The Effects of Youth Transition Programs on Labor Market Outcomes of Youth with Disabilities

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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 labor market and service information, 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

For youth with disabilities, 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 (Luecking and Wittenburg, 2009). This population, which comprises about one-eighth of American youth (NCES, 2001), has employment rates that are about 20 percentage points lower than their same-age non-disabled peers and employment spells 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 (WIOA) 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.²

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 panel data set containing more than a decade of employment and service provision information for disabled youths who applied to receive vocational rehabilitation (VR) services, we provide the first-ever assessment of the long-term employment impacts of PERT.

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

²The definition of a disability used for these types of transitioning youth programs is broader than the definition used to determine eligibility for the federal insurance programs. In the latter case, to be eligible for benefits, an individual must demonstrate a "total disability" or the inability to work. For the former, an individual must have impairments that restrict employment outcomes.
services from the Virginia Department for Aging and Rehabilitative Services (DARS), we provide the first-ever assessment of the long-term (over five year) employment impacts of a transitioning program for youth with disabilities.\footnote{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).} While the short-run impacts of transitioning youth programs are certainly important, there are good reasons to think that 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., 2015, 2017, 2018). 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 the longitudinal labor market outcome data, we introduce an innovative model to evaluate the impact of the PERT program on the long-run labor market outcomes of transitioning youth with disabilities. PERT primarily serves as a screening program aimed at providing recipients individually-tailored VR 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 VR services provided by DARS. To do this, we incorporate PERT in a modified version of the Dean et al. (2015, 2017, 2018) multivariate discrete choice model where VR services are endogenously selected and allowed to have a direct effect on labor market outcomes. Importantly, this structural approach allows us to account for the complex interactions between PERT, schooling and VR, to model the endogenous selection of VR and PERT services, and to fully assess counterfactual scenarios.

Within the model, we allow the provision of PERT, 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. Given these exclusion restrictions, the parameters are not solely identified from functional form assumptions. 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. (2015, 2017, 2018), we instrument for VR service provision 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 provision but have no direct effect on labor market outcomes.

This paper complements and extends our earlier work on the impact of VR services in Virginia (see Dean et al., 2015, 2017, and 2018). In that work, we used these panel data and a structural model of VR service provision and labor market outcomes to examine the impact of VR services on clients with intellectual disabilities (Dean et al., 2015), mental illness (Dean et al., 2017), and physical impairments (Dean et al., 2018). While the results imply substantial heterogeneity across service types and impairments, in general, VR is found to have a positive annualized median rate of return ranging from about 20% for clients with mental illness and intellectual disabilities to 169% for clients with physical impairments. In this paper, we extend the data and model used in the Dean et al. (2015, 2017, and 2018) in several important ways. Most notably, our focus in this paper is on evaluating the impact of the transitioning youth program PERT, not on VR services. To be clear, VR services are accounted for in our model as there are important interactions between PERT and VR. To do this, we introduce a model of PERT participation with participation constraints (see Section 4.1) and extend the Dean et al. (2015, 2017, 2018) model of VR to allow for interactions between PERT, schooling, and VR services (see Section 4.2). The DARS data provide information on youth who applied for services and data from the Virginia Department of Education (VDOE) provide information on the total numbers of disabled youth in each district (see Section 3.3). These VDOE data allow us to estimate the PERT selection probabilities (see Section 4.4). Importantly, the model of PERT service provision is entirely new. Finally, instead of restricting the analysis to VR clients with particular limitations (e.g., mental illness), our focus in this paper is on the population of transitioning youth with disabilities. These youth are an important but understudied subgroup, particularly in light of the WIOA legislation.

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 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. Each year, the program serves over 500 youth with significant disabilities 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 the school system. In practice, the school system recommendation is generally the binding constraint; signing up for VR services from DARS is a minor bureaucratic process that is transparent to the child and his/her family. Each school system is given a 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, provide 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 features of transitioning youth programs run by various state and privately operated organizations across the country.

4 Inter-agency-administered youth transition programs which provide out-of-school vocational diagnoses along with social, daily, and employment skills training, are the norm nationwide (Center for Workers with Disabilities, 2006). The Oregon Youth Transition Program, for example, involves a team of personnel including education, rehabilitation, and transition specialists who provide vocational guidance and other related services to disabled students in their last two years of high school (Benz et al., 2000). Similar models are also being used in the private sector. The most well-known privately operated program, the Marriott Foundation’s Bridges from School to Work Program, since 1990, has served more than 10000 special education transitioning youth from six major metropolitan areas located across the country. Students are referred through partnerships with local schools and must enter the program in the last two years of high school. The intervention consists of a one-semester vocational training program that includes career counseling and support by Bridges staff (Fabian, 2007). Unlike PERT, Bridges also includes job placement and paid work experience.

3 Data

To estimate whether PERT leads to more effective rehabilitation and schooling services, our starting point is the administrative records of DARS for the 10323 individuals who applied for VR services in state fiscal year (SFY) 2000 (July 1, 1999 – June 30, 2000). Since PERT recipients are required to apply for VR services, the DARS administrative data provide information on all PERT clients.

To avoid bias associated with left censoring (e.g., Heckman and Singer, 1984; Dean et al., 2015), 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.

In addition to the DARS administrative records, supplemental data sources supply information on the number of disabled youth, labor market outcomes, and local labor market conditions of each jurisdiction in Virginia. Each of these is discussed...
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></td>
<td></td>
<td>10323</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>9900</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>
</tbody>
</table>

Number Remaining in Sample 3073 0.298

3.1 PERT Participation, Number of Disabled Youth, and Slots by District

For each DARS applicant, we observe an indicator for PERT participation. Of the 3073 individuals in the sample, 394 participated in PERT.

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. There is substantial variation in the number of slots across districts. The mean number of slots by county is 3.76, the standard deviation is 3.99, and the range is from 0 to 34. Moreover, slots are an important and statistically significant determinant of the number of PERT participants. A simple Poisson regression model of the number of PERT participants in a county on the number of slots suggests a highly statistically significant (t-stat =10.8) and meaningful effect of slots; each slot is associated with one additional PERT participant.\(^7\) We also find the slot constraint is a significant predictor of PERT participation in our structural model estimates (see Table 12).

3.2 Department for Aging and Rehabilitative Services Data

For each DARS applicant, we observe detailed VR service information.\(^8\) Following Dean et al. (2002), we aggregate the 76 separate services provided by DARS into six service types: diagnosis & evaluation, training, education, restoration, maintenance, and other.\(^9\) Table 2 displays the fraction of cases receiving a particular purchased service for the subgroups of PERT and non-PERT recipients.\(^10\) Among the 394 PERT recipients, just over half (199) receive DARS purchased services.

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\(^6\) Also, 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 8.1.

\(^7\) In particular, let \( p_i \) be the number of PERT participants in county \( i \) and \( s_i \) be the number of available slots in county \( i \). We assume that

\[
\begin{align*}
  p_i & \sim \text{indPoisson} (\lambda_i), \ i = 1, 2, \ldots, n \\
  \log \lambda_i &= \beta \log (\alpha + s_i).
\end{align*}
\]

We include a constant \( \alpha \) because some counties have no slots. If slots are decisive in determining the number of PERT participants, then \( \beta \) should be close to 1. The estimate is 1.026 with a standard error of 0.095.

\(^8\) Each VR applicant begins by developing, with a counselor, an individualized plan which specifies the array of services to be provided. During this stage of the process, 2% were deemed ineligible, and another 8% withdrew 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.

\(^9\) Variable names are in a different font to avoid confusion. Diagnosis & evaluation is provided at intake in assessing eligibility and developing a 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, 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.

\(^10\) The DARS administrative records provide information on the receipt of purchased services but 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
### Table 2: Proportion Receiving VR Purchased Services by Type

<table>
<thead>
<tr>
<th></th>
<th>Those Receiving PERT Services</th>
<th>Those Not Receiving PERT Services</th>
<th>All VR Recipients</th>
</tr>
</thead>
<tbody>
<tr>
<td># Observations</td>
<td>199</td>
<td>1774</td>
<td>1973</td>
</tr>
<tr>
<td>Diagnosis &amp; Evaluation</td>
<td>0.427</td>
<td>0.624</td>
<td>0.604</td>
</tr>
<tr>
<td>Training</td>
<td>0.432</td>
<td>0.400</td>
<td>0.403</td>
</tr>
<tr>
<td>Education</td>
<td>0.096</td>
<td>0.167</td>
<td>0.160</td>
</tr>
<tr>
<td>Restoration</td>
<td>0.085</td>
<td>0.312</td>
<td>0.289</td>
</tr>
<tr>
<td>Maintenance</td>
<td>0.352</td>
<td>0.277</td>
<td>0.285</td>
</tr>
<tr>
<td>Other Service</td>
<td>0.477</td>
<td>0.351</td>
<td>0.363</td>
</tr>
</tbody>
</table>

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

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. While some clients receive no purchased services, others receive multiple services. For example, 129 clients receive diagnosis & evaluation along with restoration, 116 receive diagnosis & evaluation along with training, and 41 receive diagnosis & evaluation, training and restoration.

In addition to the data on service provision, the DARS administrative records provide a range of socioeconomic, demographic and health status variables. While many are standard for this type of analysis, some unusual variables are included because of the nature of the youth being considered. Special education is a dummy variable equal to 1 if the respondent received a special education certificate; 18.7% of the respondents received such education. Education information is missing for 8.5% of the sample. We include a dummy variable for when education information is 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, an intellectual disability, and substance abuse problems. Mental illness, for example, is a dummy variable equal to one if the individual’s primary or secondary disability at intake was mental illness. 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).

While some variables such as married and # dependents may be endogenous, we follow the literature (e.g., Ettner, Frank, and Kessler, 1997) and include them as meaningful indicators of responsibility and inclusion in society. Likewise, we include a dummy for receipt of government financial assistance since for this population one can work without losing one’s government assistance up to relatively high earnings thresholds. Finally, we include two transportation variables: transportation available and has driver’s license. Raphael and Rice (2002) worry about the endogeneity of these variables and find that controlling for endogeneity with some reasonable instruments has little effect on the estimated effect of transportation on employment but makes its effect on wages disappear.

The sample moments for the explanatory variables for PERT and non-PERT participants are displayed in Table 3. PERT recipients are somewhat younger than non-recipients reflecting the fact that our sample is restricted to DARS clients under the age of 25 while PERT recipients are in high school. Slightly older clients are included in the “control” group to increase the sample size. The incidence of different impairments also differs between PERT and non-PERT recipients with PERT recipients more likely to have an intellectual disability (35% versus 25%) and learning disabled (53% versus 43%) but less likely to be mentally ill (19% versus 29%).

As in Dean et al. (2015, 2017, 2018), 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. Importantly, these instruments are charge to DARS (i.e., similar benefits) Following Dean et al. (2017), 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.

31The existence of visual, hearing/speech, internal disabilities, and other miscellaneous disabilities are available in the data but not common enough or not varying enough to measure precise effects. So, while respondents with these impairments are included in the analysis, these variables are not used in the analysis.

12These variables are transformed as is described in the on-line appendices in Dean et al. (2015, 2017) and Section A2 of Dean et al. (2018).
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. 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. (2015, 2017, 2018).

Finally, using geographic identifiers in the DARS data, we include 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., 2015, 2017, 2018). 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.

### 3.3 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. 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 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 DARS data. The 8 aggregated conditions are intellectual disability, 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

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**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>2679</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>4.992</td>
</tr>
<tr>
<td>Special Education</td>
<td>0.384</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 Gov't Assistance</td>
<td>0.062</td>
<td>0.157</td>
</tr>
</tbody>
</table>

Disability Variables

<table>
<thead>
<tr>
<th>Type</th>
<th>Mean</th>
<th>Std Dev</th>
<th>Mean</th>
<th>Std Dev</th>
</tr>
</thead>
<tbody>
<tr>
<td>Musculoskeletal Disability</td>
<td>0.084</td>
<td>0.277</td>
<td>0.109</td>
<td>0.312</td>
</tr>
<tr>
<td>Mental Illness</td>
<td>0.193</td>
<td>0.395</td>
<td>0.289</td>
<td>0.453</td>
</tr>
<tr>
<td>Intellectual Disability</td>
<td>0.353</td>
<td>0.478</td>
<td>0.248</td>
<td>0.342</td>
</tr>
<tr>
<td>Learning Disability</td>
<td>0.528</td>
<td>0.499</td>
<td>0.430</td>
<td>0.495</td>
</tr>
<tr>
<td>Substance Abuse Problem</td>
<td>0.000</td>
<td>0.000</td>
<td>0.032</td>
<td>0.175</td>
</tr>
</tbody>
</table>

Extant

| Significant Disability | 0.668 | 0.471 | 0.587 | 0.492 |
| Most Significant Disability | 0.272 | 0.445 | 0.255 | 0.436 |

---

13 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).

14 A certain amount of approximation is involved in aggregating the 15 observed conditions in VDOE to 8 conditions and 5 age groups. In some cases, in a particular jurisdiction/(aggregated) condition/age cell, we observe more PERT participants (based on DARS data) than we observe disabled youth satisfying the same conditions. In total, there are 62 out of (105 * 8 * 5 = ) 4200 such occurrences. While these occurrences are not consistent with the model, they occur very infrequently and are spread out across cells and across jurisdictions. Disaggregating the sample by cells, one cell has a discrepancy of 5 youths, 2 have discrepancies of 3 youths, 8 have discrepancies of 2 youths, and 51 have discrepancies of 1 youth. Disaggregating instead by jurisdictions, three jurisdictions have discrepancies of 3 youths, 13 have discrepancies of 2 youths, and 27 have discrepancies of 1 youth. In these cases, we “add” the necessary number of youth for each cell to make the VDOE counts consistent with the DARS counts.
are 14 years old, and few who are 15 years old. The conditions with the highest participation rates are *musculo/skeletal*, *intellectual disability*, *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 statistically significant and substantial variation across jurisdictions for all of these proportions.

### 3.4 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 (conditional on working) increase 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. Similar results are found using a linear difference-in-difference model with the full set of covariates. In this model, PERT is estimated to have a substantial and statistically significant positive association with employment (0.16) and a small, insignificant negative association with conditional earnings (−0.02).\(^{16}\)

\(^{15}\)While it would be valuable to decompose quarterly earnings into wage level and hours, this is not possible in the VEC data.

\(^{16}\)The two-stage least squares estimates using the instruments described in Sections 3.1 and 3.3 are notably larger (0.64 and 1.05, respectively) and statistically significant, suggesting negative selection of PERT participation.
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. In these figures, quarters are measured relative to application date (not 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 cases, still attending school. 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.

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 who 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 around 55%, while those not receiving DARS services (both PERT recipients and non-recipients) have employment rates 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 PERT, DARS service receipt, and employment, there is no such relationship with earnings for employed people. Figure 3 shows that earnings among employed people are lower for the PERT recipients than non-recipients and that DARS service provision does not seem to be associated with earnings.

These results illustrate notable associations and interactions between PERT, VR, and the labor market outcomes over time. PERT is associated with large employment increases especially for those clients also receiving VR services, while, at the same time, there is a negative association between PERT and earnings among employed people. We caution against drawing causal conclusions from this descriptive evidence alone. The observed post-application increase in employment rates for PERT clients may be due to PERT and VR services, but it may also reflect unobserved heterogeneity associated with selection into treatment and labor market outcomes or the observed sociodemographic and health differences between PERT recipients and non-recipients. For example, the observed increase in employment for PERT recipients might partially reflect the fact that PERT recipients are younger, on average, than non-recipients. In addition, there may be important interactions between PERT, VR services, and schooling that are not accounted for in this descriptive analysis. These issues will be addressed using the structural model developed in Section 4.

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 more 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.17

After describing the PERT participation model, we then modify the Dean et al. (2015, 2017) 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 are excluded from the labor market outcome equations. 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 Dean et al. (2015, 2017, 2018), 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, ..., 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

\[ p_i^* = X_i^p \beta_p + u_i^p + \nu_i^p, \]

where \( X_i^p \) is a vector of observed exogenous explanatory variables, \( \beta_p \) is a vector of coefficients, and \( \{u_i^p, \nu_i^p\} \) are unobserved random variables whose structure is specified below.

---

17In 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 (Manski, 1977). Dean et al. (2017) and Hamilton et al. (2018) use a similar methodology to address the potential endogeneity of “walking through the front door” of the service provider.
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 16.7\% of all jurisdictions in Virginia, used more slots than they were assigned.\(^{18}\)

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

\[
p_i > P_i, \quad \forall i' \neq i, i' \in J(j),
\]

where

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

(2)

indicates if the slot constraint is violated. Thus, a jurisdiction can use more slots than allocated but with a more restrictive criterion for participation \( (P^* > 0) \).\(^{19}\) 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. (2015, 2017). 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 (Heckman, Lalonde, and Smith, 1999; Meyer, 1995).

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 \( Y_{it}^y \) be the latent value for individual \( i \) of participating in service \( k \), \( k = 1, 2, ..., 6 \), and assume that

\[
y_{ik} = X_{it}^y \beta_k^y + \delta_k^y p_i + u_{ik} + \varepsilon_{ik}^y
\]

(3)

where \( X_{it}^y \) is a vector of exogenous explanatory variables, \( p_i \) is the binary indicator for PERT participation defined in Section (4.1), \( \{ \beta_k^y, \delta_k^y \} \) are coefficients, and \( \{ u_{ik}, \varepsilon_{ik}^y \} \) 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 \( z_{it}^y \) be the latent value for \( i \) of working in quarter \( t \), and let \( z_{it} = 1 (z_{it}^y > 0) \) be the observed indicator for whether \( i \) is employed in quarter \( t \). Assume that

\[
z_{it}^y = X_{it}^y \gamma^z + \sum_{m=1}^{4} d_{itm} \sum_{k=1}^{6} [\alpha_{ikm} + p_i \alpha_{ikm}^z] y_{ik} + \left( \sum_{m=3}^{4} d_{itm} \right) p_i [\delta^z + \varphi^z s_i] + u_{it}^z + v_{it}^z
\]

(4)

where \( X_{it}^z \) is a vector of (possibly) time-varying, exogenous explanatory variables, \( d_{itm} \) is a dummy variable equal to one if the amount of time between the quarter of service receipt and \( t \) is between \( \tau_{ij} \) and \( \tau_{i+1} \), \( s_i \) is the amount of time left in school after PERT participation, and \( \{ u_{it}^z, v_{it}^z \} \) 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. Controlling for pre-service employment differences between those who will and will not receive VR services partially addresses the endogenous selection problem that arises if services are systematically assigned to those with higher or lower latent values of employment. See Section (4.5).

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

\(^{18}\)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.

\(^{19}\)This model of PERT participation is equivalent to a model with each jurisdiction maximizing the value of their PERT slots. PERT is assigned to those receiving the highest utility gains. When a particular jurisdiction has more students who would benefit from PERT participation, they can enter into a statewide market with transactions costs to obtain extra slots from other jurisdictions.

\(^{20}\)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 (8.1). Note that, while PERT interacts with \( s_i \) to affect outcomes, PERT does not influence the amount of time left in school.
where variables are defined analogously to equation (4).\textsuperscript{21}

Notice that PERT participation enters into the model in a number of ways:

1. PERT affects the choice of services provided through $\delta^y_j$ in equation (3) and the efficiency of DARS service through $\alpha^w_{1kt}$ in equation (4) and $\alpha^w_{1kt}$ 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 and/or intensity (either via expenditures or duration).

2. PERT interacts with $s_i$ to affect labor market outcomes through $\varphi^z$ in equation (4) and $\varphi^w$ in equation (5). PERT provides the school system with information about the needs of the youth. The idea here is that, the more time a student has in school, as measured by $s_i$, the more time there is to act on that information.\textsuperscript{22}

3. PERT may directly improve labor market outcomes through $\delta^z$ in equation (4) and $\delta^w$ in equation (5). The idea here is that PERT might focus a participant 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\textsuperscript{23}

\begin{equation}
\begin{aligned}
    u^y_{i} & = \lambda^y_{1} e_{i1} + \lambda^y_{2} e_{i2}, \\
    u^y_{ik} & = \lambda^y_{k1} e_{i1} + \lambda^y_{k2} e_{i2}, \\
    u^z_{it} & = \lambda^z_{1} e_{i1} + \lambda^z_{2} e_{i2} + \eta_{it}, \\
    u^w_{it} & = \lambda^w_{1} e_{i1} + \lambda^w_{2} e_{i2} + \eta^w_{it}, \\
    \eta_{it} & = \rho_1 \eta_{it-1} + \zeta^z_{it}, \\
    \eta^w_{it} & = \rho_1 \eta^w_{it-1} + \zeta^w_{it}, \\
\end{aligned}
\end{equation}

\[
\left( \begin{array}{c}
    \zeta^z_{it} \\
    \zeta^w_{it} \\
    \end{array} \right) \sim iidN \left[ 0, \sigma^2 z \begin{pmatrix}
    1 & \rho\zeta \\
    \rho\zeta & 1
\end{pmatrix} \right] ,
\]

\[
\left( \begin{array}{c}
    e_{i1} \\
    e_{i2} \\
    \end{array} \right) \sim iidN \left[ 0, I \right] ,
\]

\[
\begin{aligned}
    \varepsilon^y_{ik} & \sim iidLogistic, \\
    v^y_{i} & \sim iidN \left[ 0, 1 \right] , \\
    v^z_{it} & \sim iidN \left[ 0, 1 \right] , \text{ and} \\
    v^w_{it} & \sim iidN \left[ 0, \sigma^2 w \right] .
\end{aligned}
\]

We include $(e_{i1}, e_{i2})$ to allow for two common factors affecting all dependent variables with factor loadings $(\lambda^y_{1}, \lambda^y_{2}, \lambda^z_{1}, \lambda^z_{2})$.\textsuperscript{24}

We also allow for serial correlation and contemporaneous correlation in the labor market errors $(\eta^z_{it}, \eta^w_{it})$.\textsuperscript{24}

\textsuperscript{21}Recall that we observe measures of purchased and non-purchased VR 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 $\beta^y_j$ coefficients in equation (3) are multiplied by a service-choice “in-house service/similar benefits” parameter $\mu_1$ (to be estimated), and the $(\alpha^z_{1kt}, \alpha^w_{1kt})$ 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).

\textsuperscript{22}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.

\textsuperscript{23}See Carniero, Hansen, and Heckman (2003) for an error structure with some similarities.

\textsuperscript{24}The covariance matrix implied by this error structure is presented in Appendix 8.2.
4.4 Likelihood Function

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

\[
\begin{align*}
\theta_p &= (\beta^p, \lambda^p_1, \lambda^p_2, \bar{p}^p), \\
\theta_y &= (\beta^y_j, \delta^y_j, \lambda^y_j, \sigma^y_{\xi}, \sigma^y_{\eta})_{j=1}^6, \\
\theta_z &= \left( \gamma^z \left[ (\alpha^z_{0k}, \alpha^z_{1k})_{l=1}^4 \right] \right)_{k=1}^6, \delta^z, \varphi^z, \lambda^z_1, \lambda^z_2, \rho^z_0, \sigma^z_{\zeta}, \rho^z_\eta, \\
\theta_w &= \left( \gamma^w \left[ (\alpha^w_{0k}, \alpha^w_{1k})_{l=1}^4 \right] \right)_{k=1}^6, \delta^w, \varphi^w, \lambda^w_1, \lambda^w_2, \rho^w_0, \sigma^w_{\zeta}. 
\end{align*}
\]

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 \( u_i = (u^p_{it}, [u^y_{ik}]_{k=1}^6, [u^w_{it}]_{l=1}^T) \) and \( \bar{u}_j = \{u_i | i \in J(j)\} \)

to be the set of PERT (correlated) errors for disabled youth from jurisdiction \( j \). Then the joint likelihood contribution, conditional on \( \bar{u}_j \), for youth in jurisdiction \( j \) who are in the DARS data is

\[
L_j(\bar{u}_j) = \int_{V_j} \left[ L^y(u^y_{it}) \prod_{t=1}^T L^z(u^z_{it}, u^w_{it}) \right] \prod_{i \in J(j) \cap i \in D} d\Phi(v^p_i)
\]

where

\[
V_j = \{ v^p_i > -X^p_i \beta^p - u^p_i + \xi_{j0} \} \cup \{ v^p_i < -X^p_i \beta^p - u^p_i + \xi_{j0} \} \cup \{ v^p_i \}
\]

\[
\xi_{j0} = \max_{v_{j(i)}(i)} \left[ v_{j(i)}(i) \bar{p}^p + \rho^p_{j(i)} \right]_{j=1}^6,
\]

\[
\eta_{j0} = \arg \min_{i \in J(i)} \left( \rho_{j0} + \bar{p}^p_{j(i)} \right),
\]

\[
\xi_{j1} = \max_{v_{j(i)}(i)} \left[ v_{j(i)}(i) \bar{p}^p + \rho^p_{j(i)} \right],
\]

\[
\eta_{j1} = \arg \max_{i \in J(i)} \left( \rho_{j1} + \bar{p}^p_{j(i)} \right),
\]

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

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

\[
L^w(u^w_{it}) = 1 - \Phi \left( \bar{z}_{it}(u^w_{it}) \right),
\]

\[
\bar{z}_{it}(u^w_{it}) = X^w_{it} \gamma^w + \sum_{l=1}^4 d_{it} \sum_{k=1}^6 \alpha^w_{0kl} p_l \alpha^w_{1kl} y_{ij} \sum_{l=3}^4 d_{it} \right) p_l \delta^w + \varphi^w y_{ij} + u^z_{it},
\]

\[
L^w(u^w_{it}) = \frac{1}{\sigma_w} \phi \left( \frac{\bar{w}_{it} - \bar{w}_{it}(u^w_{it})}{\sigma_w} \right) \Phi \left( \bar{z}_{it}(u^w_{it}) \right),
\]

\[
\bar{w}_{it}(u^w_{it}) = X^w_{it} \gamma^w + \sum_{l=1}^4 d_{it} \sum_{k=1}^6 \alpha^w_{0kl} p_l \alpha^w_{1kl} y_{ij} \sum_{l=3}^4 d_{it} \right) p_l \delta^w + \varphi^w y_{ij} + u^w_{it}. 
\]
For each observation $i$, one has to condition on $\overline{u}_j$ because $\overline{u}_j$ affects $v_j$ and because of competition induced by the slot constraint. For (a), for each jurisdiction $j$, decompose the VDOE sample into mutually exclusive and mutually inclusive cells, indexed by $c$. Cells are constructed so that all of the youth in a cell have the same set of explanatory variables and no youth in a different cell have the same set of explanatory variables. Define $c(i)$ as the cell for person $i$. All of the youth in a particular cell have the same likelihood contribution since all we observe about each is that they chose not to participate in DARS. The likelihood contribution for any such individual is

$$
Pr \left( i \notin P(j) \mid c(i) = c, i \notin D, \overline{u}_j, \xi_{j0} \right)
$$

$$
= \int \left[ 1 - \Phi \left( X_i^p \beta^p + u_i^p - \xi_{j0} \right) \right] d\Phi \left( \frac{u_i^p}{1 + \sum_j \lambda_{pf}^2} \right).
$$

Define $n_{jc}$ as the number of disabled youth in jurisdiction $j$ and with characteristics consistent with cell $c$ and $n_{jc}^D$ 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

$$
\left[ Pr \left( i \notin P(j) \mid c(i) = c, i \notin D, \overline{u}_j, \xi_{j0} \right) \right]^{n_{jc} - n_{jc}^D}.
$$

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

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

where $G(\cdot \mid \Omega)$ 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 (e.g., Geweke, 1991): For each $j$,

1. Simulate $\overline{u}_j$;
2. Conditional on the simulated $\overline{u}_j$, compute $\Phi(\left( X_i^p \beta^p + u_i^p - v_j^* \right) \forall i \in P(j) : p_i = 1$;
3. Simulate $v_i^p$ \mid $p_i = 1 \forall i \in P(j) : p_i = 1$;
4. Conditional on simulated $\overline{u}_j$ and $v_i^p \mid p_i = 1 \forall i \in P(j) : p_i = 1$, compute $\xi_{j0}$;
5. Conditional on simulated $\overline{u}_j$ and $\xi_{j0}$; compute $1 - \Phi(\left( X_i^p \beta^p + u_i^p - \xi_{j0} \right)$ for those $i \in D \cap P(j) : p_i = 0$ and $\left[ Pr \left( i \not\in P(j) \mid c(i) = c, i \not\in D, \xi_{j0} \right) \right]^{n_{jc} - n_{jc}^D}$ \forall$c$;
6. Conditional on simulated $\overline{u}_j$, 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 $\mathbb{R}^2$ 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 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

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-service labor market differences between those who do and do not receive VR 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 PERT, VR service, and labor market equations. This error structure (see equation (6)) formalizes the endogenous relationship between PERT, VR, and the labor market outcomes.

Finally, we use instrumental variables to address the resulting endogenous selection problem. In particular, we assume that several instrumental variables impact PERT and VR service receipt but are excluded from the latent labor market outcome equations. We instrument for the provision of PERT participation using the school district “slot constraints” described in Section 3.1 and variation in the district subpopulations by age and type of disability described in Section 3.3 (see Figure 1). As illustrated in Sections 3.1 and 3.3 and Table 12, these instrumental variables are strongly correlated with PERT receipt. Moreover, after accounting for the local labor market conditions, these variables are plausibly independent of the structural errors. The PERT program establishes the district level constraints based largely on the historical demand for the program and characteristics of each district including, most notably, the size of the relevant population. The constraints are not based on local labor market conditions and vary little over time. Likewise, after accounting for the local labor market conditions, the size and demographics of the population of disabled youth are arguably unrelated to the employment and earning errors in Equations (4) and (5). One threat to the validity of the instruments may arise if the number of reported youth with disabilities is affected by unobserved factors that are correlated with the labor market outcome errors in our model. For example, there is some evidence that local school districts respond to financial and other incentives when determining which and how many students have disabilities (see Cullen, 2003) and that SSI benefits may induce parents to have their children diagnosed with a disability (see Kubik, 1999). However, given that we control for local labor market conditions, this variation

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Figure 4: Decomposition of Error Space

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25 There is also 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 \( \beta^m_j \) 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 \( \sigma^2_C \) and \( \rho_C \) are identified by corresponding second sample moments.

26 The results in Cullen (2003) are highly specific to Texas and may not be relevant to Virginia. In Virginia, 75% of special education resources are locally financed, and only 17% are financed at the state level (see Parrish and Chambers, 1996). In Texas, only 30% of funding is at the local level, and 56% comes from the state. The fact that, in Virginia, so much is financed locally means that it is very difficult for a small change in state funding to have a big impact on the net revenue associated with a marginal disabled student.
Following Doyle (2007), Maestas et al. (2013), and Dean et al. (2015, 2017, 2018), we instrument for VR service provisions using the propensity of an individual’s VR counselor and field office to assign clients to each service. 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., 2015, 2017, 2018). Still, as noted in Dean et al. (2017), 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. In particular, Dean et al. (2017) highlight two potential threats to the validity of these instruments. First, variation in the availability of jobs where certain services are productive might jointly affect labor market outcomes and the average behavior of counselors. Controls for local labor market conditions should, in part, address this concern. Second, unobserved variation in the ability of counselors to match clients with jobs may affect both his/her decisions about what types service to offer clients and later success in the labor market. Following Dean et al. (2017), we assume that this type of confounding effect is not important.

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 the latent value of employment and log quarterly 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: \( z_{1kt} = z_{1t} \) and \( w_{1kt} = w_{1t} \).

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 period two or more quarters prior to the initial service (see the first column of estimates) are negative and statistically significant for the employment and earnings

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27Another potential threat is related to the quality of the school district. For example, suppose wealthy school districts are more likely to label students with disabilities and they also have better schools. If this were the case, then the variable measuring the benefit of time in school could be measured with error because we do not allow for any variation across school districts.
Table 8: Program Participation Effects on Employment

<table>
<thead>
<tr>
<th>Variable</th>
<th>Prior to Program Participation</th>
<th>Quarter After Program Participation</th>
<th>First 2 Years After Program Participation</th>
<th>More than 2 Years After Program Participation</th>
<th>Short-Run Effect</th>
<th>Long-Run Effect</th>
</tr>
</thead>
<tbody>
<tr>
<td>PERT Interaction</td>
<td>-0.205 **</td>
<td>0.113 **</td>
<td>0.066 **</td>
<td>0.233 **</td>
<td>-0.271 **</td>
<td>0.438 **</td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(0.063)</td>
<td>(0.011)</td>
<td>(0.008)</td>
<td>(0.013)</td>
<td>(0.022)</td>
</tr>
<tr>
<td>Diagnosis &amp; Evaluation</td>
<td>-0.270 **</td>
<td>-0.140</td>
<td>-0.072 **</td>
<td>-0.172 **</td>
<td>-0.198 **</td>
<td>0.988 **</td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(0.060)</td>
<td>(0.012)</td>
<td>(0.006)</td>
<td>(0.016)</td>
<td>(0.009)</td>
</tr>
<tr>
<td>Training</td>
<td>-0.397 **</td>
<td>-0.599 **</td>
<td>-0.110 **</td>
<td>-0.264 **</td>
<td>-0.387 **</td>
<td>0.133 **</td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td>(0.079)</td>
<td>(0.015)</td>
<td>(0.008)</td>
<td>(0.017)</td>
<td>(0.012)</td>
</tr>
<tr>
<td>Education</td>
<td>-0.049 **</td>
<td>0.110 *</td>
<td>0.083 **</td>
<td>0.237 **</td>
<td>0.132 **</td>
<td>0.286 **</td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
<td>(0.096)</td>
<td>(0.019)</td>
<td>(0.010)</td>
<td>(0.022)</td>
<td>(0.016)</td>
</tr>
<tr>
<td>Restoration</td>
<td>0.066 **</td>
<td>0.392 **</td>
<td>0.040 **</td>
<td>-0.125 **</td>
<td>-0.026</td>
<td>-0.191 **</td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td>(0.077)</td>
<td>(0.015)</td>
<td>(0.007)</td>
<td>(0.018)</td>
<td>(0.012)</td>
</tr>
<tr>
<td>Maintenance</td>
<td>0.133 **</td>
<td>-0.007</td>
<td>-0.021</td>
<td>0.004</td>
<td>-0.154 **</td>
<td>-0.129 **</td>
</tr>
<tr>
<td></td>
<td>(0.032)</td>
<td>(0.083)</td>
<td>(0.017)</td>
<td>(0.008)</td>
<td>(0.019)</td>
<td>(0.009)</td>
</tr>
<tr>
<td>Other Services</td>
<td>-0.265 **</td>
<td>-0.172 **</td>
<td>0.047 **</td>
<td>0.207 **</td>
<td>0.312 **</td>
<td>0.472 **</td>
</tr>
<tr>
<td></td>
<td>(0.016)</td>
<td>(0.072)</td>
<td>(0.014)</td>
<td>(0.007)</td>
<td>(0.016)</td>
<td>(0.012)</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.
3. Short-run effects are the third column minus the first column, and long-run effects are the fourth column minus the first column.

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. As seen in Table 8 and Figure 5, 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 short-run indirect effect of PERT on the latent value of employment is 0.271, and the long-run effect is 0.438. Likewise, Table 9 shows that the short-run indirect effect of PERT on log quarterly earnings is 0.132 and the long-run effect 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. The estimates associated with employment are the effect of the relevant variable on the latent value of working, which we will call the employment propensity. 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 propensities (−0.397) and lower log quarterly earnings (−0.411). For education, the estimates imply selection is negatively associated with pre-service employment propensities (−0.049) and log quarterly earnings (−0.270). 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 pre-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 column. 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 propensities 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 for short-run restoration and maintenance lead to higher earnings conditional on employment.28

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, imply fairly sizable positive short-treatment employment associations.

28 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.
### Table 9: Program Participation Effects on Log Quarterly Earnings

<table>
<thead>
<tr>
<th>Variable</th>
<th>Prior to Program Participation</th>
<th>Quarter Prior to Program Participation</th>
<th>First 2 Years After Program Participation</th>
<th>More than 2 Years After Program Participation</th>
<th>Short-Run Effect</th>
<th>Long-Run Effect</th>
</tr>
</thead>
<tbody>
<tr>
<td>PERT Interaction</td>
<td>-0.068 **</td>
<td>0.043</td>
<td>0.064 **</td>
<td>0.126 **</td>
<td>0.132 **</td>
<td>0.194 **</td>
</tr>
<tr>
<td></td>
<td>(0.016)</td>
<td>(0.108)</td>
<td>(0.021)</td>
<td>(0.008)</td>
<td>(0.026)</td>
<td>(0.016)</td>
</tr>
<tr>
<td>Diagnosis &amp; Evaluation</td>
<td>-0.515 **</td>
<td>-0.596 **</td>
<td>-0.338 **</td>
<td>-0.044 **</td>
<td>0.177 **</td>
<td>0.471 **</td>
</tr>
<tr>
<td></td>
<td>(0.034)</td>
<td>(0.076)</td>
<td>(0.016)</td>
<td>(0.007)</td>
<td>(0.022)</td>
<td>(0.015)</td>
</tr>
<tr>
<td>Training</td>
<td>-0.411 **</td>
<td>-0.543 **</td>
<td>-0.196 **</td>
<td>-0.260 **</td>
<td>0.215 **</td>
<td>0.151 **</td>
</tr>
<tr>
<td></td>
<td>(0.018)</td>
<td>(0.105)</td>
<td>(0.020)</td>
<td>(0.009)</td>
<td>(0.029)</td>
<td>(0.020)</td>
</tr>
<tr>
<td>Education</td>
<td>-0.270 **</td>
<td>-0.019</td>
<td>-0.165 **</td>
<td>0.353 **</td>
<td>0.105 **</td>
<td>0.623 **</td>
</tr>
<tr>
<td></td>
<td>(0.022)</td>
<td>(0.125)</td>
<td>(0.025)</td>
<td>(0.010)</td>
<td>(0.036)</td>
<td>(0.023)</td>
</tr>
<tr>
<td>Restoration</td>
<td>-0.097 **</td>
<td>-0.012</td>
<td>-0.157 **</td>
<td>0.025 **</td>
<td>-0.060</td>
<td>0.122 **</td>
</tr>
<tr>
<td></td>
<td>(0.017)</td>
<td>(0.087)</td>
<td>(0.020)</td>
<td>(0.008)</td>
<td>(0.027)</td>
<td>(0.019)</td>
</tr>
<tr>
<td>Maintenance</td>
<td>0.038 **</td>
<td>0.104</td>
<td>0.010</td>
<td>0.061 **</td>
<td>-0.028</td>
<td>0.023</td>
</tr>
<tr>
<td></td>
<td>(0.019)</td>
<td>(0.120)</td>
<td>(0.025)</td>
<td>(0.010)</td>
<td>(0.033)</td>
<td>(0.021)</td>
</tr>
<tr>
<td>Other Services</td>
<td>-0.358 **</td>
<td>-0.330 **</td>
<td>0.020</td>
<td>0.280 **</td>
<td>0.378 **</td>
<td>0.638 **</td>
</tr>
<tr>
<td></td>
<td>(0.016)</td>
<td>(0.089)</td>
<td>(0.025)</td>
<td>(0.008)</td>
<td>(0.027)</td>
<td>(0.027)</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.
3. Short-run effects are the third column minus the first column, and long-run effects are the fourth column minus the first column.

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**Figure 5: Program Participation Effects on Employment Propensity**
tions, 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, indicate positive employment and earnings effects.29

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 estimated average employment probability from 45.1% (see Table 5) to 57.3%, or 12.2 percentage points.30 The average proportionate increase in conditional quarterly earnings is 31.3% (see Table 7), implying a composite increase in unconditional quarterly earnings of \( \left( \frac{0.573}{0.451} \right) \times 1.313 - 1 = 66.7\% \). 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, a random assignment experimental demonstration 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.

Although PERT is designed as a screening program to improve the efficacy of VR and schooling services, these results suggest it also has an important direct effect on labor market outcomes. Perhaps the PERT residential experience provides participants a better understanding how to be independent, or perhaps PERT nudges participants or their families to start focusing on the transition into adulthood. In part, these results may also be biased due to omitted interactions (see Section (5.4)) between PERT, VR services, disability types, and errors in measuring schooling and VR services. For example, the variable on the length of time left in school, \( s_i \), is not directly observed but estimated (see Appendix (8.1)). Likewise, Dean et al. (2015, 2017, 2018) find important interactions between the efficacy of VR and the disability type that, because of the limited sample size, are not included in our model. To address these potential missing and mismeasured variables, one would need to estimate a more elaborate model with significantly larger sample sizes and more detailed data on schooling and VR services. Thus, given our model and data, the estimated direct effects of PERT should be thought of as a combined

29 We allow the impact of non-purchased services to differ from purchased services (see the discussion of \( \mu_1 \) and \( \mu_2 \) in footnote 21). The estimated effect of non-purchased services on labor market outcome effects is estimated to be \( \hat{\mu}_2 = 0.189 \) 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 \( \hat{\mu}_1 = 0.020 \) with a large standard error. The small size of this estimate implies that non-purchased services appear to be almost uniformly randomly provided.

30 A probit effect of 0.306 from Table 7 translates into an increase in average employment from 0.451 to 0.573 \( [\Phi (\Phi^{-1} (0.451) + 0.306) = 0.573] \).
Table 10: Counselor and Office Effects

<table>
<thead>
<tr>
<th>Effect</th>
<th>Estimate</th>
<th>Std Err</th>
</tr>
</thead>
<tbody>
<tr>
<td>Counselor Effect</td>
<td>0.522 **</td>
<td>0.073</td>
</tr>
<tr>
<td>Office Effect</td>
<td>0.811 **</td>
<td>0.048</td>
</tr>
<tr>
<td>Diagnosis &amp; Evaluation</td>
<td>-0.313</td>
<td>0.296</td>
</tr>
<tr>
<td>Training</td>
<td>0.783 **</td>
<td>0.350</td>
</tr>
<tr>
<td>Education</td>
<td>-0.572</td>
<td>0.397</td>
</tr>
<tr>
<td>Repair</td>
<td>-1.524 **</td>
<td>0.369</td>
</tr>
<tr>
<td>Maintenance</td>
<td>-0.489</td>
<td>0.353</td>
</tr>
<tr>
<td>Other Services</td>
<td>0.200</td>
<td>0.319</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. Other than those reported, missing counselor and field office effects parameters were excluded because of multicollinearity problems.

measure that includes both the direct effect as well as some of the missing (or mismeasured) indirect 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 30.3 percentage points, conditional quarterly earnings by another 13.2%, and unconditional quarterly earnings by 59.6%. Finally, in the short-run two year post-participation period, the DARS interaction effect is estimated to increase the employment probability by another 4.8%, conditional quarterly earnings by another 13.2%, and unconditional quarterly earnings by another 5.3%. The estimated long-run effects are somewhat larger, with the employment probabilities estimated to increase by another 6.9%, conditional quarterly earnings by another 19.4%, and unconditional quarterly earnings by another 23.7%.

In total, when accounting for all three of the mechanisms, PERT is estimated to increase estimated average quarterly earnings by just over 169% in the first two years and 214% in the longer run. As noted above, however, these large estimated proportional effects imply modest level changes in average earnings.

5.2 Estimates of the Impact of Covariates

Table 10 presents estimated effects of the counselor and office instruments on VR service receipt. 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. 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_i in equation (4) and w_{it} in equation (5)). Almost all of the estimates are statistically significant. Many of the estimates are as expected 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 earnings (−0.018), 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 (Mincer, 1975). Likewise, the positive estimates for significant disabilities (relative to not significant) are puzzling. While the local labor market conditions behave in the expected way, metro labor market condition estimates are counterintuitive (see, for similar mixed results, Dean et al., 2015, 2017).

Estimates of the impact of the other covariates on service receipt are available from the authors. For the most part, the observed characteristics do not have large or statistically significant effects. Interestingly, PERT participation is 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 effects.

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>Employment Std Err</th>
<th>Log Quarterly Earnings Estimate</th>
<th>Log Quarterly Earnings Std Err</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-5.532 ** 0.027</td>
<td></td>
<td>2.165 ** 0.028</td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>0.124 ** 0.005</td>
<td></td>
<td>0.289 ** 0.005</td>
<td></td>
</tr>
<tr>
<td>White</td>
<td>0.089 ** 0.005</td>
<td></td>
<td>0.198 ** 0.005</td>
<td></td>
</tr>
<tr>
<td>Education</td>
<td>-0.058 ** 0.001</td>
<td></td>
<td>-0.016 ** 0.002</td>
<td></td>
</tr>
<tr>
<td>Special Education</td>
<td>-0.619 ** 0.034</td>
<td></td>
<td>-0.165 ** 0.018</td>
<td></td>
</tr>
<tr>
<td>Education Missing</td>
<td>-0.632 ** 0.015</td>
<td></td>
<td>-0.149 ** 0.020</td>
<td></td>
</tr>
<tr>
<td>Age/100</td>
<td>0.777 ** 0.009</td>
<td></td>
<td>0.580 ** 0.003</td>
<td></td>
</tr>
<tr>
<td>Married</td>
<td>-0.698 ** 0.016</td>
<td></td>
<td>-0.383 ** 0.015</td>
<td></td>
</tr>
<tr>
<td># Dependents</td>
<td>-0.139 ** 0.005</td>
<td></td>
<td>-0.095 ** 0.005</td>
<td></td>
</tr>
<tr>
<td>Transportation Available</td>
<td>0.174 ** 0.005</td>
<td></td>
<td>0.181 ** 0.006</td>
<td></td>
</tr>
<tr>
<td>Has Driving License</td>
<td>0.049 ** 0.0064</td>
<td></td>
<td>0.152 ** 0.006</td>
<td></td>
</tr>
<tr>
<td>Receives Govt Assistance</td>
<td>-0.827 ** 0.012</td>
<td></td>
<td>-0.812 ** 0.013</td>
<td></td>
</tr>
<tr>
<td>Musculoskeletal Disability</td>
<td>-0.407 ** 0.009</td>
<td></td>
<td>-0.241 ** 0.009</td>
<td></td>
</tr>
<tr>
<td>Mental Illness</td>
<td>-0.028 ** 0.006</td>
<td></td>
<td>-0.174 ** 0.006</td>
<td></td>
</tr>
<tr>
<td>Intellectual Disability</td>
<td>0.090 ** 0.007</td>
<td></td>
<td>0.021 ** 0.007</td>
<td></td>
</tr>
<tr>
<td>Learning Disability</td>
<td>0.405 ** 0.0064</td>
<td></td>
<td>0.375 ** 0.006</td>
<td></td>
</tr>
<tr>
<td>Substance Abuse</td>
<td>-0.452 ** 0.013</td>
<td></td>
<td>0.123 ** 0.007</td>
<td></td>
</tr>
<tr>
<td>Significant Disability</td>
<td>0.074 ** 0.007</td>
<td></td>
<td>0.123 ** 0.007</td>
<td></td>
</tr>
<tr>
<td>Most Significant Disability</td>
<td>-0.074 ** 0.008</td>
<td></td>
<td>-0.018 ** 0.009</td>
<td></td>
</tr>
<tr>
<td>Local Employment Rate</td>
<td>0.822 ** 0.162</td>
<td></td>
<td>1.084 ** 0.225</td>
<td></td>
</tr>
<tr>
<td>Metro Employment Rate</td>
<td>-0.489 ** 0.162</td>
<td></td>
<td>-0.745 ** 0.226</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.

Finally, Table 12 provides estimates associated with participation in the PERT program. The estimates imply a priority ordering among conditions where students with musculo/skeletal conditions (1.001) and intellectual disabilities (0.573) receive the highest priority, and students with learning disabilities (−0.172), hearing/visual/speech disabilities (−0.232), and internal impairments (−0.274) receive 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.33 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.

To gain a better sense of how the covariance structure works, consider the possibility that some of the factor loadings associated with service receipt or PERT participation were larger. For example, suppose that the true value of the factor loading on PERT for the first factor had been −2.0 instead of −0.003. This would imply larger, positive correlations of the random components of PERT participation with both employment and conditional earnings.34 In this case, a larger part of positive correlations between PERT participation and labor market outcomes would be attributed to the correlation of the random components, and the estimated PERT effects would be smaller. Alternatively, if the true value of the factor loading was ignored in the model (or, equivalently, set to 0), then the parameter estimates associated with the effect of PERT participation on labor market outcomes would be biased upwards. By including the PERT factor loadings and participation instruments, we are able to separately identify the factor loadings and the true PERT effects. The same reasoning applies to DARS service receipt. While none of the estimated factor loadings are large (see Table 13), it is appropriate to include

---

33For 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 (2015, 2017) 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.

34For example, the correlation of PERT participation with employment would be (−2.0) · (−0.184)/√(1 + 2.0^2) · (1 + 1.84^2) = 0.162 instead of (−0.003) · (−0.184)/√(1 + 0.003^2) · (1 + 1.84^2) = .0005.
Table 12: PERT Participation Estimates

<table>
<thead>
<tr>
<th>Variable</th>
<th>Estimate</th>
<th>Std Err</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conditions</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intellectual Disability</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</td>
<td></td>
<td></td>
</tr>
<tr>
<td>14 Years Old</td>
<td>-3.711 **</td>
<td>0.195</td>
</tr>
<tr>
<td>15 Years Old</td>
<td>-2.447 **</td>
<td>0.023</td>
</tr>
<tr>
<td>16 Years Old</td>
<td>-2.336 **</td>
<td>0.016</td>
</tr>
<tr>
<td>17 Years Old</td>
<td>-2.355 **</td>
<td>0.038</td>
</tr>
<tr>
<td>18 Years Old</td>
<td>-2.376 **</td>
<td>0.058</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.

The estimates of the other elements of the error structure are reported in Table 14. The serial correlation estimate $\rho_\eta$ is very large due to the high degree of inertia associated with labor market spells. The correlation between the two different labor market outcome errors $\rho_\zeta$ suggests a high degree of correlation between employment and earnings. The estimate of the log earnings error $\sigma_w$ is quite large, implying a 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 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 and log quarterly earnings equations are missing significant interactions of demographic characteristics and interactions of service types. The results are mixed. On one hand, the LM tests suggest that, for the most part, service interactions are not statistically significant. On the other hand, we find evidence of a number of missing interactions. We find evidence for interactions of gender and race on employment and especially on conditional log quarterly earnings (though there is no obvious pattern to the interactions) and for inclusion of a quadratic age term (with a negative coefficient) for both labor market outcomes. Also, we find that education, special education, age, # dependents, and some specific disabilities all have statistically significant interactions with being employed after service receipt relative to being employed prior to service. In part, missing interaction terms may explain why the model is overestimating the variation in employment probabilities, especially for quarters after service.

35 The test statistic for training, for example, is $\chi^2_{22} = 106.0$. The test statistics are $\chi^2_{37} = 749.5$ 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.

36 There also might be meaningful interactions between PERT and the different disability types and severity. However, given the limited number of observations that are informative about each of these interactions, LM tests for the statistical significance of these interactions are not informative.
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>$\rho$</td>
<td>0.986 **</td>
<td>0.000</td>
</tr>
<tr>
<td>$\sigma$</td>
<td>0.186 **</td>
<td>0.001</td>
</tr>
<tr>
<td>$\rho$</td>
<td>0.764 **</td>
<td>0.002</td>
</tr>
<tr>
<td>$\omega$</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 insure that $-1 < \rho < 1$.
   Standard deviations are estimated using the transformation, $\sigma = \exp(\varsigma)$ where $\varsigma$ is estimated to insure that $\sigma > 0$. Standard errors for both are derived using the delta method.

Figure 7: Predicted and Sample DARS Service Participation Probabilities with Cell Aggregation
Figure 8: Predicted and Sample Employment Probabilities Before and After DARS Service

receipt (see Figure 8); the effectiveness of services varies with person-specific characteristics that are not incorporated in the model. Likewise, as noted in Section 5.1, the omitted interaction variables may partially explain the relatively large estimated direct effects of PERT (see Table 7). In general, however, there are no simple conclusions about how these omitted variables might bias our estimates of the effects of PERT.

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, $y_i$. 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, $\delta^z = 0.306$, and $\delta^w = 0.313$);

2. DARS service interaction effects \( \{\alpha^z_{jk}\}_{jk} \) in equation (4) and \( \{\alpha^w_{jk}\}_{jk} \) 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, $\varphi^z = 0.242$, and $\varphi^w = 0.166$).

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. This is equivalent to earning an extra $987.83 per quarter.

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, 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

---

One might simulate vocational rehabilitation service choices. The most important reason to do so is that the errors in the model are correlated; thus, conditioning on the realized set of services affects the distribution of labor market errors. In general, this is a valid concern. However, in this particular case, conditioning on realized service choices does not cause a problem because of the very small estimated correlations between service choice errors and labor market errors reported in Table 13. The only estimated factor loadings with any magnitude are those associated with education services. The correlation between the education services error and the employment error is $-0.031$, and the correlation between the education services error and the conditional log quarterly earnings error is $-0.072$. All of the other correlations are an order of magnitude smaller. Figure 7 suggests that we are having trouble estimating use of education services. Thus, the decision to simulate services involves a tradeoff between correcting for small correlations and using imprecise estimates of service choices.

Variation in expected returns is caused solely by variation in explanatory variables.
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 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.

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. 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. 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 PERT 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.

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 drops from 30% to around 5%.

---

39 We assume that there was no effect of PERT participation on the fixed costs of applying for DARS services.

40 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.

41 For example, the discount factor for earnings in year 6 using a 20% quarterly discount factor is 0.013.
indirect effects of PERT on the VR service efficacy have noticeable but more modest impacts on the estimated rate of return, while the effect of PERT on VR costs has 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; Luecking and Wittenburg, 2009). In this 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 169% in the first two years and 214% in the longer run, 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.

Table 15: Reductions in Marginal Cost Expenditures Due to Participation in PERT

<table>
<thead>
<tr>
<th>Probability of Service Receipt</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>w/ PERT</td>
<td>0.140</td>
<td>0.160</td>
<td>0.040</td>
<td>0.030</td>
<td>0.160</td>
<td>0.050</td>
</tr>
<tr>
<td>wo/ PERT</td>
<td>0.270</td>
<td>0.200</td>
<td>0.090</td>
<td>0.180</td>
<td>0.160</td>
<td>0.050</td>
</tr>
<tr>
<td>Reduction</td>
<td>0.130</td>
<td>0.040</td>
<td>0.050</td>
<td>0.150</td>
<td>0.000</td>
<td>0.000</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Marginal Cost (Conditional on Receipt)</th>
<th>w/ PERT</th>
<th>wo/ PERT</th>
<th>Reduction</th>
</tr>
</thead>
<tbody>
<tr>
<td>w/ PERT</td>
<td>$0.807</td>
<td>$3.456</td>
<td>$1.425</td>
</tr>
<tr>
<td>wo/ PERT</td>
<td>$0.474</td>
<td>$2.765</td>
<td>$2.256</td>
</tr>
<tr>
<td>Reduction</td>
<td>($0.333)</td>
<td>($0.691)</td>
<td>($0.831)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Unconditional Marginal Cost</th>
<th>w/ PERT</th>
<th>wo/ PERT</th>
<th>Reduction</th>
</tr>
</thead>
<tbody>
<tr>
<td>w/ PERT</td>
<td>$0.113</td>
<td>$0.553</td>
<td>$0.057</td>
</tr>
<tr>
<td>wo/ PERT</td>
<td>$0.128</td>
<td>$0.553</td>
<td>$0.203</td>
</tr>
<tr>
<td>Reduction</td>
<td>$0.015</td>
<td>$0.000</td>
<td>$0.146</td>
</tr>
</tbody>
</table>

Note: Costs are reported in $1000.

Figure 10: Distributions of Quarterly Rates of Return
8 Appendix:

8.1 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 \( g_{20i} = 1 (g_{20i} > 0) \) is equal to 1 if the high school completion age is at least 20:

\[
g_{20i} = -1.14^{**} + 0.15 \text{Emot}_i + 0.38^{**} \text{Orth}_i - 0.27^{**} \text{White}_i \\
+ 0.17^{**} \text{Male}_i + 0.09 \text{Transp}_i - 0.24^* \text{DrLic}_i + 0.26^{**} \text{GovBen}_i + \epsilon_i
\]  

(7)

where \( \text{Emot}_i = 1 (i \text{ has an emotional disability}) \), \( \text{Orth}_i = 1 (i \text{ has a physical disability}) \), \( \text{Transp}_i = 1 (i \text{ has available transportation}) \), \( \text{DrLic}_i = 1 (i \text{ has a driver’s licence}) \), and \( \text{GovBen}_i = 1 (i \text{ has government benefits}) \). These variables are chosen because they are also available in our DARS data. 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.

Using the estimates from equation (7), we simulate the age at graduation from high school and thus \( s_i \) in equations (4) and (5).

\[\text{Over 80% of youth leave secondary schooling between the ages of 17 and 19 years old, and nearly 20% leave school between the ages of 20-25 years old.}\]
8.2 Covariance Structure

The covariance matrix of the errors $\mathbf{u}' = (u'_1, u'_2, \ldots, u'_i, \ldots, u'_{iT}, u'_{IT})$ implied by the structure in equation (6) is

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

where

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

$$
F' = \left( \begin{array}{cccc} \sum_k \lambda_{1k}^y \lambda_k^p & \sum_k \lambda_{2k}^y \lambda_k^p & \cdots & \sum_k \lambda_{jk}^y \lambda_k^p \\ \sum_k \lambda_{1k}^y \lambda_{2k}^p & \sum_k \lambda_{2k}^y \lambda_{2k}^p & \cdots & \sum_k \lambda_{jk}^y \lambda_{2k}^p \\ \vdots & \vdots & \ddots & \vdots \\ \sum_k \lambda_{1k}^y \lambda_{jk}^p & \sum_k \lambda_{2k}^y \lambda_{jk}^p & \cdots & \sum_k \lambda_{jk}^y \lambda_{jk}^p \end{array} \right) ,
$$

$$
G' = H_1 \otimes \left( \begin{array}{c} 1 \\ 1 \\ \vdots \\ 1 \end{array} \right),
$$

$$
A = \begin{pmatrix} \sum_k (\lambda_{1k}^y)^2 & \sum_k \lambda_{1k}^y \lambda_{2k}^y & \cdots & \sum_k \lambda_{1k}^y \lambda_{jk}^y \\ \sum_k \lambda_{1k}^y \lambda_{2k}^y & \sum_k (\lambda_{2k}^y)^2 & \cdots & \sum_k \lambda_{2k}^y \lambda_{jk}^y \\ \vdots & \vdots & \ddots & \vdots \\ \sum_k \lambda_{1k}^y \lambda_{jk}^y & \sum_k \lambda_{2k}^y \lambda_{jk}^y & \cdots & \sum_k (\lambda_{jk}^y)^2 \end{pmatrix} ,
$$

$$
C = H_2 \otimes \left( \begin{array}{cccc} 1 & 1 & \cdots & 1 \\ 1 & 1 & \cdots & 1 \\ \vdots & \vdots & \ddots & \vdots \\ 1 & 1 & \cdots & 1 \end{array} \right),
$$

$$
H_2 = \left( \begin{array}{cccc} \sum_k (\lambda_k^z)^2 & \sum_k \lambda_k^z \lambda_k^w & \cdots & \sum_k \lambda_k^z \lambda_{IT}^w \\ \sum_k \lambda_k^z \lambda_k^w & \sum_k (\lambda_k^w)^2 & \cdots & \sum_k \lambda_k^z \lambda_{IT}^w \end{array} \right) ,
$$

$$
D = \frac{\sigma^2}{1 - \rho^2} \begin{pmatrix} 1 & \rho \zeta & \rho \eta & \rho \eta \rho \zeta & \cdots & \rho \eta \rho \zeta^{-1} & \rho \eta \rho \zeta^{-1} \\ \rho \zeta & 1 & \rho \eta \rho \zeta & \rho \eta & \rho \eta \rho \zeta & \cdots & \rho \eta \rho \zeta^{-1} & \rho \eta \rho \zeta^{-1} \\ \rho \eta & \rho \eta \rho \zeta & 1 & \rho \zeta & \rho \zeta & \cdots & \rho \zeta & \rho \zeta \\ \rho \eta \rho \zeta & \rho \eta & \rho \zeta & 1 & \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ \rho \eta \rho \zeta^{-1} & \rho \eta \rho \zeta^{-1} & \rho \eta \rho \zeta^{-1} & \rho \eta \rho \zeta^{-1} & 1 & \rho \zeta & \cdots & \cdots \\ \rho \eta \rho \zeta^{-1} & \rho \eta \rho \zeta^{-1} & \rho \eta \rho \zeta^{-1} & \rho \eta \rho \zeta^{-1} & \rho \eta \rho \zeta^{-1} & 1 & \cdots & \cdots \end{pmatrix} ,
$$

and

$$
B = \begin{pmatrix} \sum_k \lambda_{1k}^y \lambda_{1k}^z & \sum_k \lambda_{1k}^y \lambda_{1k}^z & \cdots & \sum_k \lambda_{1k}^y \lambda_{1k}^z \\ \sum_k \lambda_{1k}^y \lambda_{1k}^z & \sum_k \lambda_{1k}^y \lambda_{1k}^z & \cdots & \sum_k \lambda_{1k}^y \lambda_{1k}^z \\ \vdots & \vdots & \ddots & \vdots \\ \sum_k \lambda_{1k}^y \lambda_{1k}^z & \sum_k \lambda_{1k}^y \lambda_{1k}^z & \cdots & \sum_k \lambda_{1k}^y \lambda_{1k}^z \end{pmatrix} .
$$

References


