The Effects of Youth Transition Programs on Labor Market Outcomes

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September 2015

Abstract

The process of "transitioning" to adulthood for youth with disabilities has long been recognized to be an important but understudied public policy concern. This paper evaluates the labor market effects of Virginia’s school-to-work vocational evaluation program, PERT. Using a unique panel data set containing more than a decade of employment and service provision, we provide the first-ever assessment of the long-term employment impacts of a transitioning program for youth with disabilities. Overall, the estimated effects are substantial: PERT has an estimated median quarterly rate of return of nearly 30%.

1 Introduction

The process of “transitioning” to adulthood, whether in terms of completion of school, entering the labor force, or household formation, has long been recognized to be an important public policy concern, especially for youth with disabilities (Luecking and Wittenburg, 2009). This population, which comprises about one-eighth of American youth (NCES, 2001), have employment rates that are about 20 percentage points lower than their same-age non-disabled peers and employment spells are about one-third shorter (Wagner et al., 2005; Newman et al., 2009). Also, with 1.3 million persons aged 14 to 30 on the Supplemental Security Income (SSI) disability benefit rolls (O’Day and Stapleton, 2009), the resulting long-term costs to society of caring for transitioning youth with disabilities are particularly high.1

To combat unsuccessful transitions, a combination of legislation, public policy, and program initiatives have now been in place for more than a quarter century to establish a formal delivery system of training programs for transitioning youth with disabilities (Shandra and Hogan, 2008). The Carl D. Perkins Vocational Education Act of 1984 required that students with disabilities be provided a vocational assessment. Subsequently, the passage of amendments in 1990 to the Individuals with Disabilities Education Act mandated transition planning for students in special education to begin no later than age 16 (Fabian, 2007). Most recently, on July 22, 2014, President Obama signed into law the Workforce Innovation and Opportunity Act which, among other things, requires state vocational rehabilitation agencies to set aside at least 15% of their program funds to provide services to transitioning students with disabilities.

This paper evaluates the labor market effects of one state’s school-to-work vocational evaluation program – Virginia’s Post-Secondary Education and Rehabilitation Transition (PERT). Using a unique panel data set containing more than a decade of employment and service provision information for almost 3100 disabled youths who applied to the Virginia Department for Aging and of Rehabilitative Services (DARS) in state fiscal year (SFY) 2000, we provide the first-ever assessment of the long-term (over five year) employment impacts of a transitioning program for youth with disabilities.2 While the short-run

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1 Fraker and Rangarajan (2009) estimate the present value of disability payments to exceed $150,000 per recipient. Also, see Fraker et al. (2014).

2 Numerous studies evaluating short-run socio-economic outcomes of such programs generally find positive labor market effects. See Allwell and Cobb (2006) and Test et al. (2009) for recent summaries. Also, see Wittenburg and Maag (2002) and Seo, Abbott, and Hawkins (2008). Finally, the ongoing Youth Transition Demonstration (YTD), a 7-site randomized controlled experiment involving 5000 youth receiving SSI disability benefits, is designed to follow post-assignment outcomes for a maximum of four years (Fraker et al., 2014).
impacts of transitioning youth programs are certainly important, there are good reasons to think the short- and long-run effects may differ. Long-run evaluations of intensive employment training for other at-risk populations – similar in many respects to the human capital development services provided transitioning youth with disabilities – imply different and, in some cases, much greater employment impacts in the period four to six years after assignment than in the initial three-year study period (Couch, 1992; Friedlander and Burtless, 1995; Hotz et al., 2006; Dean et al., 2015a, b). This is especially true for transitioning youth where there is “considerable uncertainty about the persistence of training effects” (Hotz et al., 2006).

In addition to using longitudinal outcomes data, we apply an innovative modelling approach that formalizes and estimates a structural model of service provision and labor market outcomes. PERT primarily serves as a screening program aimed at providing recipients individually-tailored DARS and schooling services. As such, PERT participation enters the model in three distinct ways: a direct effect on employment and earnings, an indirect interaction effect with schooling, and an indirect interaction effect with vocational rehabilitation (VR) services provided by DARS.

Within the model, we allow the provision of PERT and VR services and labor market outcomes to be endogenous. We address the selection problem using the longitudinal data, a factor model, and instrumental variables that are assumed to impact service receipt but not the latent labor market outcomes. In particular, we instrument for the provision of PERT services using programmatic restrictions on the number of students allowed to sign up for PERT; each school system is given a fixed number of slots to allocate. This “slot constraint” is associated with the PERT participation probability but arguably uncorrelated with unobserved labor market factors. In addition, following Doyle (2007), Maestas et al. (2013), and Dean et al. (2015a, b), we instrument for VR service provision using the propensity of an individual’s VR counselor or field office to assign clients to services. As discussed below, these counselor/field office variables are related to VR service provision but have no direct effect on labor market outcomes.

The remainder of the paper is organized as follows: The next section provides an overview of PERT and compares its salient features to those of other vocationally oriented programs serving transitioning youth with disabilities. Section 3 describes the four main data sets used in the empirical analysis, and Section 4 describes the model to be estimated and provides details on the econometric methodology directly tied to the model. Section 5 presents and interprets empirical results, and a rate-of-return analysis is provided in Section 6. The paper ends with conclusions in Section 7.

2 PERT Overview and Comparison

The PERT program was established in the mid-1980s through a grant from the U.S. Department of Education. Today PERT is administered and funded collaboratively by DARS. The program serves over 500 youth with significant disabilities annually at a cost of about $2000 per person. To be eligible for PERT services, an individual must apply for VR services from DARS, have received special education services under an Individualized Education Program, be at least 16 years of age or within 2.5 years of graduation, and be recommended for PERT services by his school system. Each school system is given a fixed number of slots to allocate among its students. Once slots have been allocated, any remaining unused slots are rationed across the state. We formalize a model of this procedure in Section 4.1.

The PERT program focuses on developing “career ladders” for students with disabilities (Horvath and Ashley, 1991). The program’s foundation is an almost two-week summer residential program that includes assessments in career vocational areas as well as independent living, residential life, recreation, and social skills. Vocational evaluation is a hands-on, competency-based career exploration process conducted by trained vocational evaluators utilizing a combination of facility-developed work samples and commercial evaluation systems.

After the two-week assessment, PERT provides a comprehensive plan tailored to the needs and abilities of each student. The plans typically involve multiple partners including DARS and the school system, cover both secondary and post-secondary schooling, and, in some cases, provides vocational training. The PERT program continues throughout the youth’s school/employment transition period providing monitoring, specialized follow-along reports based on the student’s school decision-making process, and technical assistance through local implementation meetings at participating sites. Supplemental evaluation services and vocational training may be provided during subsequent summers. Importantly, PERT is not a rehabilitation program. Rather, the PERT program assesses the needs and capabilities of at-risk adolescents with the aim of enabling more focused and effective VR and schooling rehabilitation services.

PERT shares many common features with transitioning youth programs run by various state and privately operated programs across the country. Inter-agency-administered youth transition programs which provide out-of-school vocational

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3 Among the 133 independent cities and counties in Virginia, 84 have some slots. Among those with slots, the mean number of slots is 5.9, the standard deviation is 3.6, and the maximum is 30 (Fairfax County).

4 Recent years have seen efforts to standardize the provision of vocational services to transitioning youth with disabilities through the National
Table 1: Missing Value Analysis for 2000 Cohort

<table>
<thead>
<tr>
<th>Cause</th>
<th># Obs Lost</th>
<th>Proportion of Total</th>
<th># Remain</th>
</tr>
</thead>
<tbody>
<tr>
<td>Applicants in SFY 2000</td>
<td>10323</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Missing or Questionable SSN</td>
<td>81</td>
<td>0.008</td>
<td>10242</td>
</tr>
<tr>
<td>Died While in Program</td>
<td>65</td>
<td>0.006</td>
<td>10177</td>
</tr>
<tr>
<td>Missing Gender or Date of Birth</td>
<td>1</td>
<td>0.000</td>
<td>10176</td>
</tr>
<tr>
<td>Not in Virginia</td>
<td>59</td>
<td>0.006</td>
<td>10117</td>
</tr>
<tr>
<td>Mental Illness Missing</td>
<td>1</td>
<td>0.000</td>
<td>10116</td>
</tr>
<tr>
<td>Missing Primary Disability</td>
<td>194</td>
<td>0.019</td>
<td>9922</td>
</tr>
<tr>
<td>Missing Secondary Disability</td>
<td>32</td>
<td>0.003</td>
<td>9890</td>
</tr>
<tr>
<td>Initial Service Spell before SFY 2000</td>
<td>2544</td>
<td>0.257</td>
<td>7346</td>
</tr>
<tr>
<td>Age Younger than 15 Years</td>
<td>8</td>
<td>0.001</td>
<td>7338</td>
</tr>
<tr>
<td>Age Older than 25</td>
<td>4145</td>
<td>0.565</td>
<td>3193</td>
</tr>
<tr>
<td>Neither Service nor Employment Record</td>
<td>120</td>
<td>0.016</td>
<td>3073</td>
</tr>
<tr>
<td>Number Remaining in Sample</td>
<td>3073</td>
<td>0.298</td>
<td></td>
</tr>
</tbody>
</table>

3 Data

To measure whether PERT leads to more effective rehabilitation and schooling services, we utilize data on VR services, schooling, and labor market outcomes of PERT recipients and non-recipients. DARS administrative records of applicants for VR services during SFY 2000 comprise our main source of data. For each DARS applicant, the data include a range of socioeconomic and demographic variables, information on disabilities, detailed VR service information, and an indicator for whether the respondent received PERT. All PERT recipients are DARS applicants. Supplemental data sources supply the number of disabled youth, labor market outcomes, and labor market conditions of each jurisdiction in Virginia. Each of these is discussed in turn below.  

3.1 Department for Aging and Rehabilitative Services Data

Our starting point is the administrative records of DARS for the 10323 individuals who applied for VR services in SFY 2000 (July 1, 1999 – June 30, 2000). All potential PERT recipients must first apply for VR services from DARS. To avoid bias associated with left censoring (e.g., Heckman and Singer, 1984a; Dean et. al., 2015a, b), we exclude 2544 observations where the individual’s first service spell was prior to SFY 2000. Also, given our focus on transitioning youth, we exclude individuals older than 25 (4145 observations). A number of other exclusion criteria are used with relatively small effect on the sample size (see Table 1). After sample selection, we have a sample of size 3073 individuals, 394 of whom participated in PERT.

Alliance for Secondary Education and Transition (NASET, 2005) and the National Center on Secondary Education and Transition (Grigal, Dwyre, and Davis, 2006).

5Also, we use the National Longitudinal Transition Survey (NLTS) to estimate the distribution of the age of high school completion. These data are discussed in Appendix 8.3.

6Some of the discussion and terminology in this section is similar to that in Dean et al. (2015a, b) because all three papers use the same data.

7Some clients return later to receive more DARS services. In this analysis, we ignore such returns to service. See Dean et al. (2015a, b) for a details about the frequency of such events among DARS clients.
Table 2: Proportion Receiving VR Purchased Services by Type

<table>
<thead>
<tr>
<th>Service Type</th>
<th>Those Receiving PERT Services</th>
<th>Those Not Receiving PERT Services</th>
</tr>
</thead>
<tbody>
<tr>
<td># Observations</td>
<td>199</td>
<td>1774</td>
</tr>
<tr>
<td>Diagnosis &amp; Evaluation</td>
<td>0.427</td>
<td>0.624</td>
</tr>
<tr>
<td>Training</td>
<td>0.432</td>
<td>0.400</td>
</tr>
<tr>
<td>Education</td>
<td>0.096</td>
<td>0.167</td>
</tr>
<tr>
<td>Restoration</td>
<td>0.085</td>
<td>0.312</td>
</tr>
<tr>
<td>Maintenance</td>
<td>0.352</td>
<td>0.277</td>
</tr>
<tr>
<td>Other Service</td>
<td>0.477</td>
<td>0.351</td>
</tr>
</tbody>
</table>

Note: Proportions are conditional on receiving some DARS purchased service.

3.1.1 VR Service Provision

For each individual, we observe an indicator for PERT participation and measures of VR service provision. VR applicants begin by developing, with a counselor, an individualized plan which specifies the array of services to be provided. Following Dean et al. (2002), we aggregate VR services into the six service types listed in Table 2: diagnosis & evaluation is provided at intake in assessing eligibility and developing an plan, and possibly later in the form of job counseling and placement services; training includes vocationally-oriented expenditures including those for on-the-job training, job coach training, work adjustment, and supported employment; education includes tuition and fees for a GED (graduate equivalency degree), a vocational or business school, a community college, and a university; restoration covers a wide variety of medical expenditures including dental services, hearing/speech services, eyeglasses and contact lenses, drug and alcohol treatments, psychological services, surgical procedures, hospitalization, prosthetic devices, and other assistive devices; maintenance includes cash payments to facilitate everyday living while receiving other services and covers such items as transportation, clothing, motor vehicle, and/or home modifications, and services to family members; and other consists of payments outside of the previous categories such as for tools and equipment.

The DARS administrative records provide information on the receipt of purchased services. Table 2 displays the fraction of cases receiving a particular purchased service for the subgroups of PERT and non-PERT recipients. Among the 394 PERT recipients, just over half – 199 – receive DARS purchased services. Among the non-PERT recipients, 1774 receive DARS services, and 905 do not. Clearly, PERT recipients are less likely to receive DARS purchased services. This pattern also holds for particular services such that non-PERT recipients are much more likely to have purchased services on diagnosis & evaluation, education, and restoration.

The DARS administrative data do not directly provide information for services provided internally by DARS personnel (i.e., in-house services) or provided by another governmental agency or not-for-profit organization with no charge to DARS (i.e., similar benefits) Following Dean et al. (2015a, b), we measure non-purchased service provision using three administrative data sources covering all non-purchased service expenses except for in-house counselor services. These data imply that 10.0% of VR applicants receive diagnosis & evaluation service from non-purchased services. Percentages for other services are: 1.3% for training, 4.4% for education, 4.4% for restoration, 1.1% for maintenance, and 2.4% for other services.

3.1.2 Explanatory Variables

The sample moments for the explanatory variables from the DARS data are displayed in Table 3. While many of the variables are standard for this type of analysis, some are unusual and included because of the nature of the youth being considered. Special education is a dummy variable equal to 1 for those observations where the respondent received a special education  

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8 Of the full analysis sample, 2% were deemed ineligible, and another 8% withdrew from the process prior to the development of an individualized plan for employment (IPE). The remaining 90% were eligible to receive the VR services described in this section. Of the 394 applicants who received PERT (12.8% of the total), four did not complete an IPE but kept their VR application open throughout the PERT evaluation. All but one of those completing an IPE maintained an open VR case throughout and beyond their PERT evaluation. Of these, 74% completed their IPE prior to the PERT evaluation, 5% during PERT, and 21% subsequent to PERT. DARS purchased VR services for 51% of PERT recipients, with 99% of the dollar value of those expenditures made subsequent to the PERT evaluation.

9 There are 76 separate services provided by DARS, other state agencies, and 1252 vendors. Of these vendors, 73 are employment service organizations which receive roughly half of total purchased-service dollars, usually in the form of job coach services or supported employment.

10 Variable names are in a different font to avoid confusion.
Table 3: Moments of Explanatory Variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Moments for Those Receiving PERT</th>
<th>Moments for Those Not Receiving PERT</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Std Dev</td>
</tr>
<tr>
<td># Observations</td>
<td>394</td>
<td></td>
</tr>
<tr>
<td>Socio-Demographic Variables</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>0.624</td>
<td>0.484</td>
</tr>
<tr>
<td>White</td>
<td>0.645</td>
<td>0.479</td>
</tr>
<tr>
<td>Education</td>
<td>7.459</td>
<td>4.952</td>
</tr>
<tr>
<td>Special Education</td>
<td>0.284</td>
<td>0.451</td>
</tr>
<tr>
<td>Education Missing</td>
<td>0.003</td>
<td>0.050</td>
</tr>
<tr>
<td>Age (Quarters/10)</td>
<td>6.734</td>
<td>0.380</td>
</tr>
<tr>
<td>Married</td>
<td>0.005</td>
<td>0.071</td>
</tr>
<tr>
<td># Dependents</td>
<td>0.114</td>
<td>0.587</td>
</tr>
<tr>
<td>Transportation Available</td>
<td>0.536</td>
<td>0.499</td>
</tr>
<tr>
<td>Has Driving License</td>
<td>0.099</td>
<td>0.299</td>
</tr>
<tr>
<td>Receives Govt Assistance</td>
<td>0.062</td>
<td>0.157</td>
</tr>
<tr>
<td>DisabilityVariables</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Type</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Musculoskeletal Disability</td>
<td>0.084</td>
<td>0.277</td>
</tr>
<tr>
<td>Mental Illness</td>
<td>0.391</td>
<td>0.395</td>
</tr>
<tr>
<td>Cognitive Impairment</td>
<td>0.353</td>
<td>0.478</td>
</tr>
<tr>
<td>Learning Disability</td>
<td>0.528</td>
<td>0.499</td>
</tr>
<tr>
<td>Substance Abuse Problem</td>
<td>0.000</td>
<td>0.065</td>
</tr>
<tr>
<td>Extent</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Significant Disability</td>
<td>0.668</td>
<td>0.471</td>
</tr>
<tr>
<td>Most Significant Disability</td>
<td>0.272</td>
<td>0.445</td>
</tr>
</tbody>
</table>

certificate; 18.7% of the respondents received such education.\textsuperscript{11} Education information is missing for 8.5% of the sample. Rather than exclude such observations, we included a dummy variable for when education information was missing. There are a number of measures of physical and mental disabilities available in the data. We use indicators for the existence of musculoskeletal problems, a learning disability, mental illness, a cognitive impairment, and substance abuse problem. *Mental illness*, for example, is a dummy variable equal to one if the individual’s primary or secondary disability at intake was mental illness.\textsuperscript{12} There are also three measures of the significance of the respondent’s disability: *not significant*, *significant*, and *most significant* (we use *not significant* as the base level).

The observed characteristics of PERT recipients are similar to non-recipients except for the incidence of different impairments. PERT recipients are more likely to be cognitively impaired (35% versus 25%) and learning disabled (53% versus 43%) but less likely to be mentally ill (19% versus 29%).

Finally, we construct two instrumental variables to help identify the impact of VR services on labor market outcomes: the proportion of other clients of the individual’s counselor receiving a particular service and the proportion of other clients at the individual’s field office receiving a particular service.\textsuperscript{13} Importantly, these instruments are correlated with the provision of VR services. A test of the null hypothesis that the joint density of services within offices does not vary across offices is rejected at standard significance levels. We also reject the null that each office provides each service in the same proportion, one at a time.\textsuperscript{14} The fact that there is statistically significant variation in the provision of services across offices and counselors make these viable instruments. A more detailed discussion of the instrumental variable assumptions is provided in Section 4.5 and in Dean et al. (2015a, b).

3.2 Virginia Department of Education Data

An essential part of our analysis involves estimating a model of PERT participation as described in Section 4.1. For each district, we observe detailed information on PERT participants and know the maximum number of PERT slots reserved for each jurisdiction. To estimate the PERT selection probability, we use Virginia Department of Education (VDOE) data on the size of the potential population from which PERT participants are selected; i.e., the number of teenagers between the

\textsuperscript{11}Those receiving a special education certificate are a proper subset of those receiving special education services. In fact, all PERT participants receive special education services.

\textsuperscript{12}The existence of visual, hearing/speech, internal disabilities, and other miscellaneous disabilities were available in the data but not common enough or not varying enough with dependent variables to measure precise effects. So they were not used in the analysis.

\textsuperscript{13}These variables are transformed as is described in Appendix 8.1. Also see Dean et al. (2015a, b).

\textsuperscript{14}Using a likelihood ratio test, the test statistic is 816.0 for the first hypothesis (with 265 df and normalized value of 23.0) and 1205.0 for the second (with 318 df and a normalized value of 35.2). For counselors, the analogous test statistics are 1754.1 (with 910 df and a normalized value of 19.8) and 6024.8 (with 1092 df and a normalized value of 105.6).
Figure 1: Proportions of Eligible Population Participating in PERT

ages of 14 – 18 with disabilities, disaggregated by jurisdiction (city/county), age, and condition. To do this, we aggregate the 15 conditions in the VDOE data into 8 conditions compatible with the the DARS data. The 8 aggregated conditions are  

cognitive impairment, autism, hearing/visual/speech, mental illness, musculo/skeletal, internal disability, learning disability, and traumatic brain injury.  

Figure 1 shows the proportion of those eligible who participate in PERT, disaggregated by condition and age. This figure shows notable variation in the participation probability by age and limitation. There are no PERT participants who are 14 years old, and few who are 15 years old. The conditions with the highest participation rates are musculo/skeletal, cognitive impairment, autism, and learning disability, and the conditions with the lowest participation rates are mental illness, hearing/vision/speech, internal disability, and traumatic brain injury. There is also significant variation across jurisdictions for all of these proportions.

3.3 Virginia Employment Commission Data

A unique and valuable feature of this analysis is that we have information from an administrative data source about individual quarterly earnings prior to, during, and after service receipt. In particular, we use data collected from quarterly employment records provided by employers to the Virginia Employment Commission (VEC) for purposes of determining eligibility for unemployment insurance benefits. For each DARS applicant, we observe employment and log quarterly earnings, where employment is a binary measure of working in a particular quarter in the labor market. Table 5 provides information on sample sizes and the mean employment rate and log-quarterly earnings (conditional on working) disaggregated between quarters before and after initial service provision. Employment rates and quarterly earnings increase (conditional on working) after service provision. Most notably, the employment rates increase nearly three-fold for PERT recipients and two-fold for non-PERT recipients. A naive unconditional difference-in-difference estimator implies that PERT increases employment rates but decreases log-quarterly earnings conditional on working.

Figures 2 and 3 display quarterly employment rates and earnings (conditional on working), respectively, for SFY 2000 applicants who receive substantial VR services and those that do not receive substantial services. We refer to these two groups as the treated and untreated, respectively. In these figures, quarters are measured relative to application date (not
Table 5: Moments of Employment and Earnings Variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Before Initial Service</th>
<th>After Initial Service</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td># Obs</td>
<td>Mean</td>
</tr>
<tr>
<td>PERT Participants</td>
<td>Employment</td>
<td>10691</td>
</tr>
<tr>
<td></td>
<td>Log Quarterly Earnings</td>
<td>1859</td>
</tr>
<tr>
<td>PERT Non-Participants</td>
<td>Employment</td>
<td>59023</td>
</tr>
<tr>
<td></td>
<td>Log Quarterly Earnings</td>
<td>14564</td>
</tr>
<tr>
<td>Differences</td>
<td>Employment</td>
<td>-0.073</td>
</tr>
<tr>
<td></td>
<td>Log Quarterly Earnings</td>
<td>0.025</td>
</tr>
</tbody>
</table>

Figure 2: Employment Rates

the initial service date) so that quarter 0 is the quarter of application, quarter −4 is one year prior to application, and quarter 4 is one year post-application.

Importantly, in the base quarter, the applicants in these data are relatively young – between the ages of 15 to 25 – and, in many case, still attending school in the base quarter. Figure 2 shows the employment probabilities rising steadily from almost 0 in period −12 to between 40% to 60% 2 years after the application when the respondents are between the ages of 17 to 27.17

Perhaps the most striking finding is seen by comparing the employment rates between PERT recipients and non-recipients. Prior to the DARS application, employment rates for PERT recipients are notably below the rates for applicants who do not receive PERT. Post-application, the employment rates for both groups receiving DARS services rise relative to the non-service groups, with the rates for PERT recipients increasing the most dramatically. PERT clearly is associated with notable gains in employment relative to the comparison group of young applicants that did not receive PERT. For example, one year prior to the application quarter, the employment rates are 35%-40% for non-PERT recipients and only about 12% for PERT recipients. One year after the DARS application, the employment gap between PERT recipients and non-recipients narrows. Four years after the application, the employment rates of PERT recipients match the rates of non-recipients, and DARS service provision seems to be the key distinction between the groups. In particular, the groups receiving DARS services (both PERT recipients and non-recipients) have employment rates about around 55%, while those not receiving DARS services (both PERT recipients and non-recipients) have employment around 50%. In fact, PERT recipients who received DARS services have the highest employment rates of all four groups. Thus, DARS services are associated with improved employment outcomes and the improvements are even more pronounced among the cohort receiving PERT.

While there is notable association between DARS services receipt and employment, there is no such relationship with earnings. Figure 3 shows that earnings among the employed are lower for the PERT recipients than non-recipients and that DARS service provision does not seem to be associated with earnings. Thus, VR treatment services are associated with a sharp, substantial, and sustained increase in employment but no discernible change in quarterly earnings among the

17See D’Amico and Blackorby (1992) for similar results in the National Longitudinal Transition Survey.
3.4 Bureau of Economic Analysis Data

Labor market outcomes may be influenced by local labor market conditions. Though there are no measures of local labor market conditions in either the DARS or VEC data, DARS data indicate the county of residence for each client. Using these geographic identifiers, we are able to merge data on local economic conditions provided by the Bureau of Economic Analysis (BEA, 2010). In particular, we construct measures of log employment rates at two units of geography: county and MSA/RSA level (see Dean et. al., 2015a, b). The two measures have very similar properties and a correlation of 0.99; however, they are different enough to include both in the estimation procedure.

4 Model and Econometric Methodology

In this section, we present our model of endogenous service receipt and labor market outcomes, construct the corresponding likelihood function, and discuss the identification of the model. We begin by detailing the model of PERT participation. The basic approach borrows from the standard binary choice random utility framework, but it is complicated due to institutional constraints limiting the number of slots per district and the lack of individual level data on non-participating students. We do not observe a random sample of individuals who might participate in PERT. Instead, we observe a mix of individual information about PERT participants from the DARS data and aggregate information on the size of the relevant district level population disaggregated by age and limitation (e.g., mental illness) from the VDOE data. After describing the PERT participation model, we then develop the model of VR services and labor market outcomes. In this model, PERT has a direct impact on employment and earnings and an indirect impact via VR services and schooling. We allow for unobserved factors associated with PERT participation to be associated with the unobserved variables in the VR service and labor market outcomes.

After presenting the model, we then construct the likelihood function and discuss the sources of exogenous variation used to identify the parameters. As noted above, several approaches are used to address the selection problem including the longitudinal data that allow us to account for pre-service differences, an error factor model that allows for correlation across unobserved variables, and instrumental variables that are assumed to impact service receipt but not the labor market outcomes. In particular, we instrument for the provision of PERT services using programmatic restrictions on the number of students allowed to sign up for PERT. This “slot constraint” is associated with the PERT participation probability but arguably uncorrelated with unobserved labor market factors. In addition, following Doyle (2007), Maestas et al. (2013), and

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In some ways, this problem shares features with choice-based sampling estimation problems. In both cases, there is oversampling of observations with respect to one of the dependent variables (PERT participation in our case), and, in both cases, the estimation approach involves using aggregate data on relevant population moments. See Manski 1977. Dean et al. (2015b) use a similar methodology to estimate the probability of people with mental health problems applying for services from DARS.

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Figure 3: Average Quarterly Earning for the Employed
Dean et al. (2015a, b), we instrument for VR service provisions using the propensity of an individual’s VR counselor and field office to assign clients to services. As discussed below, these counselor/field office variables are related to VR service provisions but not directly related to the labor market outcomes.

### 4.1 Model of PERT Participation

Let \( i \) index disabled youth in Virginia, \( i = 1, 2, \ldots, n \), \( j(i) \) be the jurisdiction of person (student) \( i \), and let \( J(j) \) be all of the disabled individuals \( i \) with \( j(i) = j \); i.e., all of the disabled youth living in jurisdiction \( j \). Assume the latent value for \( i \) of participating in PERT is

\[
p^*_i = X^i_p \beta^p + u^p_i + v^p_i,
\]

where \( X^i_p \) is a vector of observed exogenous explanatory variables, \( \beta^p \) is a vector of coefficients, and \( \{u^p_i, v^p_i\} \) are unobserved random variables whose structure is specified below.

As in a standard random utility model, we assume that, for student \( i \) to participate in PERT, the (latent) value of participating \( p^*_i \) is positive. In addition, however, there are institutional constraints on the maximum number of students from each jurisdiction. Overall, 22 jurisdictions, or 29.1\%, used more slots than they were assigned.\(^{19}\)

To model this process, let \( n^j_s \) be the number of PERT slots reserved for students in jurisdiction \( j \) and assume that a student participates in PERT, \( p_i = 1 \), if

\[
p^*_i > n^j_s \quad \forall i', i' \in J(j) : p_{i'} = 0; \left\{ \begin{array}{ll}
p^*_i \geq 0 & \text{if } v_{j(i)} = 0 \\
p^*_i \geq \bar{p}^* > 0 & \text{if } v_{j(i)} = 1,
\end{array} \right
\]

where

\[
v_j = 1 \left[ \sum_{i \in J(j)} p_i > n^j_s \right],
\]

indicates if the slot constraint is violated. Thus, a jurisdiction can use more slots than allocated but with a more restrictive criterion for participation (\( \bar{p}^* > 0 \)). Let \( P(j) = \{ i \in J(j) : p_i = 1 \} \) be the set of disabled youth in jurisdiction \( j \) who participate in PERT.

### 4.2 VR Services and the Labor Market

Next, we model participation in DARS and labor market outcomes using a modified version of the approach from Dean et. al. (2015a, b). While the model for VR services looks quite standard, the model for labor market outcomes includes significantly more structure than is usual in a model of treatment effects.

First, we model participation in VR service receipt. Define \( D(j) \) as the set of disabled youth in jurisdiction \( j \) who apply for DARS services. Some applicants receive VR services, and others do not. Let \( y_{ik}^* \) be the latent value for individual \( i \) of participating in service \( k, k = 1, 2, \ldots, 6 \), and assume that

\[
y_{ik}^* = X^i_y \beta^y_k + \delta^y_k p_i + u^y_{ik} + \varepsilon^y_i,
\]

where \( X^i_y \) is a vector of exogenous explanatory variables, \( p_i \) is a binary indicator for PERT participation, \( \{\beta^y_k, \delta^y_k\} \) are coefficients, and \( \{u^y_{ik}, \varepsilon^y_i\} \) are unobserved random variables whose structure is specified below. Let \( y_{ik} = 1 (y^*_{ik} > 0) \) be an observed indicator for whether \( i \) receives service \( k \).

Second, we model employment. Let \( z^*_it \) be the latent value for \( i \) of working in quarter \( t \), and let \( z_{it} = 1 (z^*_it > 0) \) be the observed indicator for whether \( i \) is employed in quarter \( t \). Assume that

\[
z^*_it = X^i_z \gamma^z + \sum_{i=1}^{4} d^i_{it} \sum_{k=1}^{6} [\alpha^z_{0ki} + p_i \alpha^z_{1ki}] y_{ik} + \left( \sum_{i=3}^{4} d^i_{it} \right) p_i [\delta^z + \varphi^z s_i] + u^z_it + v^z_it
\]

where \( X^i_z \) is a vector of (possibly) time-varying, exogenous explanatory variables, \( d^i_{it} \) is a dummy variable equal to one if the amount of time between the quarter of service receipt and \( t \) is between \( \tau_{ki} \) and \( \tau_{i+1} \), \( s_i \) is the amount of time left in

\(^{19}\)According to PERT administrators, slots are fungible, and some jurisdictions “share” slots. Eight jurisdictions filled slots even though none were allocated, and 14 with slots filled more than were allocated.
school after PERT participation, and \(u_{it}^v, v_{it}^v\) are errors whose structure is specified below.\(^{20}\) The time periods implied by the nodes we use are a) 2 or more quarters before service, b) 1 quarter before service, c) quarter after service to 8 quarters after service, and d) 9 or more quarters after service.

Finally, we model earnings. Let \(w_{it}\) be the log quarterly earnings of \(i\) at \(t\), and assume that

\[
w_{it} = X_{it}^w \gamma^w + \sum_{t=1}^{4} d_{it} \sum_{k=1}^{6} \left( \alpha_{0ki}^w + p_i \alpha_{1ki}^w \right) y_{ij} + \left( \sum_{t=3}^{4} d_{it} \right) \psi(w_i + \varphi^w s_i) + u_{it}^w + v_{it}^w \tag{5}
\]

where variables are defined analogously to equation (4).

Recall that we observe measures of purchased and non-purchased service receipt to use in the service receipt equation (equation (3)) and the labor market equations (equations (4) and (5)). However, if the only source of service receipt is in-house and/or similar benefits, then the \(\beta^k\) coefficients in equation (3) are multiplied by a service-choice “in-house service/similar benefits” parameter \(\mu_1\) (to be estimated), and the \((\alpha_{0ki}^z, \alpha_{1ki}^w)\) coefficients in equations (4) and (5) are multiplied by an outcomes “in-house service/similar benefits” parameter \(\mu_2\) (to be estimated). This allows both the service choice decisions and labor market outcomes to depend upon the source of the service (i.e., purchased vs. non-purchased).

Finally, notice that PERT participation enters into the model in a number of ways:

1. PERT affects the choice of services provided through \(\delta^v\) in equation (3) and the efficiency of DARS service through \(\alpha_{1ki}^z\) in equation (4) and \(\alpha_{1ki}^w\) in equation (5). The idea here is that PERT provides information about what type of vocational services will be most helpful to the client, thus affecting the choice of provided services and improving their efficiency.

2. PERT interacts with \(s_i\) to affect labor market outcomes through \(\varphi^z\) in equation (4) and \(\varphi^w\) in equation (5). The idea here is that PERT provides the school system with information about the needs of the youth and thus the time the school has, as measured by \(s_i\), to act on that information.\(^{21}\)

3. PERT may directly improve labor market outcomes through \(\delta^y\) in equation (4) and \(\delta^w\) in equation (5). The idea here is that PERT might focus its participants on being a productive member of the labor market and provide direct skills useful in the labor market.

### 4.3 Assumptions on the Errors

To allow for a rich correlation structure across these equations, assume that

\[
\begin{align*}
 u_i^v &= \lambda_1^v e_{i1} + \lambda_2^v e_{i2}, \\
 u_{ik}^v &= \lambda_1^v e_{i1} + \lambda_2^v e_{i2}, \\
 u_{it}^z &= \lambda_1^z e_{i1} + \lambda_2^z e_{i2} + \eta_{it}^z, \\
 u_{it}^w &= \lambda_1^w e_{i1} + \lambda_2^w e_{i2} + \eta_{it}^w, \\
 \eta_{it}^z &= \rho \eta_{it-1} + \zeta_{it}^z, \\
 \eta_{it}^w &= \rho \eta_{it-1} + \zeta_{it}^w, \\
 \begin{pmatrix} \zeta_{it}^z \\
 \zeta_{it}^w \end{pmatrix} &\sim iidN \left[ 0, \begin{pmatrix} \sigma^2_z & \rho \zeta \\
 \rho \zeta & \sigma^2_w \end{pmatrix} \right], \\
 \begin{pmatrix} e_{i1} \\
 e_{i2} \end{pmatrix} &\sim iidN \left[ 0, I \right], \\
 \varepsilon_{ik}^v &\sim iid \text{Logistic}, \\
 v_i^p &\sim iidN \left( 0, 1 \right), \\
 v_{it}^z &\sim iidN \left[ 0, 1 \right], \text{ and} \\
 v_{it}^w &\sim iidN \left[ 0, \sigma^2_w \right].
\end{align*}
\]

\(^{20}\)Since the age of graduation from high school is not observed in the DARS data, we do not directly observe \(s_i\). Instead, we simulate this random variable using the approach described in the Appendix (8.3).

\(^{21}\)See, for example, Phelps and Hanley-Maxwell (1997) for a review of vocational education programs aimed at disabled youth, Wittenburg et al. (2002) for a discussion of the need for models focused on evaluating the benefits of school/non-school interaction effects, and Test et al. (2009) for an empirical analysis of some school-based programs.
We include the \((e_{i1}, e_{i2})\) to allow for two common factors affecting all dependent variables with factor loadings \((\lambda^p_{ik}, \lambda^y_{ik}, \lambda^z_{ik}, \lambda^w_{ik})_{k=1}^2\).

We also allow for serial correlation and contemporaneous correlation in the labor market errors \((\eta^p_{it}, \eta^w_{it})\).\(^{22}\)

### 4.4 Likelihood Function

The parameters of the model are \(\theta = (\theta_p, \theta_y, \theta_z, \theta_w)\) where

\[
\theta_p = (\beta^p, \lambda^p_1, \lambda^p_2, \bar{p}^p),
\]

\[
\theta_y = (\beta^y_i, \delta^y_{ij}, \lambda^y_{ik}, \lambda^w_{ik})_{k=1}^6,
\]

\[
\theta_z = \left( \gamma^z, \left\{ a^z_{ik}, \alpha^z_{iklt} \right\}_{l=1}^4 \right)_{k=1}^6, \delta^z, \phi^z, \lambda^z_1, \lambda^z_2, \rho_\eta, \sigma^2, \rho_\xi ,
\]

\[
\theta_w = \left( \gamma^w, \left\{ a^w_{ik}, \alpha^w_{iklt} \right\}_{l=1}^4 \right)_{k=1}^6, \delta^w, \phi^w, \lambda^w_1, \lambda^w_2, \rho_\eta, \sigma^2.
\]

Disabled youth can participate in DARS and PERT. There are three relevant cases to consider in constructing the likelihood function: a) \(i \notin P(j(i)), i \notin D;\) b) \(i \notin P(j(i)), i \in D\) and c) \(i \in P(j(i)), i \notin D.\) The fourth possibility, \(i \in P(j(i)), i \notin D\) cannot occur because all PERT participants apply for DARS services. For case (a), we see only proportions of disabled youth with specific characteristics observed in the VDOE. For (b) and (c), the individual \(i\) applied for DARS services, \(i \in D,\) and we observe their behavior in both the DARS administrative data and our VEC administrative data. In these two cases, we observe PERT and DARS service participation and the labor market history.

Define \(u_i = \left( u^p_i, [u^y_{ik}]_{k=1}^6, [u^z_{it}, u^w_{it}]_{t=1}^T \right)\) and \(\overline{u}_j = \{ u_i | \forall i \in J(j) \}\) to be the set of PERT (correlated) errors for disabled youth from jurisdiction \(j.\) Then the joint likelihood contribution, conditional on \(\overline{u}_j,\) for youth in jurisdiction \(j\) who are in the DARS data is

\[
L_j (\overline{u}_j) = \int_{V_j} \left[ \prod_{t=1}^T L^y_i \left( u^y_i \right) \prod_{i \in J(j) \cap i \in D} L^w_i \left( u^w_i \right) \right] \prod_{i \in J(j) \cap i \in D} d\Phi (v^p_i)
\]

where

\[
V_j = \left\{ v^p_i > -X^p_i \beta^p - u^p_i + \xi_{j0} \right\}_{v_i \in [J(j) \cap p_i = 1]} \cup \left\{ v^p_i < -X^p_i \beta^p - u^p_i + \xi_{j0} \right\}_{v_i \in [J(j) \cap p_i = 0]} ,
\]

\[
\xi_{j0} = \max \left[ v^p_{j(i)} \beta^p, p^*_{j(i)} \right] ,
\]

\[
\tilde{i} (j(i)) = \arg \min_{v^p_{j(i)}} p^*_{j(i)} , \quad \forall \in J(j(i)): p_i = 1
\]

\[
\xi_{j1} = \max \left[ v^p_{j(i)} \beta^p, p^*_{j(i)} \right] ,
\]

\[
\tilde{i} (j(i)) = \arg \max_{v^p_{j(i)}} p^*_{j(i)} , \quad \forall \in J(j(i)): p_i = 0
\]

\[
L^y_i \left( u^y_i \right) = \prod_{k=1}^K \frac{1}{1 + \exp \left( X^y_i \beta^y_k + u^y_{ik} \right)} ,
\]

\[
L^w_i \left( u^w_i \right) = \left[ L^0_i \left( u^w_{it}, u^w_{it} \right) \right]^{1-z_{it}} \left[ L^0_i \left( u^w_{it}, u^w_{it} \right) \right]^{z_{it}} ,
\]

\[
\overline{z}_{it} (u^w_{it}) = X^z_{it} \gamma^z + \sum_{t=1}^4 d^z_{it} \sum_{k=1}^6 (a^z_{oklt} + p_i \alpha^z_{iklt}) y_{ij} + \sum_{t=3}^4 d^z_{it} \right) p_i (\delta^z + \phi^z s_i) + u^w_{it},
\]

\(^{22}\)The covariance matrix implied by this error structure is presented in Appendix 8.2.
labeled "neither," the jurisdiction picks the students with the largest values of outcome or even multiple equilibria of the sort seen in Tamer (2003). However, we avoid this problem by assuming that the number of disabled youth in jurisdiction $DARS$ data). Then, since all of the youth in cell $n$ have the same likelihood contribution since all we observe about each is that they chose not to participate in $PERT$ (based on $DARS$ data). Then, since all of the youth in cell $c$ have the same characteristics, the likelihood contribution for all of them together is

$$Pr (i \notin P (j) | c (i) = c, i \notin D, \overline{w}_j, \xi_{j0}) = \int [1 - \Phi (X^p_i \beta^p + u^p_i - \xi_{j0})] d\Phi \left( \frac{u^p_i}{1 + \sum_j \lambda_{ji}^p} \right).$$

Define $n_{jc}$ as the number of disabled youth in jurisdiction $j$ and with characteristics consistent with cell $c$ and $n^p_{jc}$ as the number of disabled youth in jurisdiction $j$ with characteristics consistent with cell $c$ that participated in $PERT$ (based on $DARS$ data). Then, since all of the youth in cell $c$ have the same characteristics, the likelihood contribution for all of them together is

$$[Pr (i \notin P (j) | c (i) = c, i \notin D, \overline{w}_j, \xi_{j0})]^{n_{jc} - n^p_{jc}}.$$

If we simplify by conditioning on whether the slot constraint is violated; i.e., we do not ensure that the errors for other youth in the same jurisdiction were consistent with the slot constraint when evaluating the likelihood function for each individual case, then the log likelihood function is

$$L = \sum_j \log \int L_j (\overline{w}_j) \prod_c [Pr (i \notin P (j) | c (i) = c, i \notin D, \overline{w}_j, \xi_{j0})]^{n_{jc} - n^p_{jc}} dG (\overline{w}_j | \Omega)$$

where $G (\cdot | \Omega)$ is the joint normal density with covariance matrix $\Omega$ implied by the error structure.

The likelihood contribution for each jurisdiction is simulated using a simulator similar to GHK (Geweke, 1991): For each $j$,

1. Simulate $\overline{w}_j$;
2. Conditional on the simulated $\overline{w}_j$, compute $\Phi (X^p_i \beta^p + u^p_i - v_j \beta^p) \forall i \in P (j): p_i = 1$;
3. Simulate $v^p_i | p_i = 1 \forall i \in P (j): p_i = 1$;
4. Conditional on simulated $\overline{w}_j$ and $v^p_i | p_i = 1 \forall i \in P (j): p_i = 1$, compute $\xi_{j0}$;
5. Conditional on simulated $\overline{w}_j$ and $\xi_{j0}$; compute $1 - \Phi (X^p_i \beta^p + u^p_i - \xi_{j0})$ for those $i \in D \cap P_j (j): p_i = 0$ and $[Pr (i \notin P (j) | c (i) = c, i \notin D, \xi_{j0})]^{n_{jc} - n^p_{jc}} \forall c$;
6. Conditional on simulated $\overline{w}_j$, compute all of the remaining terms in the likelihood function, and join together;
7. Repeat $r = 1, 2, ..., R$ times (with antithetic acceleration (Geweke, 1988), and average.

Note that one might think that there are discontinuities in the subset of the error space consistent with a particular outcome or even multiple equilibria of the sort seen in Tamer (2003). However, we avoid this problem by assuming that the jurisdiction picks the students with the largest values of $p^*$. For example, imagine a jurisdiction with two disabled students, A and B, and one slot. The decomposition of $R^2$ corresponding to choices made are represented in Figure 4. In the region labeled “neither,” the $v$ errors are both small enough so that it is not worthwhile sending either youth (both have negative
Decomposition of Error Space

Neither
A
B
Both

Figure 4: Decomposition of Error Space

value. In the region labeled “A,” the errors are such that the best choice is to send only A. Along the diagonal part of the border, each of A and B would be worth sending if the other were not going. However, on the “A” side of the boundary, A’s value of going is greater than B’s. Similarly, in the region labeled “B,” only B is sent. In the region labeled “Both,” both should be sent because each satisfies the participation criterion even when the slot restriction is violated. In general, when the jurisdiction has more than two youth, the relevant picture is a higher dimension decomposition with similar features.

4.5 Identification

There are two relevant notions of identification in this model. First, there is the general question of identification of model parameters in any nonlinear model. Covariation in the data between dependent variables and explanatory variables identifies many of the model parameters. For example, covariation between male and participation in training identifies the \( \beta_j \) coefficient in equation (3) associated with male for \( j = \text{training} \). Similarly, the covariation between white and employment status identifies the \( \gamma^w \) coefficient in equation (4) associated with white, and the covariation between white and log quarterly earnings identifies the \( \gamma^w \) coefficient in equation (5) associated with white. Second moment parameters such as \( \sigma^2_\zeta \) and \( \rho_\zeta \) are identified by corresponding second sample moments.

Second, participation in PERT, DARS services, and the labor market, may be endogenous. Three approaches are used to address this identification problem. First, as in a difference-in-difference design, we control for pre-treatment labor market differences between those who will and will not receive services. If the differences in unobserved factors that confound inference in equations (4) and (5), \( u^w_{it} \) and \( u^z_{it} \), are fixed over time, then controls for the observed pre-treatment labor market differences address the endogenous selection problem (see Meyer, 1995; Heckman et al., 1999, Section 4). Second, the factor model explicitly accounts for correlation between the unobserved variables in the service and labor market equations.

Finally, we assume that several instrumental variables impact service receipt but not the latent labor market outcomes. In particular, we instrument for the provision of PERT services using the school district “slot constraints.” These district level constraints are established by the PERT program, are based largely on the historical needs and characteristics of each district, and vary little from year-to-year. The constraints are not based on local labor market conditions. Thus, these slot thresholds, which are associated with the PERT participation probability (see Table 12), are arguably uncorrelated with unobserved individual specific labor market factors. Also, following Doyle (2007), Maestas et al. (2013), and Dean et al. (2015a, b), we instrument for VR service provisions using the propensity of an individual’s VR counselor and field office to assign clients to services. These instruments are strongly associated with service receipt (see Section 3) but unlikely to be related to the labor market structural errors. DARS clients have limited ability to select their field office, which is determined by the residential location of the client, or a counselor whom, conditional on observed characteristics, is randomly assigned. Thus, the assignment to offices and counselors is effectively random conditional on the observed characteristics of clients. (Dean et al., 2015a, b). Still, as noted in Dean et al. (2015b), this assumption might be violated if service provision decisions are based on idiosyncratic features of the local labor market that are not fully accounted for using the BEA data.
5 Estimation Results

We divide up the discussion of parameter estimates in three parts: first, the estimated effect of PERT and VR services on labor market outcomes; second, the parameters associated with observed characteristics, and third, the error structure parameters. Finally, we report results from a series of specification tests.

5.1 Pert and VR Services

We begin by examining the estimated effect of PERT and VR services on labor market outcomes. Table 7 presents direct PERT effects on employment and earnings as well as the indirect effects via schooling. PERT has a direct positive effect on both employment (0.306) and conditional log quarterly earnings (0.313), and it improves school preparation for the labor market as well (0.242 for employment and 0.166 for log quarterly earnings).

In addition, we allow for PERT to indirectly impact labor market outcomes by improving the efficiency of VR services. Tables 8 and 9 present these indirect PERT effects as well as the estimates for the effect of VR services on employment and earnings, respectively. For each labor market outcome, the effects are allowed to vary across PERT participation and the six different VR service types where the PERT effects are restricted to be the same across the six different services:

\[ z_{1k}^i = z_{1}^i \]
\[ w_{1k}^i = w_{1}^i \]

Given our rich labor market data, we are able to estimate both short-run (the first two years) and long-run (more than two years) effects of services and account for pre-service outcomes in the quarter prior to services as well as two or more quarters prior to the initial service. As noted in Section 4.5, inclusion of pre-treatment periods is a way to account for the effect of endogenous selection into services. The quarter immediately prior to initial service provision is separated out because this quarter seems likely to have a distinct impact on selection and because of the well-documented variation in labor market behaviors just prior to the application period – the Ashenfelter dip (Ashenfelter, 1978; Heckman et al., 1999).

Focusing first on the indirect effects of PERT, we see that the estimates for the quarters prior to the initial service (see the first two columns) are substantial and statistically significant for the employment equation but not the earnings equations. The estimated short- and long-run post-service coefficients (see the last two columns) are all positive, substantial, and statistically significant at the 5% significance level.

These post-service estimates should be interpreted relative to the coefficients associated with pre-service measures in the
first column. So, as seen in Table 8, prior to service provision, the indirect effect of PERT on employment is $-0.205$. In the two years after service provision, it rises to $0.066$, and then, in the longer-run, it increases further to $0.233$. Thus, the long-run indirect effect of PERT on employment is $0.438$. Likewise, Table 9 shows that the long-run indirect effect of PERT on log quarterly earnings is $0.194$. PERT appears to have important positive employment and earnings effects that work by improving the efficiency of VR service provisions.

Tables 8 and 9 also provide estimates of the direct effect of VR services. All of the coefficients for both employment and log quarterly earnings associated with periods two or more quarters prior to the initial service are substantial and statistically different than zero. For training, the estimates imply that those provided training services have lower pre-treatment employment probabilities ($-0.397$) and somewhat lower quarterly earnings ($-0.411$). For education, the estimates imply selection is positively associated with pre-service employment probabilities ($0.133$) but lower quarterly earnings ($-0.097$). In general, the results for the quarter one period prior to services are qualitatively similar although in many cases are not statistically different than zero. Overall, these results suggest a heterogeneous selection process where applicants are assigned to particular services based on underlying unobserved factors that are associated with per-service labor market outcomes.

The last two columns of results display the estimated short- and long-run effects of services on labor market outcomes. As with the PERT estimates, these estimates should be interpreted relative to the coefficients associated with pre-service measures in first two columns. For example, as seen in Table 8, prior to service provision, the effect of training on employment is $-0.397$. In the two years after service provision, it rises to $-0.110$, and then, in the longer run, it declines to $-0.264$. The long-term effect of training on those who were trained after accounting for selection into service is $-0.264 + 0.397 = 0.133$. The effects of each service type across the four time periods can be observed easily in Figure 5. Relative to employment propensities prior to service provision, we observe that PERT and all services except for restoration and maintenance increase employment probabilities in both the short- and long-run.

Table 9 displays estimates for the effect of service provision on log quarterly earnings and the relative effects can be observed easily in Figure 6. For earnings effects, PERT and all services except short-run restoration and maintenance lead to higher earnings conditional on employment.23

The results from the structural model estimates presented in this section suggest a much more complex and nuanced picture than found in the simple before-and-after analysis displayed in Figures 2 and 3. Recall that these figures, which display the unconditional mean employment and earnings outcomes respectively, reveal little pre-program differences between VR recipients and non-recipients, fairly substantial positive post-treatment employment associations, particularly for those receiving PERT, and almost no relationship between services and earnings. After conditioning on observed covariates, accounting for six different service types rather than a single treatment indicator, and using instrumental variables in a model with endogenous service provision, the structural model estimates also reveal a strong effect of PERT on employment. In contrast, however, the estimates from this model reveal a notable effect on earnings. With respect to VR services, we find evidence of pre- and post-program labor market differences which, except for restoration and maintenance, suggest positive

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23 All $F$-statistics testing for the joint significance of the short-term and long-term log quarterly earnings and employment effects relative to the effect prior to program participation are statistically significant with $p$-values less than $0.0001$. 

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Table 9: Program Participation Effects on Log Quarterly Earnings

<table>
<thead>
<tr>
<th>Variable</th>
<th>PERT Interaction</th>
<th>Diagnosis &amp; Evaluation</th>
<th>Training</th>
<th>Education</th>
<th>Restoration</th>
<th>Maintenance</th>
<th>Other Services</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Prior to Program Participation</td>
<td>Quarter Prior to Program Participation</td>
<td>First 2 Years After Program Participation</td>
<td>More than 2 Years After Program Participation</td>
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<tr>
<td></td>
<td>$-0.068**$</td>
<td>$-0.515**$</td>
<td>$-0.411**$</td>
<td>$-0.270**$</td>
<td>$-0.097**$</td>
<td>$0.038**$</td>
<td>$-0.358**$</td>
</tr>
<tr>
<td></td>
<td>$(0.016)$</td>
<td>$(0.014)$</td>
<td>$(0.018)$</td>
<td>$(0.022)$</td>
<td>$(0.017)$</td>
<td>$(0.019)$</td>
<td>$(0.016)$</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes:
1. Standard errors are in parentheses.
2. Single-starred items are statistically significant at the 10% level, and double-starred items are statistically significant at the 5% level.
Figure 5: Program Participation Effects on Employment

Figure 6: Program Participation Effects on log Quarterly Earnings
employment and earnings effects.\textsuperscript{24}

Given the nonlinearity of the model, the parameter estimates do not directly measure the effects of PERT participation on labor market outcomes. The direct effect of PERT increases the average employment probability from 45.1\%, (see Table 5) to 57.6\%, or 12.5 percentage points.\textsuperscript{25} The average proportionate increase in conditional quarterly earnings is 31.3\% (see Table 7), implying a composite increase in unconditional quarterly earnings of \((0.576 + 1.313) - 1 = 66.6\%\). While notably larger than the estimated effects of training programs provided to disadvantaged adult populations (e.g., Hotz et. al., 2006), these estimates are within the upper range of results found in the Youth Transition Demonstration (YTD) project (see Fraker et. al., 2014). For example, three years after enrollment, the Miami YTD program is estimated to increase employment by nearly 8 points and earnings by over 50\%. Moreover, given the average (unconditional) quarterly earnings are only $1240, the large estimated proportional effects translate into modest level effects.

In addition to the direct effect of PERT on labor market outcomes, our model also allows for indirect effects via schooling and VR services. The addition of one year of schooling increases the employment probability by another 30.1 percentage points, conditional quarterly earnings by another 16.6\%, and unconditional quarterly earnings by 53.4\%. Finally, in the short run, the addition of DARS interaction effects increases employment probabilities by another 7.5\%, conditional quarterly earnings by another 22.8\%, and unconditional quarterly earnings by another 33.4\%, and in the long run, increases employment probabilities by 9.9\%, conditional quarterly earnings by another 36.3\%, and unconditional quarterly earnings by 33.4\%..

5.2 Estimates of the Impact of Covariates

Table 10 presents estimated effects of the counselor and office instruments on service receipt.\textsuperscript{26} There are two types of coefficient estimates reported in the table: a) the counselor and office variables and b) the missing counselor variable for cases when the relevant counselor does not have enough other clients to measure the counselor instrument.\textsuperscript{27} The counselor and office instruments have large and statistically significant effects on service provision across clients.

Table 11 reports the effects of demographic variables on the two labor market outcomes of interest \(z_{it}^{*}\) in equation (4) and \(w_{it}\) in equation (5)). Almost all of the estimates are statistically significant. Many of the estimates are as expected

\begin{table}[h]
\centering
\caption{Counselor and Office Effects}
\begin{tabular}{lcc}
\hline
 & Estimate & Std Err \\
\hline
Counselor Effect & 0.522 & 0.073 \\
Office Effect & 0.811 & 0.048 \\
Missing Counselor Effects & & \\
Diagnosis & & \\
& & \\
Training & 0.783 & 0.350 \\
Education & -0.572 & 0.397 \\
Restoration & -1.524 & 0.369 \\
Maintenance & -0.489 & 0.353 \\
Other Services & 0.200 & 0.319 \\
\hline
\end{tabular}
\end{table}

Notes:
1. Single-starred items are statistically significant at the 10\% level, and double-starred items are statistically significant at the 5\% level.
2. Other than those reported, missing counselor effects to estimate both with any precision.

Employment and earnings effects.\textsuperscript{24}

A probit effect of 0.306 from Table 7 translates into an increase in average employment from 0.451 to 0.576 \([\Phi (\Phi^{-1} (0.451) + 0.306) = 0.576]\).

Estimates of the impact of covariates on service receipt are available from the authors. For the most part, the other observed characteristics do not have large or statistically significant effects on service receipt. One notable exception is the impact of PERT participation on service usage which is mostly estimated to have a negative impact on VR service receipt. This may occur because, to some degree, PERT is a substitute for other DARS services, or it may occur because, on average, counselors discover that standard DARS services will not be of much use to clients. It is not clear how to tease out these two important effects.

We allow the impact of non-purchased services to differ from purchased services: see \(\mu_1\) and \(\mu_2\) discussed in Section 4.2). The estimated effect of non-purchased services on labor market outcome effects is estimated to be \(\mu_2 = 0.189\) and is statistically significantly different from both zero and one at the 5\% level. To the degree that DARS service receipt mostly has positive effects on labor market outcomes, this estimate implies that non-purchased services are significantly less effective than purchased services.

In contrast, the estimated effect of being a non-purchased service on service receipt is \(\mu_1 = 0.020\) with a large standard error. This small size of this estimate implies that receipt of non-purchased services appears to be almost uniformly randomly provided.

We restrict missing office effects coefficients to be zero because there are not enough cases and those that exist are too highly correlated with missing counselor effects to estimate both with any precision.
### Table 11: Labor Market Effects

<table>
<thead>
<tr>
<th>Variable</th>
<th>Employment Estimate</th>
<th>Std Err</th>
<th>Log Quarterly Earnings Estimate</th>
<th>Std Err</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-5.532 ** 0.027</td>
<td>2.165 ** 0.028</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>0.124 ** 0.005</td>
<td>0.289 ** 0.005</td>
<td></td>
<td></td>
</tr>
<tr>
<td>White</td>
<td>0.089 ** 0.005</td>
<td>0.198 ** 0.005</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Education</td>
<td>-0.058 ** 0.004</td>
<td>-0.106 ** 0.004</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Special Education</td>
<td>-0.619 ** 0.014</td>
<td>-0.165 ** 0.018</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Education Missing</td>
<td>-0.632 ** 0.015</td>
<td>-0.149 ** 0.020</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age/100</td>
<td>0.589 ** 0.032</td>
<td>0.095 ** 0.033</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Married</td>
<td>-0.698 ** 0.014</td>
<td>-0.383 ** 0.015</td>
<td></td>
<td></td>
</tr>
<tr>
<td># Dependents</td>
<td>-0.139 ** 0.005</td>
<td>-0.095 ** 0.005</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Transportation Available</td>
<td>0.174 ** 0.005</td>
<td>0.181 ** 0.006</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Has Driving License</td>
<td>0.049 ** 0.006</td>
<td>0.152 ** 0.006</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Receives Govt Assistance</td>
<td>-0.827 ** 0.013</td>
<td>-0.812 ** 0.013</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Musculoskeletal Disability</td>
<td>-0.407 ** 0.008</td>
<td>-0.241 ** 0.009</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mental Illness</td>
<td>-0.028 ** 0.006</td>
<td>-0.174 ** 0.006</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cognitive Impairment</td>
<td>0.090 ** 0.007</td>
<td>0.021 ** 0.007</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Learning Disability</td>
<td>0.405 ** 0.006</td>
<td>0.375 ** 0.006</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Substance Abuse</td>
<td>-0.452 ** 0.013</td>
<td>-0.123 ** 0.007</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Significant Disability</td>
<td>0.074 ** 0.007</td>
<td>0.123 ** 0.007</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Most Significant Disability</td>
<td>-0.074 ** 0.008</td>
<td>-0.018 ** 0.009</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Local Employment Rate</td>
<td>0.822 ** 0.162</td>
<td>1.084 ** 0.225</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Metro Employment Rate</td>
<td>-0.489 ** 0.162</td>
<td>-0.745 ** 0.226</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: Single-starred items are statistically significant at the 10% level, and double-starred items are statistically significant at the 5% level.

including positive effects of *male* on employment (0.124) and earnings (0.289), positive effects of *white* on employment (0.089) and earnings (0.198), negative effects of *special education* on employment (−0.619) and earnings (−0.165), positive effects of *age* on employment (0.777) and earnings (0.580), negative effects of *musculoskeletal problems* on employment (−0.407) and earnings (−0.241), negative effects of *mental illness* on employment (−0.028) and earnings (−0.174), negative effects of *substance abuse* on employment (−0.452) and earnings (−0.468), negative effects of *most significant* disabilities (relative to *not significant*) on employment (−0.074), and the positive effect of *has driver’s license* on both labor market outcomes. However, some of the estimates are counterintuitive. In particular, the negative estimates for *education* on employment (−0.058) and earnings (−0.016) are unexpected, but may reflect negative labor market experience effects. While the local labor market conditions behave in the expected way, metro labor market condition estimates are counterintuitive (see Dean et al. 2015a, b for similar mixed results).

Finally, Table 12 provides estimates associated with participation in the PERT program. The estimates imply a priority ordering among conditions with students with musculo/skeletal conditions (1.001) and cognitive impairments (0.573) receiving the highest priority and students with learning disabilities (−0.172), hearing/visual/speech disabilities (−0.232), and internal disabilities (−0.274) receiving the lowest priority. Between the ages of 15 – 18, there is a relatively constant demand for students across age. Finally, jurisdictions violating the slot constraint require PERT recipients to meet higher minimum standards (0.122) than other jurisdictions (see equation (2)).

### 5.3 Estimates of the Covariance Structure

Our model has a rich error covariance structure, as seen in equation (6). This allows for the possibility that unobservables associated with service provision are correlated with unobservables associated with labor market outcomes.

Table 13 displays the estimated factor loadings. The factor loadings for *Factor 1* exhibit positive correlations between employment and earnings, negative correlations of both with education service provision, and statistically insignificant loadings for the other services. In contrast, the factor loadings for *Factor 2* imply no meaningful correlations. With the exception of *education* in *Factor 1* and *PERT* in *Factor 2*, none of the service factor loadings are significant, suggesting minimal selection associated with participation in DARS services or PERT.

The estimates of the other elements of the error structure are reported in Table 14. The serial correlation estimate $\rho_p$ is very large due to the high degree of inertia associated with labor market spells. The correlation between the two different

---

28For example, the estimated factor loading for *Factor 1* for employment (−0.184) and earnings (−0.418) have the same signs. The fact that we do not see the same result in Dean (2015a, b) might be explained by the difference in populations across these papers. DARS staff provided several other possible explanations. One suggestion was that, in wealthy counties, people would provide education services from family resources, thus causing a negative correlation. However, a Lagrange Multiplier test checking for an interaction between the factor loading and county per capita income, though statistically significant, has the opposite sign implied by this explanation.
### Table 12: PERT Participation Estimates

<table>
<thead>
<tr>
<th>Conditions</th>
<th>Estimate</th>
<th>Std Err</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cognitively Impaired</td>
<td>0.573 **</td>
<td>0.033</td>
</tr>
<tr>
<td>Autism</td>
<td>0.397 **</td>
<td>0.044</td>
</tr>
<tr>
<td>Hearing/Visual/Speech</td>
<td>-0.232</td>
<td>0.224</td>
</tr>
<tr>
<td>Mental Illness</td>
<td>0.475 **</td>
<td>0.027</td>
</tr>
<tr>
<td>Musculo/Skeletal Disability</td>
<td>1.001 **</td>
<td>0.141</td>
</tr>
<tr>
<td>Internal Disability</td>
<td>-0.274 **</td>
<td>0.121</td>
</tr>
<tr>
<td>Learning Disability</td>
<td>-0.172 **</td>
<td>0.021</td>
</tr>
<tr>
<td>Traumatic Brain Injury</td>
<td>0.000</td>
<td></td>
</tr>
<tr>
<td>Age 14 Years Old</td>
<td>-3.711 **</td>
<td>0.195</td>
</tr>
<tr>
<td>Age 15 Years Old</td>
<td>-2.447 **</td>
<td>0.023</td>
</tr>
<tr>
<td>Age 16 Years Old</td>
<td>-2.336 **</td>
<td>0.016</td>
</tr>
<tr>
<td>Age 17 Years Old</td>
<td>-2.355 **</td>
<td>0.038</td>
</tr>
<tr>
<td>Age 18 Years Old</td>
<td>-2.376 **</td>
<td>0.058</td>
</tr>
<tr>
<td>Slot Violation Threshold</td>
<td>0.122 **</td>
<td>0.004</td>
</tr>
</tbody>
</table>

Notes:
1. Single-starred items are statistically significant at the 10% level, and double-starred items are statistically significant at the 5% level.
2. The coefficient on Traumatic Brain Injury (TBI) is fixed at 0, and other condition estimates should be interpreted relative to TBI.

### Table 13: Covariance Factor Loadings

<table>
<thead>
<tr>
<th>Variable</th>
<th>Factor 1 Estimate</th>
<th>Factor 1 Std Err</th>
<th>Factor 2 Estimate</th>
<th>Factor 2 Std Err</th>
</tr>
</thead>
<tbody>
<tr>
<td>Diagnosis &amp; Evaluation</td>
<td>0.023</td>
<td>0.049</td>
<td>0.014</td>
<td>0.050</td>
</tr>
<tr>
<td>Training</td>
<td>0.012</td>
<td>0.060</td>
<td>-0.044</td>
<td>0.060</td>
</tr>
<tr>
<td>Education</td>
<td>0.175 **</td>
<td>0.075</td>
<td>0.104</td>
<td>0.074</td>
</tr>
<tr>
<td>Restoration</td>
<td>0.007</td>
<td>0.064</td>
<td>0.044</td>
<td>0.066</td>
</tr>
<tr>
<td>Maintenance</td>
<td>0.052</td>
<td>0.067</td>
<td>-0.046</td>
<td>0.066</td>
</tr>
<tr>
<td>Other Services</td>
<td>0.009</td>
<td>0.060</td>
<td>-1.768</td>
<td></td>
</tr>
<tr>
<td>PERT</td>
<td>-0.003</td>
<td>0.014</td>
<td>-0.015 *</td>
<td>0.009</td>
</tr>
<tr>
<td>Employment</td>
<td>-0.184 **</td>
<td>0.002</td>
<td>-0.001</td>
<td>0.002</td>
</tr>
<tr>
<td>Log Quarterly Earnings</td>
<td>-0.418 **</td>
<td>0.002</td>
<td>-0.189 **</td>
<td>0.002</td>
</tr>
</tbody>
</table>

Notes:
1. Single-starred items are statistically significant at the 10% level, and double-starred items are statistically significant at the 5% level.
2. The identifying condition associated with the factor loadings is that the factor loadings for the six different services are orthogonal. We impose this condition by computing the factor loading for factor 2 on other services as a function of the other 11 relevant factor loadings. The factor loadings associated with labor market outcomes are not part of the orthogonality condition.
Table 14: Other Covariance Terms

<table>
<thead>
<tr>
<th>Variable</th>
<th>Estimate</th>
<th>Std Err</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\rho_1$</td>
<td>0.986 **</td>
<td>0.000</td>
</tr>
<tr>
<td>$\sigma_1$</td>
<td>0.186 **</td>
<td>0.001</td>
</tr>
<tr>
<td>$\rho_2$</td>
<td>0.764 **</td>
<td>0.002</td>
</tr>
<tr>
<td>$\sigma_w$</td>
<td>1.184 **</td>
<td>0.001</td>
</tr>
</tbody>
</table>

Notes:
1. Double-starred items are statistically significant at the 5% level.
2. Correlation terms are estimated using the transformation,
   $\rho = \frac{2\exp(\varsigma)}{1 + \exp(\varsigma)} - 1$
   where $\varsigma$ is estimated to ensure that $-1 < \rho < 1$.
3. Standard deviations are estimated using the transformation, $\sigma = \exp(\varsigma)$ where $\varsigma$ is estimated to ensure that $\sigma > 0$. Standard errors for both are derived using the delta method.

Predicted and Sample DARS Service Participation Probabilities with Cell Aggregation

Figure 7: Predicted and Sample DARS Service Participation Probabilities with Cell Aggregation

labor market outcome errors $\rho_\varsigma$ suggests a high degree of correlation between the employment and earnings. The estimate of the log earnings error $\sigma_w$ is quite large, implying standard deviation in quarterly earnings due to unobserved factors on the order of $6574$. It is unclear how much of this variation is due to variation in wages and how much is due to variation in hours.

5.4 Specification Tests

Standard goodness-of-fit tests imply the model fails to match the service provision and employment probabilities; there is a statistically significant difference between the model predictions and the observed probabilities. Additional insight is found by comparing the predicted and sample probabilities. Figure 7 shows where predicted and aggregated sample service participation probabilities differ. Deviations between the 45° line and the “sample lines” at any particular predicted probability represent that part of DARS service participation probability that the estimated model is not predicting. While there are some significant deviations, it is clear that we are capturing the major features of the participation data. Figure 8 plots the deviations between predicted and sample employment probabilities for the periods before and after service receipt. Overall, we are estimating too much variation in employment probabilities, especially for employment after service.

Finally, we use a series of Lagrange Multiplier (LM) tests to assess whether the employment equation is missing significant interactions of demographic characteristics and interactions of service types. The results are mixed. On one hand, the LM tests suggest service interactions are not statistically significant. On the other hand, we find that education, special education, age, married, # dependents, some specific disabilities, and has driver’s license all have statistically significant interactions with being after service receipt. In part, this may explain why the model is overestimating the variation in employment

\[ \chi^2_{22} = 106.0 \]  for employment probabilities before service receipt and $\chi^2_{37} = 2983.7$ for employment probabilities after service receipt. Details on the testing methods and results are available from the authors.
probabilities, especially for quarters after service receipt (see Figure 8); the effectiveness of services varies with person-specific characteristics that are not incorporated in the model.

6 Rate of Return

6.1 Benefits

We simulate the private labor market benefits of PERT using the structural model estimates summarized in Section 5. In particular, for each DARS applicant, we compute the present discounted value of PERT by comparing the difference in quarterly earnings with and without PERT. VR service provisions are fixed at the realized values, \( y_t \). In our model, PERT affects labor market outcomes in three distinct ways:

1. direct effects (\( \delta^z \) in equation (4) and \( \delta^w \) in equation (5); in Table 7, \( \hat{\delta}^z = 0.306 \) and \( \hat{\delta}^w = 0.313 \));

2. DARS service interaction effects \( \left\{ \alpha^z_{ijk} \right\}_{jk} \) in equation (4) and \( \left\{ \alpha^w_{ijk} \right\}_{jk} \) in equation (5); see estimates in Tables 8 and 9); and

3. School interaction effects (\( \varphi^z \) in equation (4) and \( \varphi^w \) in equation (5); in Table 7, \( \hat{\varphi}^z = 0.242 \) and \( \hat{\varphi}^w = 0.166 \)).

Given this, we compute the present discounted value of PERT for each individual for a 10-year window of labor market outcomes after the initial service quarter. The estimated mean discounted benefits are $30713 with a standard deviation of $27444 using a 10-year window and a 5% annual discount rate. In addition to estimating mean benefits, we can also examine the distribution of benefits across VR recipients. Figure 9 displays the distribution of 10-year expected discounted benefits across the 3073 VR applicants using an annual discount rate of 5%. For total discounted benefits (all four effects), the median expected return is $22389 ($2596 per year, on average), and 10% of recipients have expected returns above $59905 ($6946 per year, on average). This figure also decomposes the expected return into the different estimated labor market effects of PERT. Exclusion of the direct effects reduces the median expected discounted benefit from $22389 to $5596, while excluding the DARS service interaction effects reduces the median to $14145. The school interaction effects, which are not displayed in the figure, are very small. The figure shows, however, that the relative size of the effects varies across the population. For individuals with relatively low total expected discounted benefits, the sizes of the direct effects are much larger than the sizes of the service interaction effects, while, for individuals with relatively high total expected discounted benefits, the sizes are very similar.

\[ \text{This is equivalent to earning an extra } $987.83 \text{ per quarter.} \]

\[ \text{Variation in expected returns is caused solely by variation in explanatory variables.} \]
6.2 Expenditures

There are two expenditure effects of PERT. The first, more obvious one is that PERT costs money. The average cost per client of participating in PERT is $1952. The other expenditure effect is on the change in expenditures on DARS services.\footnote{We assume that there was no effect of PERT participation on the fixed costs of applying for DARS services.} This effect has two sources: the effect of PERT participation on a) the probability of receiving DARS services; and b) the marginal cost of DARS services conditional on service receipt. Table 15 presents the sample means of DARS service probabilities and conditional expenditures disaggregated by PERT participation.\footnote{We could have used the model estimates of the marginal effect of PERT participation on DARS service receipt to explain variation in service receipt probabilities. However, the model estimates are consistent with the sample differences except for maintenance and other services, both of which have very small effects on expenditures.} For conditional marginal costs (middle panel), PERT participation increases conditional expenditures on diagnosis & evaluation and training and reduces conditional expenditures for the other four DARS services. However, PERT participation reduces the probability of receipt (first panel) of all services except for maintenance and other services. The total effect (third panel) is a reduction in expenditures on all DARS services. This may occur either because PERT participation is a substitute for DARS services or because PERT participation provides more information about individuals leading to more effective use of DARS services. In evaluating the costs of PERT, the marginal costs of VR services vary with the conjectured PERT receipt indicator according to the results in Table 15. For example, the VR costs for clients who received restoration services from DARS are assumed to be $267 less if the client also received PERT.
6.3 Rate of Return

Figure 10 shows the distribution of the total quarterly rates of return using 5- and 10-year horizons. Several general lessons emerge from this figure. First, while there is significant variation across individuals, the quarterly rates are generally very large. For example, 10% of VR clients have long-run quarterly rates of return that fall below 10%, the median quarterly rate of return is nearly 30%, and 30% of clients have rates of return in excess of 50%. Second, the 5- and 10-year rates of return are similar. This occurs because the rates of return are so high.\textsuperscript{34}

Figure 11 decomposes the long-run rate of return into the different labor market and costs effects of PERT. The direct effects of PERT have the most pronounced impact on the rate of return. When these are excluded, just over 20% of clients are estimated to have negative rates of return, and the median quarterly rate of return drop from 30% to around 5%. The indirect effects of PERT on the VR service efficacy have a noticeable but more modest impact on the estimated rate of return, while the cost effects of PERT have almost no impact on clients with the lowest rates of return but a more pronounced impact on clients with higher rates of return.

7 Conclusions

There is a growing interest in developing innovative and effective programs for youth with disabilities to aid in the process of transitioning from high school to the labor market (Dean et. al., 2006; and Luecking and Wittenburg, 2009). In this

\textsuperscript{34}For example, the discount factor for earnings in year 6 using a 20\% quarterly discount factor is 0.013.
paper, we examine one such program – PERT – using a unique panel data set containing more than a decade of employment and service provision information for almost 3100 disabled youths who applied to the Virginia Department of Rehabilitative Services, in SFY 2000. Combining these data with a structural model of PERT participation, VR service provision, and employment and earnings, we provide the first-ever assessment of the long-term (over five-year) employment impacts of a transitioning program for youth with disabilities. The results paint a very positive but complex picture of the impact of this type of comprehensive, individualized vocational assessment program on the long-run labor market returns for transitioning youth with disabilities. Overall, the estimated effects of PERT are striking: PERT increases average quarterly earnings by just over 167% and has an estimated median quarterly rate of return of nearly 30%. The large proportional effects imply modest level changes in employment and earnings. Finally, we find that much of this return is associated with the direct effect of PERT on employment and earnings, but the indirect effects via the impact of PERT on the efficacy and costs of VR service provision also play an important role. In contrast, the indirect effect of PERT on the provision of schooling has a positive but relatively small impact on the estimated ROR.

8 Appendix:

8.1 Counselor and Field Office Effects

We use as an instrument in equation (3), a transformation of the proportion of other clients of the same counselor provided each service $k$, i.e., a counselor effect. We also use a transformation of the proportion of other clients from the same office provide service $k$, i.e., an office effect. We transform the counselor and office effects using an inverse normal distribution function to make it more likely that, as the counselor and office effects vary, their effect on service probabilities can vary by approximately the same amount. To consider why this is attractive, consider a counselor who almost always uses a particular service. We want to allow for the possibility that this will imply that all of the clients of the counselor are very likely to receive that service. Limiting the counselor effects to vary between $(0, 1)$ makes it harder for that to occur. On the other hand, using an inverse distribution function for a distribution with the real line as support makes the range $(-1, 1)$.

While such a transformation makes sense analytically, in practice, it might cause problems for values of the untransformed effect at or near the boundaries. We propose a “fix” that both makes sense and solves the boundary problem. In particular, we propose replacing the untransformed effect $r_{ik}$ with

$$r^*_{ik} = (1 - \omega_i) r_{ik} + \omega_i \bar{r}_k$$

where $ar{r}_k$ is the mean value of $r_{ik}$ across all counselors (offices), $\omega_i = \kappa_i^{-1}$, and $\kappa_i$ is the number of clients seen by counselor $i$ (office $i$). This specification allows the counselor effect and office effect to be more important for those counselors (offices) who have many observed clients. In fact, it has a certain Bayesian flavor to it.

There are some respondents who either have missing counselor or office information or who have a counselor (or office) with no other clients. For such cases, we can not create our effects. Because of such cases, we include a set of dummies for missing counselor and/or missing office effects. It turns out that these dummies are very highly correlated, and most of the missing office effects must be excluded from the model to avoid a singular Hessian.

Tables A.1 and A.2 provide information about the moments of the transformed counselor and office effects. One can see that there is significant variation in both. There is some evidence of left-tailed skewness but no unreasonable outliers. The lack of outliers occurs despite zeroes for some programs for some counselors and field offices because of the weighted average inherent in equation (7).

\[\text{In fact, when a counselor (office) has only one other client, we treat it as missing also.}\]
Table A.2: Moments of Normal Logistic Transformed Counselor Effects

<table>
<thead>
<tr>
<th>Service</th>
<th>Mean</th>
<th>Std Dev</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Diagnosis &amp; Evaluation</td>
<td>-0.548</td>
<td>0.437</td>
<td>-2.261</td>
<td>1.483</td>
</tr>
<tr>
<td>Training</td>
<td>-0.293</td>
<td>0.58</td>
<td>-2.382</td>
<td>1.997</td>
</tr>
<tr>
<td>Education</td>
<td>-1.239</td>
<td>0.773</td>
<td>-2.812</td>
<td>1.082</td>
</tr>
<tr>
<td>Restoration</td>
<td>-1.312</td>
<td>0.616</td>
<td>-2.699</td>
<td>0.783</td>
</tr>
<tr>
<td>Maintenance</td>
<td>-0.904</td>
<td>0.666</td>
<td>-2.589</td>
<td>1.423</td>
</tr>
<tr>
<td>Other Service</td>
<td>-0.845</td>
<td>0.886</td>
<td>-2.7</td>
<td>1.306</td>
</tr>
</tbody>
</table>

8.2 Covariance Structure

The covariance matrix of the errors $u_i' = (u_i^g, u_{i1}, u_{i2}^g, ..., u_{iJ}, u_{i1}^w, u_{i1}^w, ..., u_{iT}, u_{iT}^w)$ implied by the structure in equation (6) is

$$
\Omega = \begin{pmatrix}
E & F' & G' \\
F & A & B' \\
G & B & C + D
\end{pmatrix}
$$  (8)

where

$$
E = \sum_k (\lambda_k^p)^2,
$$

$$
F' = \begin{pmatrix}
\sum_k \lambda_k^y \lambda_k^p & \sum_k \lambda_k^y \lambda_k^p & \cdots & \sum_k \lambda_k^y \lambda_k^p \\
\sum_k \lambda_k^y \lambda_k^p & \sum_k \lambda_k^y \lambda_k^p & \cdots & \sum_k \lambda_k^y \lambda_k^p \\
\vdots & \vdots & \ddots & \vdots \\
\sum_k \lambda_k^y \lambda_k^w & \sum_k \lambda_k^y \lambda_k^w & \cdots & \sum_k (\lambda_k^p)^2
\end{pmatrix},
$$

$$
G' = H_1 \otimes \begin{pmatrix} 1 & 1 & \cdots & 1 \\
1 & 1 & \cdots & 1 \\
\vdots & \vdots & \ddots & \vdots \\
1 & 1 & \cdots & 1
\end{pmatrix}_{T \times T},
$$

$$
H_1 = \begin{pmatrix}
\sum_k \lambda_k^y \lambda_k^p & \sum_k \lambda_k^y \lambda_k^w \\
\sum_k \lambda_k^y \lambda_k^p & \sum_k \lambda_k^y \lambda_k^w & \cdots & \sum_k \lambda_k^y \lambda_k^w \\
\vdots & \vdots & \ddots & \vdots \\
\sum_k \lambda_k^y \lambda_k^w & \sum_k \lambda_k^y \lambda_k^w & \cdots & \sum_k (\lambda_k^p)^2
\end{pmatrix},
$$

$$
A = \begin{pmatrix}
1 & 1 & \cdots & 1 \\
1 & 1 & \cdots & 1 \\
\vdots & \vdots & \ddots & \vdots \\
1 & 1 & \cdots & 1
\end{pmatrix}_{T \times T},
$$

$$
C = H_2 \otimes \begin{pmatrix} 1 & \rho & \rho & \cdots & \rho^{T-1} & \rho^{T-1} \\
\rho & 1 & \rho & \cdots & \rho^{T-2} & \rho^{T-2} \\
\rho & \rho & 1 & \cdots & \rho^{T-2} & \rho^{T-2} \\
\vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\
\rho & \rho & \rho & \cdots & 1 & \rho \\
\rho & \rho & \rho & \cdots & \rho & 1
\end{pmatrix},
$$

$$
D = \frac{\sigma^2}{1 - \rho^2}
$$

and

$$
B = \begin{pmatrix}
\sum_k \lambda_k^x \lambda_{ik}^p & \sum_k \lambda_k^x \lambda_{ik}^w \\
\sum_k \lambda_k^x \lambda_{ik}^p & \sum_k \lambda_k^x \lambda_{ik}^w & \cdots & \sum_k \lambda_k^x \lambda_{ik}^w \\
\vdots & \vdots & \ddots & \vdots \\
\sum_k \lambda_k^x \lambda_{ik}^p & \sum_k \lambda_k^x \lambda_{ik}^w & \cdots & \sum_k \lambda_k^x \lambda_{ik}^w
\end{pmatrix},
$$

25
8.3 Simulating Remaining Quarters of Schooling:

While the model allows the effect of PERT services to be interacted with the remaining quarters of schooling (see equations (4) and (5)), the age of graduation from high school is not observed in the DARS data. To learn about the age of graduation for youth with disabilities, we use data from Wave V (2009) of the National Longitudinal Transition Survey 2 (NLTS2). Fielded biennially between 2001 and 2009, the NLTS2 is designed to be representative of students receiving special education as a whole and for 12 disability categories. The Wave 5 survey, when the youth were in their early twenties, has 5300 respondents.

While 4 years of high school is the modal choice (approximately 60% to 80% over different disability groups), there are significant proportions in high school for more or less than 4 years. To some degree, this occurs because these students just need more time to finish a standard (or modified) high school curriculum. However, in many cases, this occurs because disabled students are taking advantage of extra opportunities available to them to extend their high school career and prepare better for life beyond high school.

Focusing on a subsample of 1246 transitioning youth from the NLTS with learning disability, emotional disturbance, or orthopedic disabilities, we estimate a probit model where the dependent variable \( g20_i = 1 (g20_i > 0) \) is equal to 1 iff the high school completion age is at least 20:36

\[
g20_i = -1.14^{**} + 0.15 Emot_i + 0.38^{**} Orth_i - 0.27^{**} White_i + 0.17^{**} Male_i + 0.09 Transp_i - 0.24^{*} DrLic_i + 0.26^{**} GovBen_i + u_i
\]

where \( Emot_i = 1 (i \text{ has an emotional disability}), \ Orth_i = 1 (i \text{ has a physical disability}), \ Transp_i = 1 (i \text{ has available transportation}), \ DrLic_i = 1 (i \text{ has a driver’s licence}), \) and \( GovBen_i = 1 (i \text{ has government benefits}) \). These variables are chosen because they are also available in our DARS data. Using the estimates from equation (9), we simulate the age at graduation from high school and thus \( s_i \) in equations (4) and (5).

References


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36 Over 80% of youth leave secondary schooling between the ages of 17 and 19 years old, and nearly 20% leave school between the ages of 20-25 years old.

37 Learning disability is the excluded group. Numbers in parentheses below are standard errors, single-starred items are statistically significant at the 10% level, and double-starred items are statistically significant at the 5% level.


