not as informationally demanding and can be more easily incentivized: targeting those who are most employable if coached. Having observed the results of many job coaching experiments, program planners may have a pretty good idea of who will be most employable when coached. Such a second best scheme may have an unintended negative effect on overall employment if those who are more employable with the program would have been likely to find jobs even without the program. Surprisingly, we find that for the job coaching program in South Carolina, targeting employability is nearly as effective as targeting gains.

Our findings show that an effective job coaching program in SC has the potential to be even more effective at increasing employment by retargeting program resources. In an earlier paper, McInnes et al. (2010) find that job coaching services for the average placement in SC cost about $7100 but save $10,000 in avoided shelter workshop payments. The McInnes study is the only one we are aware of that controls for observed and unobserved differences between the coached and non-coached, and they find that ignoring heterogeneity substantially biases estimated program effects. After controlling for heterogeneity, they still find that the job coaching roughly triples the odds of employment and that the effects of job coaching persist for as much as four years after the coaching took place. Our study shows that these gains from job coaching could be increased if program resources are re-allocated. While it may be difficult for program administrators to calculate marginal gains for all possible enrollees, we find that a simple targeting rule based on employability if coached would achieve about an 11 percent increase in employment. These gains in employment will benefit the state by reducing the need to provide alternative day services that are more costly than job coaching. In addition, there are the intangible benefits of increased social skills and life satisfaction that come with stable employment in the community. While difficult to value, these benefits are potentially quite substantial and give us even more reason to find the most effective way to allocate program resources.

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APPENDIX

Appendix Table: DDSN Services

Service Name	Service Definition
Adult Companion	Non-medical care, supervision, and socialization provided to an adult (age 21 or older).
Career Preparation	Services aimed at preparing participants for careers through exposure to and experience with various careers and through teaching such concepts as compliance, attendance, task completion, problem solving, safety, self-determination,and self-advocacy.
Community Services	Services aimed at developing one's awareness of, interaction with and/or participation in his/her community through accrual of social capital.
Day Activity Services	Activities and services provided in therapeutic settings to enable participants to achieve, maintain, improve or decelerate the loss of personal care, social or adaptive skills.
Day Habilitation	Assistance with acquisition, retention, or improvement of self-help, socialization and adaptive skills in a non-residential DDSN licensed facility.
Employment Services (Group)	Intensive, on-going supports for participants for whom competitive employment at or above minimum wage is unlikely. Enclave - A small group of people (usually 8 or less) with developmental disabilities, who work under the supervision of an employee of the provider agency, in a community business/industry along side non-disabled employees to produce goods or services controlled by the community business/industry (ex. janitorial services at a specific business/industry etc.). The contractual relationship is between the business/industry and the provider agency, whereby the provider agency then pays the individual. Mobile Work Crew - A small group of people (usually 8 or less) with developmental disabilities, who work under the supervision of an employee of the provider agency, as a self-contained business who typically move to different worksites, by selling a service (ex. landscaping, janitorial) to purchasers within the community excluding provider agencies. The contractual relationship is between the business/industry and the provider agency, whereby the provider agency then pays the individual.

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Employment Services (Individual)	Intensive, on-going supports for participants for whom competitive employment at or above minimum wage is unlikely. Assessment, job development, placement, and training involve direct facilitation and instruction by DDSN job coach staff. Individual community placement provides support in; community based instruction, career awareness, skills acquisition, strategic on the job training, long term support and follow-along. Ongoing supports and identification of long term natural supports are imperative for the person with significant disabilities to participate in competitive employment and to ensure job stabilization without support throughout the tenure of the placement.
ICF/ID - Community	An ICF/ID is a facility licensed for the primary purpose of providing health or habilitative services to people with intellectual or related disabilities who require the aggressive, consistent implementation of a program of specialized and generic training, treatment and health services.
Individual Rehab.	Medical or remedial services that have been recommended by a physician or other Licensed Practitioner of the Healing Arts with the scope of their practice under SC State Law and as further determined by the SC Department of Health and Human Services for maximum reduction of physical or mental disability and restoration of a consumer to their best possible functional level.
Prevocational Services	Preparation for paid or unpaid employment, but not directed at tracking job-specific skills.
Residential Rehab.	Care, supervision, and skills training in a non-institutional setting.
Respite Care - Hourly	Care provided on a short-term basis because of the absence or need for relief of those persons normally providing the care in the participant's home.
Service Coordination	provided to people who are eligible for DDSN services to assist them to access a full array of community services including medical, social, educational and other needed services that are effective, cost efficient and necessary to avoid costly residential placement thereby making it possible for people to reside in their own homes and communities.
Support Center	Non-medical care, supervision and assistance provided in a non-institutional, group setting outside of the individual's home to people who because of their disability are unable to care for and supervise themselves.
Supported Employment	Intensive/extended employment supports to individuals for whom employment at or above the minimum wage is unlikely.