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Does Job Coaching Work? : Evidence from South Carolina*

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Abstract

Providing employment-related services, including supported employment through job coaches, to individuals with developmental disabilities has been a priority in federal policy for the past twenty years starting with the Developmental Disabilities Assistance and Bill of Rights Act in 1984. We take advantage of a unique panel data set of all clients served by the SC Department of Disabilities and Special Needs between 1999 and 2005 to investigate whether job coaching leads to stable employment in community settings. The data contain information on individual characteristics, such as IQ and the presence of emotional and behavioral problems, that are likely to affect both employment propensity and likelihood of receiving job coaching. We control for unobserved heterogeneity and endogeneity using fixed effects and instrumental variable models. Our results show that unobserved individual characteristics and endogeneity strongly bias naive estimates of the effects of job coaching. However, even after controlling for these, an economically and statistically significant effect remains.

JEL codes: J29, I38, J14
Key terms: Supported employment, job coaching, employment of the disabled

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1 Introduction

Providing employment-related services to individuals with developmental disabilities has been a priority in federal policy for the past twenty years starting with the Developmental Disabilities Assistance and Bill of Rights Act in 1984 which is re-authorized in 2000. Supported employment, using job coaches, is introduced as part of that policy (PL 98-527) as a mechanism to achieve paid employment in integrated settings in the community for adults with severe disabilities (McGaughey, Kiernan, McNally, Gilmore and Keith, 1995; Wehman and Kregel, 1998; Rusch and Braddock, 2004). It is estimated that about 1.2 to 1.5% of adults in the United States meet the criteria for having developmental disabilities as defined in the Developmental Disabilities Assistance and Bill of Rights Act of 2000 (Yamaki and Fujiura, 2002). Developmental disabilities are defined as mental and physical impairments originating in childhood that are likely to continue indefinitely and result in functional limitations in three or more "major life areas." These life areas include self-care, language, learning, mobility, self-direction, independent living, and economic self-sufficiency.

While employment in an integrated setting is associated with higher wages and opportunities to expand social networks, evidence suggests that 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). According to the American Association on Intellectual and Developmental Disabilities (AAIDD) the average cost of a supported employment placement is $4,000, and half of all placements cost less than $3,000 per person. AAIDD compares this cost to the $7,400 annual cost of serving an individual in a day program. A simple comparison of the costs indicates that the supported employment is approximately 20-60 percent cheaper than other day services. While these studies suggest job coaching is an affordable and effective policy, it is possible that some of the apparent benefits of job coaching are due to underlying differences between those who receive coaching and those who do not. Our study is the first to examine the effectiveness of job coaching while controlling for the endogeneity of the participation decision.

We take advantage of a unique panel data set of all clients served by the South Carolina Department of Disabilities and Special Needs between 1999-2005 to investigate the effectiveness of using job coaches to increase employment. Supported employment services in South Carolina are provided to individuals with mental retardation by 38 not-for-profit service providers (disability and special needs boards, henceforth called "boards") that serve county or multi-county areas. Thus, we have variation in the availability of job coaches over time and across boards. The data also contain information on individual characteristics, such as IQ and the presence of emotional and behavioral problems, that are likely to affect both employment propensity and likelihood of receiving job coaching. Because of the panel nature of the data, we are able to control for both unobserved heterogeneity and endogeneity using fixed effects and instrumental variable models.

Our results show that job coaching increases the probability of employment by up to 10 times, depending on the model used. In the raw data, employment rate is about 6 times higher among those who receive job coaching compared to those who do not. After controlling for individual observed and unobserved characteristics, board, year, and endogeneity of job coaching, some of these differences wash away. However, even in the presence of all controls, the effect of job coaching on employment probability stays strong and significant. Our results, moreover, shed light into the process of job coaching. We find that individuals who are likely to be job coached are also likely to be employed and that endogeneity of job coach participation strongly biases the estimated effect of job coaching. We also present estimates of the how job coaching and employment probabilities are explained by characteristics of the individual and local labor market.

We describe the Supported Employment Program in South Carolina in the following section and then discuss our data and variables in the third section. Section 4 describes the latent variable models of program participation and employment and our estimation strategy. Section 5 presents the empirical results, and Section 6 concludes.

2 Supported Employment in South Carolina

Supported employment programs have 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; 4) follow-up. Job coaches are supposed to wean themselves out of the workplace after the training phase and then maintain contact in case a problem arise during employment. In South Carolina, 38 local boards provide supported employment services to individuals with mental retardation, and the programs may differ by board, particularly before 2003, when statewide standards for supported employment were put into place. Larger boards may have a job coach supervisor, while smaller boards may be supervised by a day services director at the board who has many other non-employment related responsibilities. Larger boards may also have established a network of employer contacts that enables good placements, while smaller boards are more dependent on the job development skills of the individual job coach and the community ties of board members. Job coaches must have a high school degree or equivalent and pass state law enforcement checks, but are often inexperienced and lack formal training.

While boards may 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. We do not have data on waiting lists, but officials at the Department of Disabilities and Special Needs (DDSN) perceive that waits between the referral and onset of supportive employment services have been declining over the period of our data. Prior to 2003, some job coaches would find clients among those receiving DDSN benefits without a referral from a case manager. Following a referral, there may be period of instruction and assessment aimed at improving the client's general job skills and awareness of community-based employment opportunities. Once a specific job has been identified and a job coach assigned, the process is expected to last at least a year beginning with six months of on-site training followed by at least six months of follow-up in which the coach maintains monthly contact with the client. While independence and job stability are the goal, retraining and "follow along" may last for a year or more.

Finding a good match, according to our discussion with officials in the program, is a big part of the coaching process, and bad matches result in rapid turnover. Our measure of employment success, defined below, will be based on employment in the year following any receipt of job coaching services and will exclude employment for low wages or short duration(defined below).

Because we cannot observe the process by which individuals are allocated to job coaches, we cannot preclude the possibility that those who have the best employment prospects are more likely to want (or be chosen for) job coaching. While there are no performance bonuses or other incentive mechanisms to lead job coaches to be overly concerned with maximizing apparent success, studies of other vocational rehabilitation programs have found evidence that such sorting does occur. Previous studies find that some programs attract those who have the most to gain from participation (Anderson, Burkhauser and Raymond, 1993; and Bassi,1983) while others do not (Aakvik, Heckman and Vytlacil, 2005). Because job coaches in South Carolina were able to directly recruit clients to receive coaching prior to 2003 and are likely still to have had great influence on who participated after 2003 (because job coaching does not officially commence until a job is found), we need to consider the non-randomness of the job coaching assignment.

3 Data and Variables

The data consist of individuals in South Carolina who have mental retardation and are clients of one of the 38 disability boards in South Carolina at any time between years 1999 and 2005.[1] 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 was autism were excluded. Because there were very few individuals whose race was not identified as African American or white in the data, these individuals were also excluded. Over all seven years, there are 62,826 person-year observations. Descriptive statistics for the sample are

[1] The data are stripped of personal identifiers and are part of an ongoing system of surveillance of employment. The employment surveillance system has university IRB approval.

shown in Table 1. About half (51%) of the sample is African American, and just under half (46%) of the sample is female. The average age and IQ are, respectively, 37.7 and 50.4. About 24% of the sample has some emotional or behavioral problems reported, and about the same percent live in a supervised setting. Table 1 also provides descriptive statistics separately for individuals who receive some job coaching and those who do not. On average, the job coached group consists of individuals who have higher IQ's (54.6 versus 49.7) and who are younger (35.82 versus 38.09). Job coached individuals are also more likely to be African American (55% versus 51%), male (56% versus 53%), and have no emotional or behavioral problems (25% versus 19%).

[Table 1 here]

In our model of job coaching, we measure the effect of job coaching in year $t-1$ on the probability of employment in the subsequent year t. Because this requires 2 years of observation, we can model employment outcomes for 6 years (2000-2005). We construct an (unbalanced) panel of employment outcomes that includes an individual in year t whenever his history is observed in the previous year. The one exception is that individuals who were not observed in the data in $t-1$ were included and classified as not having a job coach in $t-1$. This includes individuals who did not receive any services from DDSN (including job coaching) in $t-1$ and individuals who turned 21 in t.

Because supported employment 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 et al., 2006; Pierce et al., 2003; Moran et al., 2002). Our data set is limited in that we cannot observe whether those weeks of employment are with one or several different employers. In addition, because we cannot differentiate between on-going on-site coaching, follow-up contact, and any re-training that occurs if there are job changes, we have only a bivariate measure of job coaching (some or none) in year $t-1$. We also do not observe how a job placement affects any benefits an individual may receive. However, we do know that job coaches are required to document that clients have been informed about the impact on benefits that a particular job placement will have. A final limitation to note about our data is that the employment reports are obtained from board staff who are more likely to accurately report the employment status of people who have more contact with the staff, including those who are getting coaching.

About 15.5% of the sample is employed in any given year, but as shown in Table 2, this varies from a high of 20% in 2000 to a low of 11% in 2004. The overall labor market conditions worsen during the sample period with the average county unemployment rate rising from the lowest point of 3.82% in 2000 to 7.3% in the 2005. Mirroring these employment trends, the probability of receiving job coaching also falls during the period, from over 16% receiving job coaching at the beginning of the sample to only 10% by the end. This decrease in job coaching may be attributed to tightening state budgetary constraints, but may also reflect better accounting of job coaching hours due to an increase in auditing efforts. The reduction in job coaching at the individual level is also seen when aggregated to the disability board level. The job coaching hours per person served by the disability board (FTERatio) declines over the sample period by about one hour per person served by the board.

[Table 2 here]

4 Model and Estimation

In the canonical model of employment, a person is employed if he is offered a job with a wage greater than his reservation wage. Thus, any analysis of employment probability should consider all factors that affect the wage offers in the market and the reservation wage of the individual. Recall that for this study a person is considered to be employed if they are working for at least 23 weeks in a given year and earning at least $50 per those week they work. Given this definition of employment, individuals who are doing work for very low pay or for short periods of time are classified as unemployed. Hence, our focus is on measuring the extent to which job coaching affects the likelihood of finding a job for a meaningful period of time at a non-trivial wage in integrated settings. We hypothesize that the probability of employment will depend on socio-demographic factors that affect the reservation wage and the returns in the labor market.

The model we are using is a standard employment model specified simply as follows

$$Y_{it} = X_{it}'\beta + \epsilon_{it}$$

where Y_{it} is i's employment status at time t, X_{it} consists of a vector of socioeconomic and demographic characteristics of the individual, β is a coefficient vector to be estimated, and ϵ_{it} is a matrix of individual and time-varying shocks. The X_{it} vector includes a constant and individual demographic characteristics, such as age, gender, race, as well as several variables typically unavailable to the econometrician, such as IQ, an index of emotional and behavior problems, and an indicator for living in a supervised residence. Characteristics of the local labor market and an indicator for the disability board are also included. Of particular interest is the indicator variable for whether or not the individual received job coaching in the year prior to the one for which we observe the employment outcome. Our goal is to measure the extent to which job coaching increases employment propensity.

If job coaches are assigned randomly, then we could easily estimate the effects of job coaching by comparing the probability of employment across those who received job coaching and those who did not. However it is much more likely that the assignment process was not random and that there is correlation between the factors that led to the receipt of a job coach and the probability of employment. For example, individuals with emotional and behavioral problems may be less likely to receive job coaching, and *ceteris paribus,* less likely to be employed. Thus, our choice of model will depend on the assumptions about ϵ_{it}. We first estimate the above model on our data, treating it as a pooled cross-section, with ϵ_{it} assumed to be independent and identically distributed. This will be our baseline model. Following these estimates we consider the possibility of unobserved characteristics that may be fixed over time. If such fixed factors exist, we will have an omitted variable bias, and we have to consider a composite error term instead, that is:

$$\epsilon_{it} = \upsilon_{it} + \nu_i$$

The next step in our choice of model will depend on the assumptions about ν_i. We will estimate two versions: random effects and fixed effects. While random effects require that ν_i's are uncorrelated with X_{it}, fixed effects does not require this restriction.

Next, we correct for the possible endogeneity of the treatment, job coaching, using instrumental variables methods. Ideally we would estimate panel data models with instrumental variables and fixed effects while still accounting for the binary nature of our dependent variables, but this proves econometrically challenging. Therefore, we report results from a variety of specifications that take into account some, but not all, features of our data generating process and then compare estimates across specifications to gauge whether our estimates are sensitive to changes in specification. While we could use probit models for some specifications, these models do not admit fixed effects, making conditional logits our preferred model. We also consider linear probability models that allow for both instrumental variables (IV) and panel fixed effects. Linear models are easy to estimate, but have the disadvantage of introducing heteroskedasticity and ignoring the bounds that estimated probabilities should lie between zero and one.[2] We correct for heteroskedasticity by bootstrapping the standard errors. However, even the IV probit models we use do not fully respect the binomial nature of program participation. All IV approaches we consider here require a two stage estimation approach in which the prediction of job coaching probability we generate in the first stage is no longer a binary measure when used in the second stage. The extent of the bias arising from the "continuous-ization" of the binary choice variables, especially when the first stage fit is

[2] We estimate all models using *STATA*. Because we consider a variety of specifications, we report the *STATA* command along with the estimation results.

not very good, may be large. Carrasco's (2001) results, for example, illustrate this problem for binary fertility and labor participation decisions of women.

Estimation results are presented in the following section . As we discussed above, when measuring the effects of a labor market intervention such as job coaching, it is important to know how the disability boards assign job coaches to clients. Hence, we begin with models of job coaching assignment.

5 Results

A simple comparison of means for our sample(Table 2) shows that supported employment is associated with a substantial increase in the likelihood of being employed in the following year, but it also shows that individuals who receive job coaching differ in meaningful ways from those who do not. We begin our analysis of the effectiveness of the job coaching by first considering the factors that predict whether or not an individual receives job coaching. Because we have been able to obtain little information about how job coaches are allocated to clients, we interpret our results as descriptive rather than structural estimates. We consider both panel and pooled cross sectional models of job coaching in Table 3. We include probit and logit models for the pooled cross section, but because we wish to compare coefficient estimates across fixed effects and random effects specifications, we restrict attention to logit models for the panel analysis.

The results across models are qualitatively similar and show that many of the factors we would expect to influence a person's ability to find employment are also associated with whether an individual participates in supported employment. Age has a non-linear effect on job coaching, with smaller increases in the likelihood of participation as age increases. Women are less like to be engaged in supported employment, while African Americans are more likely. We would expect that having a higher IQ and an absence of emotional and behavioral problems would be desirable labor market characteristics, and we find that these factors also raise the likelihood of receiving job coaching. Individuals are also more likely to participate in the program if they live in counties with low unemployment. Job coaches may have lower cost of serving individuals who live in supervised conditions, and so it is not surprising that this factor is associated with a significant increase in the likelihood of participation. We also include a measure of job coaching availability (FTERatio), and find that individuals who are served by boards with a higher amount of full time equivalent job coaches per adult served by the board are significantly more likely to receive job coaching. We discuss the inclusion of this variable in our job coaching models in more detail below.

[Table 3 here]

Next we turn to models of employment. Table 4 presents the results of pooled cross section logit regressions that control for observable factors that affect employment probability. We include disability board fixed effects in all specifications.[3] These cross sectional models do not take advantage of the panel nature of the data to control for unobserved differences across individuals, and thus, serve as a baseline for assessing whether those factors confound the estimated effect of job coaching. The first two columns in Table 4 show results for probit and logit models, while the third column shows probit estimates when we instrument for job coaching. We save discussion of the results from this model until we describe our instrumental variable strategy more thoroughly. As expected, we find that having a higher IQ, better local labor market conditions, or no reported emotional and behavioral problems raises the odds of having a stable, high-wage job. Above we found that individuals in supervised housing conditions are more likely to be job coached, and, other things the same, these individuals are also more likely to be employed. We also find that being female or white is associated with a reduced likelihood of employment, and that age increases the likelihood of employment at a decreasing rate. In these simple cross-sectional models, we see that having a job coach in the preceding year has a strong and significant effect on the probability of employment. Indeed,

[3] We considerred adding year dummies to all models in the paper, but were unsure about what they would be capturing given our controls for local labor market conditions. We found they were not significant at any reasonable level, and including year effects generally had little effect on coefficient estimates for other variables but did increase standard errors.

looking at the odds ratios from the logit model shown towards the bottom of the table, we see that the odds of employment are increased by a factor of 9.33 when an individual has received job coaching in the preceding year. Contrasting this result to the simple means comparisons in Table 2, we see that controlling for observed differences between those who are job coached and those who are not reduces the odds ratio for job coaching by about 30% (from about 15.5 with no controls to 9.33), but the effect of job coaching remains strikingly large.

[Table 4 here]

Given the differences in observables between those who are job coached and those who are not, we expect that there may be other unobserved differences that explain part of the apparent effectiveness of job coaching. These unobserved differences may be uncorrelated with the individual characteristics we observe, but it is more plausible that there is some correlation between the observed and unobserved differences. Consequently, we consider both random effects and fixed effects panel logistic regressions. These results are shown in the first two columns of Table 5 and are generally consistent with our estimates from the pooled cross section. We still find that job coaching has a positive and significant effect on the probability of employment, but the estimated effect is much smaller when the model allows for correlation between ν_i' and X_{it}. Nonetheless, even after controlling for unobserved, time-consistent differences across individuals, the odds ratio for job coaching remains economically significant at around 1.8. That is, participants in supported employment are 1.8 times more likely to be working in stable, high wage jobs the following year compared to their non-job coached counterparts.

[Table 5 here]

The above analysis has shown that our results are sensitive to whether and how we allow for unobserved, time-consistent differences across individuals. If we assume such differences are uncorrelated with the observable variables, then our estimated job coaching coefficient is about three times as large as when we use a fixed effects specification. Surprisingly, the precision of the estimate is unchanged, even though the conditional logit with fixed effects is estimated on a smaller sample (roughly 16,000 observations from 2500 individuals for the fixed effects specification versus over 57,000 observations from 11,000 individuals for the random effects specification). This is because the fixed effect model cannot use observations for which the dependent variable is unchanged over the course of the sample (that is, the always employed and never employed).

Given these results and our strong *a priori* beliefs that there are some unobserved factors that effect both selection into job coaching and employment probability, we also consider an instrumental variables (IV) approach. In choosing our instrument, we follow a strategy similar to Aakvik, Heckman and Vytlacil (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, Heckman and Vytlacil 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 measure of job coaching availability, FTERatio. This measures the full time equivalent job coaching hours per adult served by each disability board in each year. We have already seen in Table 3 that the FTERatio is a statistically significant predictor of participation in supported employment.

We begin our IV models with a simple pooled cross section IV probit reported in the last column of Table 4. Where statistically significant, the coefficient estimates have the same sign as the non-IV probit, and we still find a strong positive effect from job coaching. We then consider panel data models, but because non-linear probability IV panel data models are difficult to estimate with available statistical packages, we estimate linear probability (LP) models and use bootstrapping to get heteroskedasticity-robust standard errors. The IV-LP estimates are reported in the middle two columns of Table 5, and we include non-IV LP models in the last two columns for the sake of comparison. All our IV estimates pass the

Kleibergen-Paap underidentification test. The coefficient estimate on job coaching has the same sign in all four linear probability models, and is statistically significant at least at the 5% level in all but the IV fixed effects model. The drop in statistical significance going from random effects to fixed effects appears to be due more to an increase in the standard error rather than a decline in the size of the coefficient. To better understand what is happening with our estimated job coaching effect from the LP-IV model with fixed effects, we graph the distribution of the 1000 bootstrapped coefficient estimates in Figure 1. We exclude two outliers (-8.7 and 22) to make the graph reasonably compact, and see that the distribution is slightly skewed, with more extreme positive observations than negative ones. The 95% empirical confidence interval is [0.018, 2.36] and do not include zero.

[Figure 1 here]

Taken together, we find job coaching is a significant predictor of having a stable, high-wage job with at least a 5% level of significance in all panel specifications except the LP-IV with fixed effects (where it is significant at the 6% level). Our results also show the importance of considering how job coaching participants are selected into the program. First, in comparing random effects to fixed effects specifications, we find that the job coaching effect is always smaller with fixed effects. Thus, correlation between participants observable characteristics and unobserved individual-specific factors leads the random effects models to overstate the positive impact of job coaching. Second, we see that instrumenting for job coaching reduces the precision of the estimated job coaching effect, but the effects on the magnitudes are unclear. Because the job coaching variable in the second stage of an IV model is continuous rather than dichotomous, the job coaching coefficient is not necessarily directly comparable to the non-IV versions of the model. To illustrate the impact of controlling for endogeneity using IV, we calculate the estimated impact of having a job coach (relative to no coach) for a "typical" individual in our sample for the LP models and report them in Table 6. These are not true counterfactuals because we are comparing the model predictions for two groups of individuals in our data who have similar characteristics but differ in their actual job coaching status.[4] Table 6 shows again that allowing for possible correlation between unobserved individual specific effects reduces the estimated job coaching effect. We also see that the models with IV reveal a slightly stronger effect of job coaching than the corresponding non-IV model predictions. Thus, while IV estimates reduce the precision of our estimates, they do not reduce their economic significance.

[Table 6 here]

5.1 Conclusions

Since the Developmental Disabilities and Assistance and Bill of Rights Act of 1984, increasing employment in integrated settings for individuals with developmental disabilities through supported employment has been a primary goal of federal policy. While evaluations of job coaching programs suggest that they are effective and cost-effective, previous studies do not adequately address endogeneity concerns. Our analysis using a unique seven-year panel data set from South Carolina (1999-2006) suggests that such concerns are warranted. We see that 56% of individuals with job coaches are working in the following year compared to 9% of those who are not job coached, but that those who receive coaching are also more likely to have favorable job characteristics such as higher IQs and an absence of emotional and behavioral problems. Using fixed effects and IV models to address endogeneity and unobserved heteroskedasticity washes away much of the effect of job coaching, but an economically and statistically significant effect remains. We find that job coaching increases the odds of employment by roughly 1.5 times.

While these results are encouraging from the perspective of the policy maker, there is much more work to be done to understand how job coaching programs may be best deployed.

[4] A true counterfactual would compare the predicted outcomes with and without job coaching for a given group (for example, the treated or the untreated). The "typical" individual we consider is a black male with no reported emotional or behavior problems between the ages of 30 to 40 with an IQ score between 50 and 60 living in a supervised facility in a county served by one of the 4 largest disability boards. We compare predicted employment probabilities from the model for members of this group who were actually job coached to those who were not.

Our results indicate that observed and unobserved differences explain a large portion of the improvement in the probability of employment. Further research is needed to understand more about the process by which individuals are allocated to job coaching. While the focus of this paper is to measure the mean effects of the job coaching paper, we hope in further research to use new techniques to disaggregate the benefits of job coaching and find whether improved targeting would enhance program success.

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TABLES & FIGURES

Table 1. Descriptive Statistics for the Pooled Sample and by Job Coaching Status

	Pooled Sample		Not Job Coached		Job Coached	
Variable	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
jobcoach	0.14	0.35				
employed	0.16	0.36	0.09	0.28	0.56	0.50
wages	118.35	66.17	101.87	60.50	134.14	67.52
unemploy	6.11	2.30	6.15	2.30	5.83	2.26
large board	0.43	0.50	0.43	0.50	0.39	0.49
fteratio	0.00	0.00	0.00	0.00	0.01	0.00
iqscore	50.36	13.18	49.67	13.29	54.62	11.56
emotional problems	0.24	0.43	0.25	0.44	0.19	0.39
supervised	0.28	0.45	0.27	0.44	0.31	0.46
secondary autism	0.03	0.16	0.03	0.16	0.01	0.10
age	37.77	11.43	38.09	11.62	35.82	9.92
black	0.51	0.50	0.51	0.50	0.55	0.50
female	0.46	0.50	0.47	0.50	0.44	0.50
	N=62826		N=54051		N=8775	

Table 2. Means of Employment and Job Coaching Variables by Year

	1999	2000	2001	2002	2003	2004	2005
jobcoached	0.16	0.16	0.17	0.15	0.14	0.12	0.10
	(0.37)	(0.36)	(0.37)	(0.35)	(0.35)	(0.32)	(0.30)
employed	0.15	0.18	0.20	0.16	0.18	0.11	0.12
	(0.36)	(0.39)	(0.40)	(0.37)	(0.38)	(0.32)	(0.32)
wages	122.71	116.17	117.97	120.61	121.51	112.52	115.84
	(64.97)	(63.95)	(63.72)	(65.93)	(72.44)	(64.31)	(66.45)
unemp	4.65	3.82	5.64	6.34	7.17	7.29	7.32
	(2.55)	(1.15)	(1.75)	(1.75)	(2.03)	(1.91)	(1.88)
large board	0.43	0.43	0.42	0.43	0.43	0.43	0.42
	(0.49)	(0.50)	(0.49)	(0.50)	(0.49)	(0.49)	(0.49)
fteratio	0.00	0.00	0.01	0.01	0.00	0.00	0.00
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
sample size	8356	8691	7840	8812	9156	9783	10188

*Standard deviations shown in parentheses

Table 3: Models of Job Coaching

Dependent variable = Job Coached

	Panel Data Models		Pooled Data Models	
	xtlogit	xtlogit	probit	logit
	RE	FE		
fteratio2	30.847	31.669	10.276	18.416
	(5.085)**	(5.699)**	(1.848)**	(3.252)**
age	0.350		0.092	0.173
	(0.023)**		(0.005)**	(0.009)**
age2	-0.005		-0.001	-0.002
	(0.000)**		(0.000)**	(0.000)**
female	-0.318		-0.099	-0.178
	(0.083)**		(0.015)**	(0.027)**
black	0.334		0.110	0.203
	(0.088)**		(0.016)**	(0.028)**
IQ score	0.064		0.019	0.033
	(0.003)**		(0.001)**	(0.001)**
emotional problems	-0.850		-0.303	-0.562
	(0.101)**		(0.019)**	(0.035)**
supervised	1.368	0.775	0.448	0.810
	(0.097)**	(0.217)**	(0.018)**	(0.033)**
unemployment rate	-0.111	-0.143	-0.034	-0.062
	(0.015)**	(0.018)**	(0.005)**	(0.009)**
constant	-12.088		-3.232	-5.843
	(0.671)**		(0.145)**	(0.259)**
board dummies	YES	YES	YES	YES
number of observations	50221	9558	50221	50221
number of individuals	10996	1798		

Standard errors in parentheses. * significant at 5% ** significant at 1%

Table 4: Pooled Data Models of Employment			
Dependent variable=Employed			
	logit	probit	ivprobit
job coached	2.233	1.300	3.032
	(0.030)**	(0.017)**	(0.181)**
age	0.142	0.076	0.018
	(0.008)**	(0.004)**	(0.015)
age2	-0.002	-0.001	-0.000
	(0.000)**	(0.000)**	(0.000)
female	-0.347	-0.190	-0.093
	(0.026)**	(0.014)**	(0.030)**
black	0.264	0.149	0.055
	(0.027)**	(0.015)**	(0.028)
IQ score	0.014	0.008	-0.003
	(0.001)**	(0.001)**	(0.002)
emotional problems	-0.451	-0.246	-0.026
	(0.034)**	(0.018)**	(0.048)
supervised	0.356	0.199	-0.087
	(0.032)**	(0.018)**	(0.056)
Unemployment rate	-0.132	-0.069	-0.026
	(0.009)**	(0.005)**	(0.010)**
constant	-5.417	-3.006	-1.836
	(0.240)**	(0.128)**	(0.410)**
board dummies	YES	YES	YES
number of observations	57979	57979	50221
odds ratio for job coached	9.33		
Standard errors in parentheses. * significant at 5% ** significant at 1%			

Table 5: Panel Data Models						
Dependent variable: Employed						
	xtlogit		xtivreg		xtreg	
	RE	FE	RE	FE	RE	FE
job coached	1.570	0.599	1.122	0.771	0.228	0.078
	(0.052)**	(0.052)**	(0.174)**	(0.405)+	(0.004)**	(0.005)**
age	0.216	-0.050	-0.002	-0.019	0.013	-0.005
	(0.019)**	(0.039)	(0.003)	(0.006)**	(0.001)**	(0.002)*
age2	-0.003	-0.001	0.000	0.000	-0.000	-0.000
	(0.000)**	(0.000)**	(0.000)	(0.000)	(0.000)**	(0.000)**
female	-0.546		-0.021		-0.037	
	(0.071)**		(0.006)**		(0.004)**	
black	0.478		0.012		0.029	
	(0.076)**		(0.007)		(0.004)**	
IQ score	0.033		-0.001		0.002	
	(0.003)**		(0.001)*		(0.000)**	
emotional problems	-0.792		-0.000		-0.050	
	(0.086)**		(0.012)		(0.005)**	
supervised	0.884	0.755	-0.027	0.010	0.057	0.064
	(0.081)**	(0.157)**	(0.018)	(0.028)	(0.005)**	(0.011)**
Unemployment rate	-0.198	-0.010	-0.008	-0.001	-0.013	-0.001
	(0.012)**	(0.020)	(0.002)**	(0.002)	(0.001)**	(0.001)
constant	-8.469		0.073		0.001	0.412
	(0.576)**		(0.042)		(0.033)	(0.103)**
Board dummies	YES	YES	YES	YES	YES	YES
Number of observations	57979	16426	50221	48835	57979	57979
Number of Individuals	11268	2556	10996	9610	11268	11268
Odds ratios	5	1.8				
Standard errors in parentheses. + significant at 6% * significant at 5% ** significant at 1%						

Table 6: Predicted Employment Probabilities *(for a black man with no emotional problems between the ages of 30 and 40 and with an IQ score between 50 and 60 living in a supervised facility under either of the four largest disability boards)*								
	xtivreg				xtreg			
	RE		FE		RE		FE	
prediction type	xb*	xbu**	xb	xbu	xb	xbu	xb	xbu
job coached	1.17	0.84	0.84	0.76	0.56	0.64	0.31	0.62
not job coached	0.04	0.17	0.07	0.21	0.32	0.32	0.23	0.34
*fitted values **xb+ u_i, prediction including effect								

dtbpFU5.6144in4.0923in0ptFigure 1: Empirical Confidence Intervaluntitled.wmf