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The Distribution of Returns to Education for People with Disabilities

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ABSTRACT

The Distribution of Returns to Education for People with Disabilities*

This note takes a first look at the distribution of returns to education for people with disabilities, a particularly disadvantaged group whose labor market performances have not been well studied or documented. Using a nonparametric approach, we uncover significant heterogeneity in the returns to education for these workers, which is drastically masked by the conventional parametric methods. Based on these estimates, we construct the Sharpe ratio of human capital investment (taking into account its substantial risk), and our results corroborate on the claimed importance of human capital in improving these workers' wages. Our stochastic dominance tests, however, show that the returns to education for workers with disabilities, as a group, may have been affected more adversely in the most recent recession, relative to their non-disabled counterparts.

JEL Classification: C14, I12, I26; I31

Keywords: disability, education, risk, heterogeneity

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1 Introduction

A significant proportion of working-age people (approximately 8-15 percent)[1] have disabilities. Disability is often associated with poverty, and the presence of a disability can severely limit one's ability to escape poverty. Many welfare programs have been implemented to help financially support these individuals, while legislations such as the American with Disabilities Act (ADA) have been enacted to help provide them equal access to labor market opportunities. However, current U.S. disability policy faces major challenges. The two largest government support programs—Social Security Disability Insurance (DI) and Supplemental Security Income (SSI)—are under extreme fiscal pressure. The DI trust fund is projected to be exhausted 2016 (Congressional Budget Office, 2011), until a 2015 Bipartisan Budget Act, which pushed projected exhaustion to 2022 (Congressional Budget Office, 2015). The SSI is facing the fiscal pressures of other programs funded by general revenue.

Proposed changes to DI and SSI look to improve vocational rehabilitation services, such as education, retaining, and job search support (Auto and Duggan, 2010; Burkhauser and Daly, 2011; and Mann and Stapleton, 2012). Many other education, training, and rehabilitation programs such as those in the Workforce Investment Act of 1998 have also been in place to enhance the skills and knowledge of workers with disabilities to increase their productivity (Hollenbeck and Kimmel, 2008). These programs operate on the supply side of the labor market and are called "supply-side interventions", as opposed to demand-side interventions that simply expend the number of employment opportunities (Hollenbeck and Kimmel (2008)). Returns to education for individuals with disabilities can be an important measure or indication of the potential effectiveness of these programs, and such information is particularly useful and needed in light of the current budget conditions. For example, as noted in Hollenbeck and Kimmel (2008), the larger the returns to education, the more likely there is room for improving disabled workers' labor market outcomes and potentially an underinvestment in such interventions. Knowledge of the magnitude of the returns to education for various groups could also help determine the places in which resources are most needed and potentially more productive.

Despite the potentially important role of education in determining the labor market performances of disabled workers and its usefulness for policy making, efforts to quantify such role and to provide estimates of the returns to education for this particularly disadvantaged group have been sporadic at best. More important, nearly all efforts focus on estimating a single, average rate of return for a particular group. However, individuals could differ in many dimensions, such as their costs and discount rates, and hence their returns to education, as

[1]This figure varies with data sources, operating definitions of disability, and estimation methodologies.

economic theory would predict (Card, 1995). The single estimate of the return to education can mask the potentially substantial heterogeneity in the returns across the population and therefore may not be particularly informative for policy. This point is unfortunately lost in the current methodological debates that focus on the issue of endogeneity (Dickson and Harmon, 2011).

The presence of hetergoeneity implies that educational investment, just as any other investment, involves risk. Such risk is not captured by the average returns to education. For example, while the average returns to education may be larger for disabled workers than non-disabled workers, educational programs may not necessarily be more beneficial for *all* the disabled workers if the risk (e.g., variance) of the returns to education is also large and many workers have extremely low returns to education and hence low wages. When testing rationality and optimality of educational investment for people with disabilities, we should also take into account risk. Therefore, a greater and deeper understanding of the returns to education, especially its heterogeneity, for people with disabilities is warranted, and it will shed more lights on the potential effectiveness of educational programs.

Our paper takes a first step to understand the heterogeneity in the returns to education for individuals with disabilities by estimating its distribution. The OLS results may be biased (because linear wages equations are assumed in estimation), and more importantly, cannot accomodate heterogeneity (because constant returns to education are imposed). In contrast, we employ nonparametric estimation techniques that relax functional restrictions and enable us to estimate observation-specific returns to education and hence obtain a distribution of estimates. Moreover, in light of recent evidence on the importance of the timing of human capital investment (e.g., Cunha et al., 2006), we also distinguish workers by the timing of disability, specifically, between workers with early and late onset disability. For example, it may be difficult for people who encounter disability later in life to readapt and apply their skills, leading to lower rates of return to education (Lamichhane and Sawada, 2013). We also examine the role of various types of disabilities in determining the returns to education. To facilitate comparison, we also present the results for non-disabled workers.

Using three waves of the Survey of Income and Program Participation (SIPP), we find that the conventional parametric Mincer models are biased, and that there exists substantial heterogeneity in the returns to education. Using the nonparametric estimates, we are able to construct measures such as the Sharpe ratio of human capital investment (a measure of the returns to education taking into account risks), which is a more useful measure for evaluating the potential effectiveness of supply-side interventions. The Sharpe ratios indicate substantially larger returns to educational investment than that for those for other financial assets; this result corroborates the claimed importance of human capital in improving labor market outcomes. We further conduct stochastic dominance tests to provide uniform comparison of the distribution between types of disability, taking into account the entire distribution. We fail to find any dominance relations between individuals with and without disabilities in the first two waves, while we do find clear first-order dominance in the most recent recession. This result indicates that the returns to distribution are better for workers without disabilities than for workers with disabilities, and that labor market conditions may have worsened even more for workers with disabilities. This result is much stronger than what is implied by the OLS results.

The outline of the paper is as follows. Section 2 describes empirical methods and Section 3 the data. Section 4 presents the estimation results and Section 5 discusses the potential impacts of endogeneity and sample selection on our results. Section 6 concludes.

2 Estimation Methods

2.1 Preliminaries

To anchor our results to past studies, we choose the Mincer notion of rates of return rather than other notions such as Becker's that uses both direct and opportunity costs, or Heckman et al. (2006) that use option values as most current rate of return estimates have adopted Mincer's earnings function approach.

To begin, the parametric Mincer regression model is given by

$$\ln(y_i) = \alpha + \beta s_i + \gamma_1 \cdot age_i + \gamma_2 \cdot age_i^2 + \delta z_i + \epsilon_i, \tag{1}$$

where $\ln(y_i)$ is the log annual earnings for observation i. s is years of schooling, age is individual age, capturing working experience, and z a vector of commonly used demographic characteristics such as race, gender and region; ϵ is an additive error term. β captures the returns to education, which is assumed to be constant across individuals and groups. The simple specification in (1) can be misspecified, leading to inconsistent estimates of the returns to education. For example, as noted in both Card (1999) and Heckman et al. (2003), an important source of misspecification in the Mincer model is the "assumptions of linearity in schooling and separability between schooling and experience". A higher-order polynomial parameterization does not necessarily lead to a better fit of the data (Card, 1999). To accommodate these issues, we now turn to a nonparametric approach (see, also, Henderson et al. (2011)).

The nonparametric regression model is given by

$$\ln(y_i) = m(s_i, age_i, z_i) + \varepsilon_i, \qquad i = 1, ..., n, \tag{2}$$

where $m(\cdot)$ is the unknown smooth wage function of (s, age, z). The covariates can be classified into two types: x_i^c (a vector of continuous regressors) and x_i^u (a vector of regressors that assume unordered discrete values); ε is an additive error, and n is the number of observations. Let $x_i = [x_i^c, x_i^u]$. In our case, x^c contains $q_c = 2$ elements: years of education and age. x^u contains commonly used demographic characteristics such as race, gender, and region (i.e., $q_u = 3$). The model is left unspecified, allowing for any higher-order terms and arbitrary interactions among the regressors.

We are interested in the gradient of the nonparametric function with respect to schooling, which is analogous to our parametric parameter β. We choose the popular Local-Linear Least-Squares (LLLS) estimator of the unknown function and it's gradient. This method is simply weighted least-squares whereby the weights are kernel functions (as opposed to inverted variance terms as in generalized least-squares). In short, the estimation method locally estimates the function and it's gradient by giving larger weight to observations closer to the point of interest. Specifically, taking a first-order Taylor expansion of (2) with respect to x yields

$$\ln(y_i) \approx m(x) + (x_i^c - x^c)\beta(x) + \varepsilon_i$$

where $\beta(x)$ is defined as the partial derivative of $m(x)$ with respect to x^c. To estimate the model, we consider a variant of the local-linear least-squares (LLLS) estimator.[2] The LLLS estimator of $\delta(x) \equiv (m(x), \beta(x))'$ is given by

$$\widehat{\delta}(x) = \left(X'K\left(x\right)X\right)^{-1} X'K\left(x\right)\ln y \tag{3}$$

where X is a $n \times (q_c + 1)$ matrix with ith row being $(1, (x_i^c - x^c))$ and $K(x)$ is a diagonal n by n matrix of kernel weighting functions for mixed continuous and categorical data with bandwidth parameter vector h. We use Generalized Kernel Estimation (Li and Racine, 2004; Racine and Li, 2004) to estimate the conditional mean and gradient. Closer inspection of the estimator in (3) shows that the estimate is specific to x. In other words, we obtain a derivative estimate (for each regressor) for each x (and hence each individual). This allows

[2]In short, LLLS performs weighted least-squares regressions at a point x with weights determined by a kernel function and bandwidth vector. Specifically, more weight is given to observations in the neighborhood of x. This is performed over the range of x and then the unknown function is estimated by connecting the point estimates. Some of the benefits of LLLS are that it requires no assumptions on the underlying functional form and allows for heterogeneity in the partial effects. Further, if indeed the true functional form is linear, the LLLS estimator nests the OLS estimator when the bandwidth is very large.

us to observe heterogeneity in the partial effect of schooling across the population. Note that our nonparametric, individual-specific estimates take into account all possible reasons why returns to education may differ across individuals, e.g., the timing of disability status and the type of disability. For example, years of schooling could have differential impacts on individual wages due to the quality of the education; such differential impacts are captured by our individual-specific estimate of returns to education. We will also investigate the sources of heterogeneity by examining the two most common causes of disability.

2.2 Practical Implementation

To implement Generalized Kernel Estimation, three practical issues warrant further discussion. The first two are concerned with estimation, and the last inference. For a more detailed explanation of the methods and implementations, see, e.g., Henderson and Parmeter (2015).

2.2.1 Choice of Kernel Function

The first practical issue of implementation of LLLS is concerned with the choice of the kernel function, $K(\cdot)$. The Generalized Kernel Estimation permits both continuous and discrete variables. In particular, the generalized kernel is the product of different kernel functions specifically designed for each type as follows (recall that $X_i = [X_i^{c'}, X_i^{u'}] = [(X_{1i}^c, \ldots, X_{q^c i}^c)', (X_{1i}^u, \ldots, X_{q^u i}^u)'].$):

$$K\left(\frac{X_i - X}{h}\right) = \Pi_{s=1}^{q_c} k^c(X_{si}^c, X_s^c, h_s^c) \Pi_{s=1}^{q_u} k^u(X_{si}^u, X_s^u, h_s^u)$$

where the Gaussian kernel function for continuous variables is given by

$$k^c\left(X_{si}^c, X_s^c, h_s^c\right) = \frac{1}{\sqrt{2\pi}} \exp\{-\frac{1}{2}\left(\frac{X_i^c - X^c}{h^c}\right)^2\}$$

The kernel function for unordered discrete variables (Aitchison and Aitken (1976)) is given by

$$k^u\left(X_{si}^u, X_u^c, h_s^u\right) = \begin{cases} 1 - h_s^u & \text{if } X_{si}^u = X_s^u \\ \frac{h_s^u}{d_s - 1} & \text{otherwise} \end{cases}$$

where d_s is the number of unique values the s^{th} variable can take.

The rate of convergence of the LLLS estimator depends solely on the number of continuous variables, and the number of discrete variables does not add to the "curse of dimensionality" problem (Li and Racine, 2004). It is widely believed in the literature that the choice of kernel functions matters little in the nonparametric estimation (see, e.g. textbook discussions in Henderson and Parmeter (2015) and Li and Racine (2007)).

2.2.2 Choice of Bandwidth

The second practical issue is concerned with selection of an optimal bandwidth vector (which is often considered to be the most salient factor in the nonparametric estimations). Given the choice of a kernel function, the value of h determines the size of the neighborhood around a point X, and the observations within this neighborhood are given more weight in estimation. A relatively small bandwidth means a relatively small neighborhood and relatively few points will be given weight in estimation, resulting in estimates with smaller bias yet more variance. On the other hand, a large bandwidth means a large neighborhood and more points will be utilized in estimation, resulting in estimates with larger bias yet less variance . The key issue is to balance the trade-off between bias and precision. To avoid any arbitrariness in our selection, we opt for a popular choice of optimal bandwidth selection method – least squares cross validation (LSCV). Stone (1984) shows that this method is asymptotically optimal "in the sense of minimizing the estimation integrated square error" (Li and Racine, 2007, p.18).[3]

2.2.3 Inference

We employ a wild bootstrap procedure for estimation of standard errors. The wild bootstrap is generally preferred because it is consistent under both homoskedasticity and heteroskedasticity (see, e.g., Henderson and Parmeter (2015), p. 135, for the intuition and theoretical discussions of the method). Specifically, the procedure is as follows:

1. Compute the two-point wild bootstrap errors from the recentered residuals by $\epsilon_i^* = \frac{1-\sqrt{5}}{2}(\widehat{\epsilon}_i - \overline{\widehat{\epsilon}_i})$ with probability $\frac{1+\sqrt{5}}{2\sqrt{5}}$ and $\epsilon_i^* = \frac{1+\sqrt{5}}{2}(\widehat{\epsilon}_i - \overline{\widehat{\epsilon}_i})$ with probability $1 - \frac{1-\sqrt{5}}{2\sqrt{5}}$, where $\widehat{\epsilon}_i = y_i - \widehat{m}(x_i)$ is the residuals and $\overline{\widehat{\epsilon}_i}$ the sample average of $\widehat{\epsilon}_i$.

2. Generate $\ln y_i^* = \widehat{m}(x_i) + \epsilon_i^*$. Re-estimate the wage equation, $\widehat{m}^*(x_i)$ and the derivative, $\widehat{\beta}^*(x)$, using the sample of $\ln y_i^*$ and x_i.

3. Repeat steps 1 and 2 399 times. Standard errors are obtained by taking the standard deviation of the sampling distribution of the bootstrapped point estimates for each particular estimate.

[3]A useful feature of the LSCV procedure, among others, is its ability to detect whether a continuous variable enters the function linearly in the LLLS case (Hall et al. 2007). A very large bandwidth ($h \to \infty$) (which implies $K(\cdot) \to K(0)$, a constant) implies each observation is given an equal weight in estimation, which makes the original minimization problem essentially an OLS problem over the whole support.

3 Data

Data are from the 2001, 2004, and 2008 SIPP panels. SIPP panels follow a multistage-stratified representative sample of the U.S. civilian non-institutionalized population for about two and a half years. For each panel, there are multiple waves of data. In each wave, respondents answered a series of "core" questions on demographics, wages, education, and family structure in the current month and the three months since the previous interview.

The SIPP data provide detailed information on both disability and disability onset in one wave of each panel; the latter one is generally not available in other datasets. Specifically, we utilize data from the Topical Module on Adult Function Limitations and Disability (hereafter the Disability TM). The Disability TM was collected once for each panel, specifically, in the 2001 SIPP Wave 5 (June 2002 - September 2002), 2004 SIPP Wave 5 (June 2005 - September 2005), and 2008 SIPP Wave 6 (May 2010 - August 2010). The Disability TM is indeed the source of the Census Bureau's most comprehensive estimates of the population with disabilities—published in Americans with Disabilities series (e.g., Brault, 2012). Each panel has only one Disability Topical Module, and we will use the wave of the panel data that contains both core and diability questions. Individuals from each panel are different, and the three years of data used in our analysis are cross-sectional. Such data also allow us to examine how the distributions of the returns to education vary over time, and how economic conditions impact the distributions.

The SIPP begins with a self-reported health question, "[w]ould you say [your] health in general is excellent, very good, good, fair or poor?" and then followed with an extensive series of 29 disability-related questions asking about impairment (e.g., blindness), functional limitations (e.g., difficulty walking), activity limitations (e.g., preparing meals), use of assistive devices (e.g., using a wheelchair), and a select set of mental conditions (e.g., learning disability). After these questions, respondents who report any of the functional limitations and/or poor or fair health are asked whether the main condition is among those listed in Table A1. A respondent is considered to have a disability if he or she reports having one of these conditions, except "other." We focus on those workers with a physical disability (see Table A1 for classifications). After a respondent reports the main chronic condition, he or she is asked the year and month the condition started to "bother" him or her. We define an early-onset disability as being a disability that begins when an individual is 16 years old and younger, inclusive, because in most states, age 16 is the earliest a student may drop out of school and this cut-off leaves us a reasonably large sample size.

Although it is possible that people may move in and out of disability over time, we are not able to exclude the people who are temporarily disabled because of data avaiability. However, these individuals account for a very small percentage of the popuIuation. As shown in Table A1, most of the physical conditions should be considered as chronic diseases. Our data also show that approximately 94% of the physically disabled people have the main condition for at least one year.

4 Estimation Results

4.1 Average Returns to Education

We first notice that regardless of the type of disability and empirical methods, the returns to education are positive, suggesting that education improves the productivity of all individuals. The estimates range from 7.5% to 11.9%, with the magnitudes consistent with what the prior literature has typically found. The mean nonparametric estimates, however, are all larger than the corresponding parametric ones. In other words, imposing a linear functional form in the relationship between education and wages leads to severely downward biased estimates in the average returns to education. The comparison between the nonparametric and parametric results suggests a (crude measure of the) bias ($= \frac{\beta^{NP}-\beta^{OLS}}{\beta^{OLS}} \times 100$) varies across disability status and years, ranging from 8.411 to nearly 30 percent.

The returns differ by the type of disability. Unlike the OLS results, the nonparametric results show that the individuals with disabilities, on average, have lower returns to education than non-disabled individuals, regardless of the type of disability and sample period.

Finally, we find that the returns to education respond differently to business cycles between groups. Both parametric and nonparametric results suggest that there exists a consistently increasing trend of the returns to education for both individuals without disabilities and with late-onset disabilities over time, but an inverted U-shape in the trend for individuals with early-onset disabilities (i.e, first increased at a fast rate during the post dot-com bubble period and then decreased in the most recent recession, to a level even lower than the initial year 2001). However, despite the similar patterns, the magnitude of the changes over time implied by the OLS results differ drastically from those implied by the nonparametric results. For example, for individuals with late-onset disabilities, the OLS results imply that the returns to education increase by only 2 percent during the period of 2001-2008 ($\frac{0.084-0.082}{0.082} \approx 0.024$), while the nonparametric results suggest the increase can be as large as 16 percent ($\frac{0.109-0.094}{0.094} \approx 0.16$). For individuals with early-onset disabilities, the OLS estimates suggest that the return to education decreased by nearly 30 percent ($\frac{0.075-0.107}{0.107} \approx -0.299$) during the most recent recession from 2004, while the nonparametric results suggest a smaller decrease of about 19 percent ($\frac{0.094-0.116}{0.116} \approx -0.190$).

Our results indicate that the OLS results can overestimate the impact of worsened economic conditions on the returns to education for the individuals both without disabilities and with early-onset disabilities (consistent with Henderson et al. (2011)), and underestimate the long-run growth in the returns to education for those with late-onset disabilities. The differences between the OLS and nonparametric results stem from the fact that the OLS approach failes to take into account the nonlinearity in the conditional mean function and is thus biased. Moreover, as shown in Loken et al. (2012), the linear OLS is a weighted average of the marginal effects discovered here, with a particular weighting scheme. The weighting scheme depends on both the level of schooling and the sampling distribution of schooling. Specifically, the weight for the returns to education at a given level of education is proportional to the differences in the conditional mean of the schooling above and below that given level of education. Moreover, more weight is assigned to the returns to the educational level around the sample median of the distribution of education. As a result, the time trend implied by the OLS results could be a result of both changes in the true effects (captured by our NP results) and changes in the sampling distribution of education over time.

4.2 Evidence of Heterogeneity

In addition to *between-group* heterogeneity, our estimates enable us to further uncover *within-group* heterogeneity in returns to education for individuals with disabilities, which has not been done previously in the literature. Here we consider several ways to examine the heterogeneity both across and within groups.

4.2.1 Percentiles

We report two sets of results regarding the distribution of returns to education. We first report the results at select percentiles ($\tau = 10, 25, 50, 75, 90$). We notice that there exists substantial within-group heterogeneity in the returns to education, which is drastically masked by the average returns. For example, in 2004, the estimates range from 5.8% (at 10^{th} percentile) to 16.9% (at 90^{th} percentile) among individuals with early-onset disabilities, while the average returns are 11.6%. Moreover, we find that individuals without disabilities do not necessarily always perform better those with disabilities. For example, in 2001, individuals with early-onset disabilities in the lower tail of the distributions actually have higher returns to education than their counterparts among individuals without disabilities. This result is again masked by the comparison of the average returns only.

4.2.2 Within Group Variation

Existence of substantial within-group heterogeneity is also evidenced by examining the standard deviation of individual returns to education for each group. The extent of heterogeneity also varies with type of disability and time. Unlike the average returns, we do not observe that the variance of the returns to education for non-disabled workers increased over time. Instead, we observe a rather stable, and even slightly decreased variance for them. On the other hand, for disabled workers, we do observe the variance of the returns to education has increased from year 2001 to 2008, while the trend is not monotonic. Comparing the variance of returns to education between disability types, we can find that the variance is larger for individuals without disabilities than those with disabilities in early periods (2001). The direction of the difference is, however, reversed in 2008; we instead observe that the variance is larger for individuals with disabilities.

4.2.3 Risk and the Sharpe Ratio of Human Capital

The fact that large variation exists in the returns to education, regardless of disability type, implies that human capital is a risky asset, just as other forms of financial investments. The question is: when taking into account the risk properties of human capital returns, are these returns still large enough to justify the importance made for education, especially for workers with disabilities? To answer this question, we follow Palacios-Huerta (2003) to calculate a human capital Sharpe ratio, $|\mathbb{E}(R^e)|/\sigma(R^e)$, as defined in finance theory; where R^e is the returns to education in excess of the risk-free rate (here we use the U.S. Treasury Bill[4]). The idea behind this measure is very intuitive: the expected returns to any investments should also be adjusted for its risk (captured by the standard deviation of the returns). Sharpe (1966)'s seminal paper shows that under the assumption of normally distributed returns, a (risky) asset with the largest expected risk premium relative to its standard deviation maximizes the expected utility problem. The Sharpe ratio provides a sufficient statistic for the investment problem that does not rely on the preferences of the policymaker or anyone who is evaluating the potential effecitiveness of educational programs.

These results are reported in Panel B of Table (3). Regardless of disability type, the Sharpe ratios are much larger than the Sharpe ratio of the U.S. equity index typically found in the literature. This result suggests that even in the absence of human capital externality, the important role of education is well justified by simplying looking at the Sharpe ratio, consistent with Palacios-Huerta (2003). Comparing the Sharpe returns between disability

[4] Available for download at `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`

types, we find that the reward to variability ratio of the investment has increased over time for individuals without disability, while that has decreased slightly for those with late on-set disability and plummeted for those with early on-set disability. These results suggest that educational programs could be potentially beneficial for all individuals even after adjusting for its risk, but could be more financially beneficial for non-disabled individuals in more recent years.

4.2.4 Stochastic Dominance Results

The Sharpe ratio is based only on mean-variance characteristics of the distribution and useful only if the distribution is Gaussian. However, there could be some "high-order" moments that could differ from normality. As noted in Smetters and Zhang (2014), when the normality assumption fails to hold, it is possible to find an investment with smaller Sharpe ratios is actually preferred to (or first-order stochastically dominates) an alternative with large Sharpe ratios.

To further evaluate the potential relative effectiveness of educational programs across groups, we conduct stochastic dominance tests to rank the distributions between type of disability. Stochastic dominance tests are useful because they consider the entire distribution and imposes minimally restrictive assumptions regarding a policy maker's welfare function. Specifically, a finding of first order dominance (FSD) implies that any individual with a social welfare function (increasing in earnings) would prefer one distribution to another, concluding that one group enjoys uniformly higher returns to education than the other group. A finding of second order dominance (SSD) implies that any individuals with a social welfare function (increasing in earnings but averse to dispersion) would prefer one distribution to another, concluding that one group enjoys higher returns to education than the other group.

Our stochastic dominance tests are based on a generalized Kolmogorov-Smirnov test discussed in Eren and Henderson (2008), Linton et al. (2005) and Maasoumi and Heshmati (2000). Let U_1 denote the class of all *increasing* von Neumann-Morgenstern type utility functions u that are increasing in returns to schooling (i.e. $u' \geq 0$), and U_2 the class of utility functions in U_1 such that $u'' \leq 0$ (i.e. concave). Concavity implies an aversion to dispersion (capturing the risks of investment in schooling):

First Order Dominance:

Returns to education, β_i^A, for individuals of Group A First Order Stochastically Dominate (FSD) returns to education, β_i^B, for individuals of Group B *if and only if*

1. $F_A(\beta) \leq F_B(\beta)$ for all β with strict inequality for some β.

Second Order Dominance:

Returns to education, β_i^A, for individuals of Group A Second Order Stochastically Dominate (SSD) returns to education, β_i^B, for individuals of Group B *if and only if*

1. $\int_{-\infty}^{\beta} F_A(t)dt \leq \int_{-\infty}^{\beta} F_B(t)dt$ for all β with strict inequality for some β.

FSD implies SSD. Higher order SD rankings are based on narrower classes of preferences. The tests for FSD and SSD are based on the following functionals:

$$d = \sqrt{\frac{N_A N_B}{N_A + N_B}} \min \sup [F_A(\beta) - F_B(\beta)] \quad (4)$$

$$s = \sqrt{\frac{N_A N_B}{N_A + N_B}} \min \sup \int_{-\infty}^{\beta} [F_A(t) - F_B(t)]dt \quad (5)$$

where N_A and N_B are the respective sample sizes for Groups A and B. Test statistics are based on the sample counterparts of d and s, employing empirical CDFs. We use a bootstrap based implementation of the test statistics. Specifically, we repeat the calculation of the statistics 1000 times and obtain the empirical distribution of the test statistics. If the the probability of the statistic d lying in the non-positive interval (i.e., Pr$[d \leq 0]$) is large, say .90 or higher, and $\widehat{d} \leq 0$, we infer first-order dominance (FSD) to a high degree of statistical confidence. We can infer second-order dominance (SSD) based on s and Pr$[s \leq 0]$ in a similar fashion.

The results are reported in Table 3. In the first two waves, we generally do not observe a clear ranking, in stark contrast to the comparison of the Sharpe ratios. For example, although the Sharpe ratio implies that individuals with early-onset disabilities have higher returns than those without disabilities, the SD tests imply that such conclusion holds only for very specific welfare functions and are not statistically significant. The only exception is for the comparison between individuals with early and late-onset disabilities in year 2001. Both the Sharpe ratios and SD tests imply that individuals with early-onset disabilities perform better in terms of returns to education. This result is powerful, indicating that anyone who prefers higher wages and is averse to wage dispersion (or risk) will conclude that individuals with early on-set, as a group, have better returns to education. This result is consistent with the conjecture that the earlier the on-set, the easier to adapt and hence those with early-onset disabilities have higher returns to education.

We do not observe a clear dominance relation between individuals with and without disabilities; that is, as a group, individuals without disabilities do not necessarily perform better than those with disabilities. This is because in the lower tail of the distribution, some individuals without disabilities actually have even lower returns than those with disabilities (as seen above). This result is completely masked by either looking at the mean returns or the Sharpe ratio.

However, the SD results completely change post Great Recession (year 2008). We now observe FSD dominance relations, implying that individuals without disabilities have better returns to education than those with disabilities, regardless of the type. This result suggests that individuals with disabilities may be affected even more adversely in the most recent recession.

4.3 By Disability Type

In this subsection, we further explore the role of different types of disabilities in determining the returns to education. Such an exercise would provide further explanations of the heterogeneity in the returns to education uncovered above, and even more detailed information about the potential effectiveness of educational programs for individuals with disabilities.

We focus on two types of disabilities for which a large enough sample is available: (1) arthritis or rheumatism and (2) back or spine issues. These two types of disabilities are the top two causes of disability. For example, the CDC report on Prevalence and Most Common Causes of Disability—United States 2005 states that "Arthritis or rheumatism was the most common cause of disability overall (19.0%; estimated population affected = 8.6 million) and for women (24.3%). Back or spine problems was the second most common cause of disability overall (16.8%, estimated population affected = 7.6 million) and the most common cause for men (16.9%)."[5] A 2013 CDC mobility and mortality weekly report confirms that mobility is the most frequently reported disability, and the top two causes of mobility limitations are arthritis and back and spine problems, which account for over 35% of all disability.[6]

Results are presented in Tables (4)-(7). We notice that consistent with the baseline results, there again exists substantial heterogeneity in the returns to education for each disability type. Such results are masked by the OLS results and imply substantial risks associated with education. Taking these risks into account, the Sharpe ratios indicate that education is an important way to improve individuals' labor market outcomes.

In the interest of space, we highlight and summarize the similarities and differences in the results across groups. First, we find that our nonparametric estimates are not necessarily larger than the OLS results in all cases. Second, the time trends differ across groups. While for individuals with late on-set and back or spine issues, we continue to find a increasing trend in the returns to education, such trend does not exist for individuals with late on-set

[5] Source:`https://www.cdc.gov/mmwr/preview/mmwrhtml/mm5816a2.htm`

[6] Source: Prevalence of Disability and Disabiity Type Among Adults – United States, 2013 Weekly July 31, 2015. `https://www.cdc.gov/mmwr/preview/mmwrhtml/mm6429a2.htm`.

and arthritis or rheumatism. Instead, we find that the returns have decrased and become flattened after 2004. Even more severely, for both groups with early on-set, we find that the returns have decreased monotonically over time. These patterns are at stark odds with those implied by the OLS results. The OLS results suggest an increasing trend for individuals with arthritis or rheumatism, regardless of the timing of disability. The OLS results suggest that the trend is an inverted-U shape for disable individuals with back or spine issues and late on-set. For those with back or spine issues and early on-set, even though the OLS results also suggest a decreasing trend in the returns to education, the magnitdue of the decline is, however, drastically overestimated.

Third, the returns adjusted for risks also vary differently over time. Among the workers with early on-set disabilities, the Sharpe ratios have plummeted for those with back or spine problems, while the Sharpe ratios first increased in 2004 and then decreased in 2008 for those with arthritis or rheumatism. The pattern is very different for workers with late on-set disabilities. Specifically, the Sharpe ratios first increased in 2004 and then decreased in 2008 for those with back or spine problems, while the Sharpe ratios have actually increased over time for those with arthritis or rheumatism.

Finally, we generally do not observe a clear dominance relation between individuals with and without arthritis or rheumatism before the most recent recession. Individuals with arthritis or rheumatism do not appear to perform worse than those non-diabled individuals. However, we observe dominance relations between individuals with arthritis (regardless of the timing of the disability) and non-disabled individuals. For individuals with back or spine problems, the situation is even worse. In both recessions (2001 and 2008), individuals with early on-set and back or spine disabilities perform worse than both non-disabled workers and those with late on-set disabilities (in the second-order stochastic dominance sense). These results are indicative of the worsened situation for the individuals with disabilities as a group in the recessions. These results are much stronger than those implies by the OLS results.

5 Endogeneity and Sample Selection

Our paper has thus far focused on the nonlinearity of the wage function and heterogeneity in returns to education. Two important empirical issues warrant further discussions: one is the endogeneity and measurement error issue, and the other the sample selection issue. The first issue arises when an individual's education is also related to other determinants of wages such as unobservable ability or when education is mis-reported. The second issue arises when individuals self-select into the labor force and we do not observe wages for those who do not work. The literature has shown a negative impact of disability on employment, which in turn suggests that individuals with disabilities who work may be a selective group. Both issues are particularly challenging in practice. While it is relatively straightforward to resolve these issues in the linear context (using methods such as IV estimation and Heckman-like selection models), nonparametric methods adequately addressing either issue, let alone both, remain an active yet challenging area. Furthermore, these methods typically rely on exclusion restrictions that are hard to find and often controversial in practice. Henderson et al. (2011) also note that in the presence of heterogeneity, it is nearly impossible to adopt the IV strategy in this context since the IV can only identify the effects for subgroups whose educational decisions are impacted by the IV (i.e. the compliers), and an IV may be needed for every individual. In light of such difficulty, we leave these important issues for future research.

Whether and how the aformentioned issues affect our nonparametric estimates is, however, unclear, *a priori*. As Koop and Tobias (2002) show, our focus is on the heterogeneity in the returns to education, and "this need not be affected by ability bias even if the mean return is affected". Furthermore, Griliches (1977) and Harmon et al. (2003) suggest that "measurement error and ability bias could cancel each other out". Such proposition seems to be confirmed by Angrist and Krueger (1991) using U.S. data, Hogan and Rigobon (2002) and Harmon et al. (2003) using UK data. Surveying the literature, Card (2008) also notes that existing evidence from IV estimations is not too far away from those obtained using the simple Mincer approach. As a result, Harmon et al. (2003) argue that "there is no advantage to IV". More importantly, given the strong evidence of subtantial heterogeneity we find in this paper, it is hard to argue that our results will go away once one corrects for the ability bias and measurement error.

The impact of sample selection also depends on the direction of the selection. For example, if there exists positive selection, i.e., individuals with larger returns to education and hence higher wages will enter the labor force, it is more likely that the estimates will be biased downward. In this case, our estimates actually provide useful lower bounds for the true returns to education. Moreover, our nonparametric estimates are "local" estimates and thus may be less impacted by the sample selection issue, especially for those in the upper tail of the distribution of education and wages.

6 Concluding Thoughts

Our paper is among the first attempts to highlight the heterogeneity in the returns to education among people with disabilities. Although largely descriptive, this paper nevertheless presents a first-hand documentation of many interesting patterns in the returns to education for this particularly disadvantaged group. Our paper differs from Hollenbeck and Kimmel (2008) in that we address a completely different empirical issue, namely functional form and heterogeneity in the returns. We do not think one issue is necessarily more important than another. Instead, both issues are relevant for sound policy-making, calling for a more systematic framework that can address all them altogether. The development of such methods are still at its infancy, however, and we thus leave this for future research.

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Table 1: The Distribution of main condition into physical and mental conditions

Group	No Ddisability	Early Physical	Late Physical	No Ddisability	Early Physical	Late Physical	No Ddisability	Early Physical	Late Physical
		2001			2004			2008	
Log(wage)	2.69	2.44	2.52	2.69	2.43	2.51	2.70	2.42	2.52
	(0.60)	(0.54)	(0.57)	(0.60)	(0.57)	(0.55)	(0.62)	(0.56)	(0.56)
Schooling	13.62	13.23	12.79	13.70	13.22	13.12	13.89	13.11	13.24
	(2.76)	(2.41)	(2.73)	(2.68)	(2.43)	(2.49)	(2.73)	(2.66)	(2.75)
Age	40.77	39.60	46.36	41.15	39.89	46.99	42.04	40.38	47.48
	(9.59)	(9.84)	(9.33)	(9.75)	(10.51)	(9.35)	(10.19)	(11.11)	(9.62)
Male	0.53	0.46	0.43	0.52	0.44	0.43	0.51	0.47	0.42
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.49)	(0.50)	(0.50)	(0.49)
Race									
White	0.83	0.88	0.81	0.82	0.83	0.79	0.81	0.83	0.77
	(0.38)	(0.33)	(0.39)	(0.39)	(0.38)	(0.41)	(0.39)	(0.38)	(0.42)
African American	0.12	0.09	0.13	0.12	0.11	0.13	0.11	0.10	0.14
	(0.32)	(0.28)	(0.34)	(0.32)	(0.31)	(0.33)	(0.32)	(0.30)	(0.35)
Other	0.05	0.03	0.06	0.07	0.06	0.08	0.08	0.07	0.08
	(0.22)	(0.18)	(0.23)	(0.25)	(0.24)	(0.28)	(0.27)	(0.26)	(0.28)
Region									
Northeast	0.18	0.17	0.17	0.16	0.14	0.15	0.18	0.19	0.16
	(0.39)	(0.38)	(0.37)	(0.37)	(0.35)	(0.36)	(0.39)	(0.39)	(0.37)
Midwest	0.25	0.34	0.27	0.26	0.27	0.25	0.25	0.28	0.25
	(0.43)	(0.48)	(0.44)	(0.44)	(0.44)	(0.43)	(0.43)	(0.45)	(0.43)
South	0.36	0.26	0.34	0.36	0.4	0.36	0.36	0.27	0.36
	(0.48)	(0.44)	(0.47)	(0.48)	(0.49)	(0.48)	(0.48)	(0.45)	(0.48)
West	0.22	0.22	0.23	0.21	0.2	0.24	0.21	0.26	0.23
	(0.41)	(0.42)	(0.42)	(0.41)	(0.40)	(0.42)	(0.41)	(0.44)	(0.42)
N	19973	229	2249	26568	333	3195	22770	322	2646

Notes: Data are from the 2001, 2004, and 2008 Survey of Income and Program Participation (SIPP) panels. Means and standard deviations (in the parentheses) are presented.

Table 2: Estimates of Returns to Education

	Year 2001			Year 2004			Year 2008		
	No Disability (1)	Early Physical (2)	Late Physical (3)	No Disability (4)	Early Physical (5)	Late Physical (6)	No Disability (7)	Early Physical (8)	Late Physical (9)
Panel A: Parametric OLS Results									
Estimates	0.092	0.084	0.082	0.100	0.107	0.082	0.106	0.075	0.084
	(0.001)	(0.014)	(0.004)	(0.001)	(0.011)	(0.003)	(0.001)	(0.011)	(0.003)
Panel B: Non-Parametric Results									
Average Estimates	0.110	0.101	0.094	0.119	0.116	0.096	0.123	0.094	0.109
Standard Deviation	0.028	0.011	0.024	0.027	0.043	0.017	0.025	0.032	0.045
Implied Bias for OLS (percentage)	19.565	20.238	14.634	19.000	8.411	17.073	16.038	25.333	29.762
Sharpe Ratio	2.533	5.464	2.323	3.967	2.389	4.976	4.327	2.433	2.090
10^{th} Percentile	0.079	0.093	0.064	0.087	0.058	0.081	0.095	0.071	0.055
	(0.018)	(0.022)	(0.015)	(0.007)	(0.017)	(0.010)	(0.010)	(0.026)	(0.023)
25^{th} Percentile	0.095	0.098	0.079	0.108	0.071	0.091	0.111	0.084	0.096
	(0.007)	(0.020)	(0.014)	(0.007)	(0.028)	(0.012)	(0.008)	(0.022)	(0.021)
50^{th} Percentile	0.112	0.102	0.093	0.124	0.136	0.097	0.127	0.099	0.118
	(0.010)	(0.016)	(0.020)	(0.013)	(0.020)	(0.009)	(0.008)	(0.022)	(0.020)
75^{th} Percentile	0.129	0.107	0.110	0.136	0.152	0.105	0.139	0.111	0.130
	(0.014)	(0.020)	(0.008)	(0.008)	(0.020)	(0.008)	(0.009)	(0.032)	(0.019)
90^{th} Percentile	0.142	0.112	0.121	0.146	0.169	0.111	0.148	0.120	0.154
	(0.010)	(0.021)	(0.014)	(0.008)	(0.020)	(0.016)	(0.008)	(0.024)	(0.023)
N	19973	229	2249	26568	333	3195	22770	322	2646

Table 3: Stochastic Dominance Tests

			First Order		Second Order	
Group A	Group B	Observed Ranking	d	$\Pr[d \leq 0]$	s	$\Pr[s \leq 0]$
Panel A: Year 2001						
No Dis.	Early Phy.	None	1.94	0.00	51.74	0.00
No Dis.	Late Phy.	None	0.28	0.10	7.21	0.10
Early Phy.	Late Phy.	Early Phy. SSD Late Phy.	2.16	0.00	-0.09	**0.97**
Panel A: Year 2004						
No Dis.	Early Phy.	None	4.93	0.00	5.68	0.00
No Dis.	Late Phy.	None	0.59	0.00	14.41	0.00
Early Phy.	Late Phy.	None	4.45	0.00	216.11	0.00
Panel A: Year 2008						
No Dis.	Early Phy.	No Dis FSD Early Phy.	-0.10	0.55	-0.11	**0.99**
No Dis.	Late Phy.	No Dis. SSD Late Phy.	3.19	0.00	-0.25	**1.00**
Early Phy.	Late Phy.	None	0.69	0.00	42.22	0.04

Notes: Data are from the 2001, 2004, and 2008 Survey of Income and Program Participation (SIPP) panels. d, s are test statistics for first- and second-order dominance, respectively. $\Pr[d \leq 0], \Pr[s \leq 0]$ are p-values based on 1000 replications. If the the probability of the statistic d lying in the non-positive interval (i.e., $\Pr[d \leq 0]$) is large, say .90 or higher, and $\widehat{d} \leq 0$, we infer first-order dominance (FSD) to a high degree of statistical confidence.

Table 4: Estimates of Returns to Education (Non-disable vs Disable Individuals with Arthritis or Rheumatism)

	Year 2001			Year 2004			Year 2008		
	No Disability (1)	Early Physical (2)	Late Physical (3)	No Disability (4)	Early Physical (5)	Late Physical (6)	No Disability (7)	Early Physical (8)	Late Physical (9)
Panel A: Parametric OLS Results									
Estimates	0.092	0.083	0.081	0.100	0.097	0.084	0.106	0.097	0.091
	(0.001)	(0.089)	(0.009)	(0.001)	(0.027)	(0.008)	(0.001)	(0.023)	(0.008)
Panel B: Non-Parametric Results									
Average Estimates	0.110	0.165	0.148	0.119	0.100	0.104	0.123	0.099	0.104
Standard Deviation	0.028	0.218	0.084	0.027	0.013	0.039	0.025	0.075	0.037
Implied Bias for OLS (percentage)	19.565	98.795	82.716	19.000	3.093	23.810	16.038	2.062	14.286
Sharpe Ratio	2.533	0.583	1.308	3.967	7.073	2.379	4.327	1.108	2.392
10^{th} Percentile	0.079	-0.234	0.076	0.087	0.086	0.077	0.095	-0.001	0.049
	(0.018)	(0.117)	(0.043)	(0.007)	(0.024)	(0.030)	(0.010)	(0.044)	(0.027)
25^{th} Percentile	0.095	0.129	0.118	0.108	0.093	0.089	0.111	0.039	0.089
	(0.007)	(0.031)	(0.064)	(0.007)	(0.020)	(0.017)	(0.008)	(0.019)	(0.029)
50^{th} Percentile	0.112	0.266	0.148	0.124	0.093	0.107	0.127	0.098	0.116
	(0.010)	(0.170)	(0.058)	(0.013)	(0.020)	(0.023)	(0.008)	(0.010)	(0.020)
75^{th} Percentile	0.129	0.299	0.186	0.136	0.115	0.118	0.139	0.159	0.131
	(0.014)	(0.237)	(0.048)	(0.008)	(0.018)	(0.018)	(0.009)	(0.011)	(0.020)
90^{th} Percentile	0.142	0.300	0.251	0.146	0.115	0.138	0.148	0.212	0.139
	(0.010)	(0.238)	(0.104)	(0.008)	(0.018)	(0.036)	(0.008)	(0.018)	(0.019)
N	19973	22	434	26568	43	637	22770	47	526

Table 5: Estimates of Returns to Education (Non-disable vs Disable Individuals with Back or Spine Problems)

	Year 2001			Year 2004			Year 2008		
	No Disability (1)	Early Physical (2)	Late Physical (3)	No Disability (4)	Early Physical (5)	Late Physical (6)	No Disability (7)	Early Physical (8)	Late Physical (9)
Panel A: Parametric OLS Results									
Estimates	0.092	0.157	0.082	0.100	0.148	0.092	0.106	0.118	0.087
	(0.001)	(0.040)	(0.007)	(0.001)	(0.031)	(0.006)	(0.001)	(0.050)	(0.007)
Panel B: Non-Parametric Results									
Average Estimates	0.110	0.146	0.091	0.119	0.137	0.102	0.123	0.084	0.122
Standard Deviation	0.028	0.018	0.015	0.027	0.043	0.011	0.025	0.094	0.063
Implied Bias for OLS (percentage)	19.565	-7.006	10.976	19.000	-7.432	10.870	16.038	-28.814	40.230
Sharpe Ratio	2.533	5.964	3.635	3.967	2.904	7.767	4.327	0.709	1.688
10^{th} Percentile	0.079	0.148	0.073	0.087	0.043	0.091	0.095	-0.019	0.053
	(0.018)	(0.040)	(0.012)	(0.007)	(0.045)	(0.010)	(0.010)	(0.032)	(0.022)
25^{th} Percentile	0.095	0.148	0.080	0.108	0.125	0.098	0.111	-0.015	0.094
	(0.007)	(0.040)	(0.013)	(0.007)	(0.028)	(0.016)	(0.008)	(0.029)	(0.007)
50^{th} Percentile	0.112	0.152	0.095	0.124	0.143	0.104	0.127	0.128	0.130
	(0.010)	(0.033)	(0.013)	(0.013)	(0.023)	(0.019)	(0.008)	(0.026)	(0.038)
75^{th} Percentile	0.129	0.152	0.103	0.136	0.182	0.109	0.139	0.162	0.156
	(0.014)	(0.033)	(0.015)	(0.008)	(0.038)	(0.012)	(0.009)	(0.040)	(0.068)
90^{th} Percentile	0.142	0.152	0.107	0.146	0.188	0.112	0.148	0.183	0.186
	(0.010)	(0.033)	(0.012)	(0.008)	(0.029)	(0.012)	(0.008)	(0.037)	(0.046)
N	19973	51	693	26568	85	895	22770	57	689

Notes: Data are from the 2001, 2004, and 2008 Survey of Income and Program Participation (SIPP) panels.

Table 6: Stochastic Dominance Tests (Non-disable vs Disable Individuals with Arthritis or Rheumatism)

			First Order		Second Order	
Group A	Group B	Observed Ranking	d	$\Pr[d \leq 0]$	s	$\Pr[s \leq 0]$
Panel A: Year 2001						
No Dis.	Early Phy.	None	0.85	0.01	34.48	0.15
No Dis.	Late Phy.	None	1.08	0.00	22.64	0.00
Early Phy.	Late Phy.	None	0.67	0.01	10.24	0.37
Panel A: Year 2004						
No Dis.	Early Phy.	None	0.39	0.00	2.18	0.83
No Dis.	Late Phy.	No Dis. SSD Late Phy.	0.80	0.00	-0.15	0.00
Early Phy.	Late Phy.	None	0.82	0.00	6.26	0.07
Panel A: Year 2008						
No Dis.	Early Phy.	No Dis SSD Early Phy.	1.56	0.00	-0.14	0.57
No Dis.	Late Phy.	No Dis. FSD Late Phy.	-0.13	0.00	-0.29	0.76
Early Phy.	Late Phy.	None	1.68	0.00	0.17	0.02

Notes: Data are from the 2001, 2004, and 2008 Survey of Income and Program Participation (SIPP) panels. d, s are test statistics for first- and second-order dominance, respectively. $\Pr[d \leq 0], \Pr[s \leq 0]$ are p-values based on 1000 replications. If the the probability of the statistic d lying in the non-positive interval (i.e., $\Pr[d \leq 0]$) is large, say .90 or higher, and $\widehat{d} \leq 0$, we infer first-order dominance (FSD) to a high degree of statistical confidence.

Table 7: Stochastic Dominance Tests (Non-disable vs Disable Individuals with Back or Spine Problems)

			First Order		Second Order	
Group A	Group B	Observed Ranking	d	$\Pr[d \leq 0]$	s	$\Pr[s \leq 0]$
Panel A: Year 2001						
No Dis.	Early Phy.	No Dis. SSD Early Phy	0.09	**0.96**	-0.04	**1.00**
No Dis.	Late Phy.	None	0.71	0.00	5.08	0.00
Early Phy.	Late Phy.	Early Phy. SSD Late Phy.	0.05	0.40	-0.07	0.57
Panel A: Year 2004						
No Dis.	Early Phy.	None	0.87	0.00	4.44	0.00
No Dis.	Late Phy.	None	0.80	0.24	7.06	0.36
Early Phy.	Late Phy.	None	1.00	0.00	25.87	0.00
Panel A: Year 2008						
No Dis.	Early Phy.	No Dis. SSD Early Phy	3.09	0.00	-0.13	0.25
No Dis.	Late Phy.	No Dis. SSD Late Phy	4.15	0.00	-0.19	0.63
Early Phy.	Late Phy.	Late Phy. SSD Early Phy.	1.35	0.00	-0.12	0.77

Notes: Data are from the 2001, 2004, and 2008 Survey of Income and Program Participation (SIPP) panels. d, s are test statistics for first- and second-order dominance, respectively. $\Pr[d \leq 0], \Pr[s \leq 0]$ are p-values based on 1000 replications. If the the probability of the statistic d lying in the non-positive interval (i.e., $\Pr[d \leq 0]$) is large, say .90 or higher, and $\widehat{d} \leq 0$, we infer first-order dominance (FSD) to a high degree of statistical confidence.

7 Online Appendix (NOT FOR PUBLICATION)

7.1 Coding

Table A1: Coding of main condition into physical and mental conditions

Main condition	Coding: Physical	Coding: Mental
Alcohol or drug problem or disorder		P
AIDS or AIDS Related Condition (ARC)	P	
Arthritis or rheumatism	P	
Back or spine problems (including chronic stiffness and deformity)	P	
Blindness or vision problems	P	
Broken bone/fracture	P	
Cancer	P	
Cerebral palsy	P	
Deafness or hearing problems	P	
Diabetes	P	
Epilepsy	P	
Head or spinal cord injury	P	
Heart trouble	P	
Hernia or rupture	P	
High blood pressure	P	
Kidney problems	P	
Learning disability		P
Lung or respiratory problems	P	
Mental or emotional problem or disorder		P
Intellectual disability		P
Missing legs, feet, arms, hands, or fingers	P	
Paralysis of any kind	P	
Senility/Dementia/Alzheimer's Disease		P
Speech Disorder	P	
Stiffness or deformity of the leg, foot, arm, or hand	P	
Stomach trouble (including ulcers, gallbladder, or liver conditions)	P	
Stroke	P	
Thyroid trouble or goiter	P	
Tumor, cyst, or growth	P	

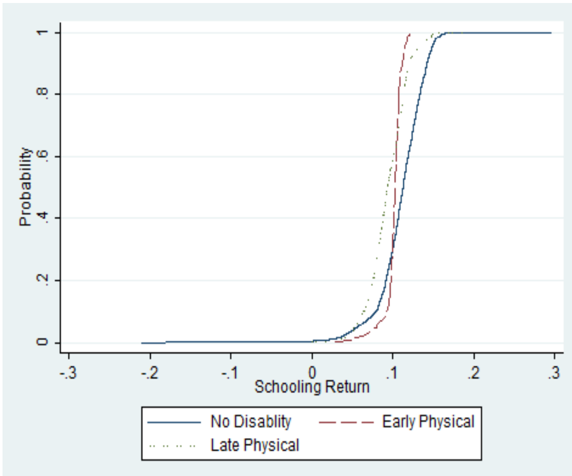
Notes: Data are from the 2001, 2004, and 2008 Survey of Income and Program Participation (SIPP) panels. "P" indicates that it is a type of disability specific to the column type.

Table A2: The Distribution of main condition into physical and mental conditions

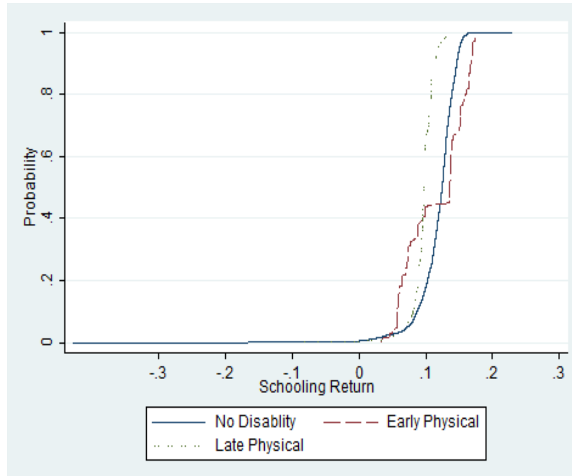
	2001 Frequency	2001 Percent	2004 number	2004 Percent	2008 number	2008 Percent
Alcohol or drug problem or disorder	8	0.31%	23	0.62%	9	0.29%
AIDS or AIDS Related Condition (ARC)	4	0.16%	10	0.27%	7	0.22%
Arthritis or rheumatism	**456**	**17.88%**	**680**	**18.45%**	**573**	**18.35%**
Back or spine problems	**744**	**29.18%**	**980**	**26.59%**	**746**	**23.89%**
Blindness or vision problems	88	3.45%	115	3.12%	123	3.94%
Broken bone/fracture	93	3.65%	114	3.09%	81	2.59%
Cancer	65	2.55%	80	2.17%	81	2.59%
Cerebral palsy	4	0.16%	11	0.30%	8	0.26%
Deafness or hearing problems	219	8.59%	284	7.70%	211	6.76%
Diabetes	155	6.08%	253	6.86%	273	8.74%
Epilepsy	11	0.43%	14	0.38%	17	0.54%
Head or spinal cord injury	29	1.14%	38	1.03%	33	1.06%
Heart trouble	115	4.51%	159	4.31%	128	4.10%
Hernia or rupture	34	1.33%	40	1.09%	37	1.18%
High blood pressure	98	3.84%	151	4.10%	188	6.02%
Kidney problems	17	0.67%	18	0.49%	19	0.61%
Learning disability	4	0.16%	20	0.54%	26	0.83%
Lung or respiratory problems	99	3.88%	181	4.91%	139	4.45%
Mental or emotional problem or disorder	40	1.57%	84	2.28%	93	2.98%
Mental retardation	18	0.71%	31	0.84%	19	0.61%
Missing legs, feet, arms, hands, or fingers	10	0.39%	10	0.27%	8	0.26%
Paralysis of any kind	2	0.08%	17	0.46%	9	0.29%
Senility/Dementia/Alzheimer's disease	2	0.08%	0	0.00%	8	0.26%
Speech disorder	6	0.24%	3	0.08%	14	0.45%
Stiffness or deformity of the leg, foot , arm, or hand	135	5.29%	226	6.13%	165	5.28%
Stomach trouble (including ulcers, gallbladder, or liver conditions)	44	1.73%	57	1.55%	47	1.50%
Stroke	13	0.51%	35	0.95%	25	0.80%
Thyroid trouble or goiter	25	0.98%	33	0.90%	20	0.64%
Tumor, cyst, or growth	12	0.47%	19	0.52%	16	0.51%

Notes: Data are from the 2001, 2004, and 2008 Survey of Income and Program Participation (SIPP) panels. Number (percentage) is the actual counts (share) of the observations in the sample.

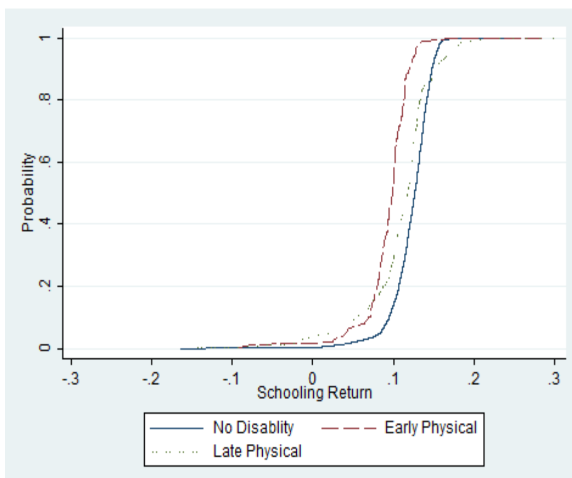
7.2 Stochastic Dominance Tests (Graphs)



(a) 2001

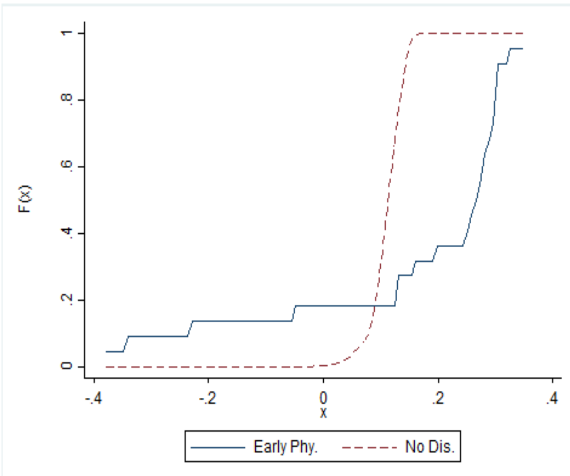


(b) 2004

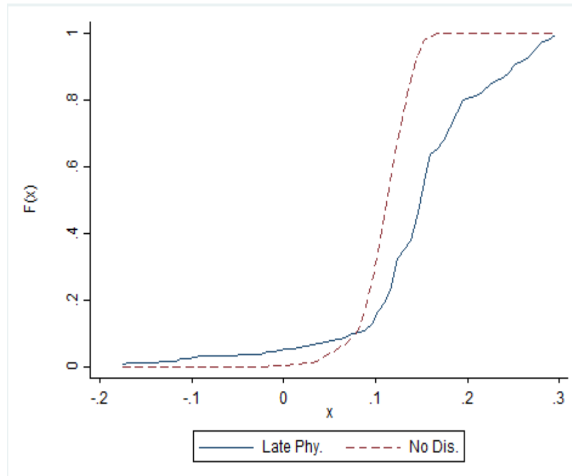


(c) 2008

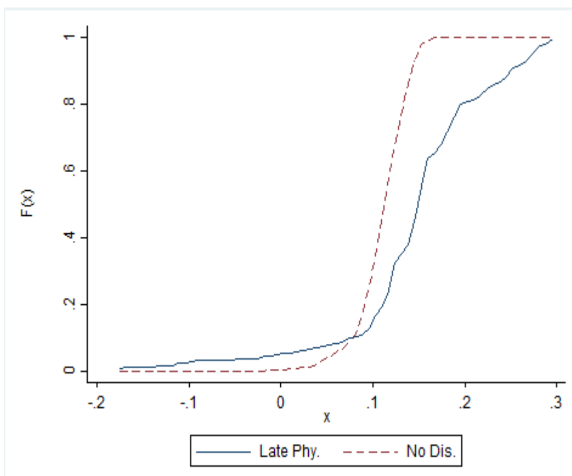
Figure 1: Cumulative Distribution Functions of Returns to Education



(a) 2001

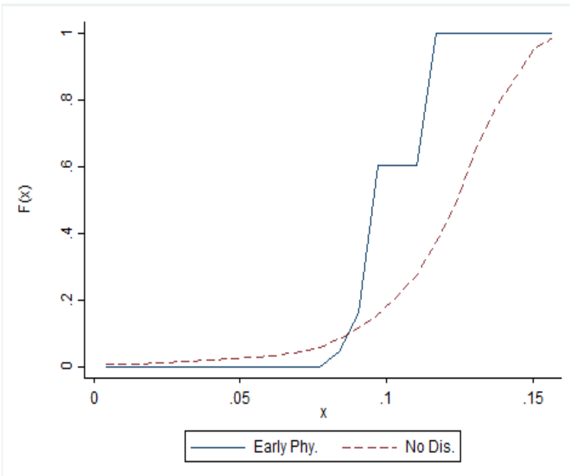


(b) 2001

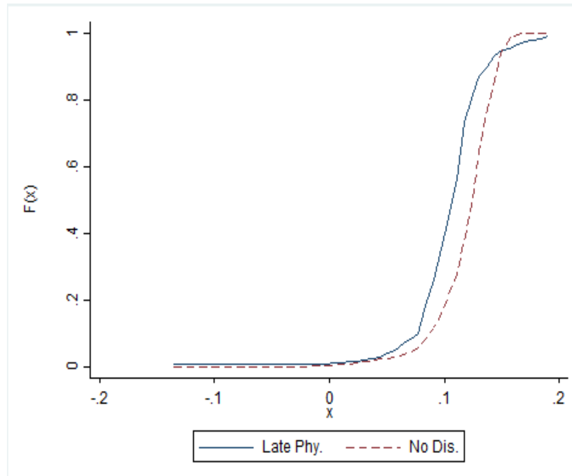


(c) 2001

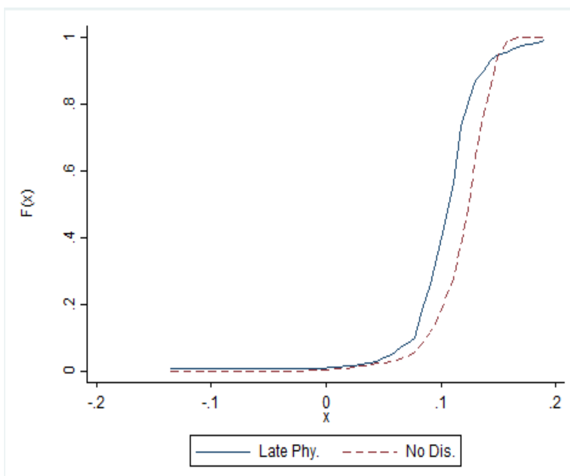
Figure 2: Cumulative Distribution Functions of Returns to Education between Non-Disable and Disable Workers (with Arthritis)



(a) 2004

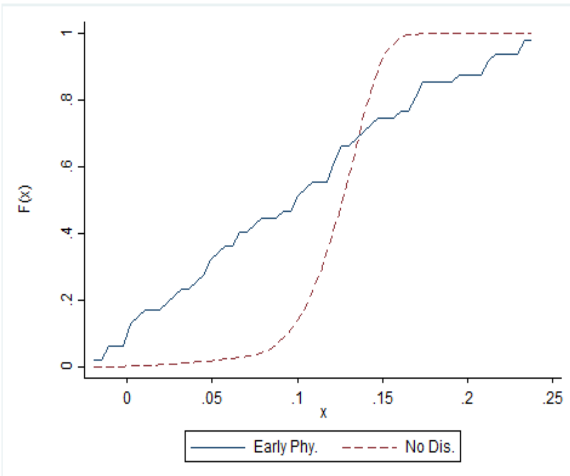


(b) 2004

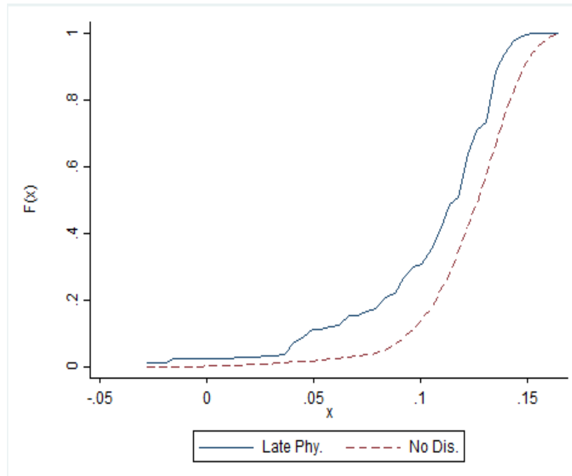


(c) 2004

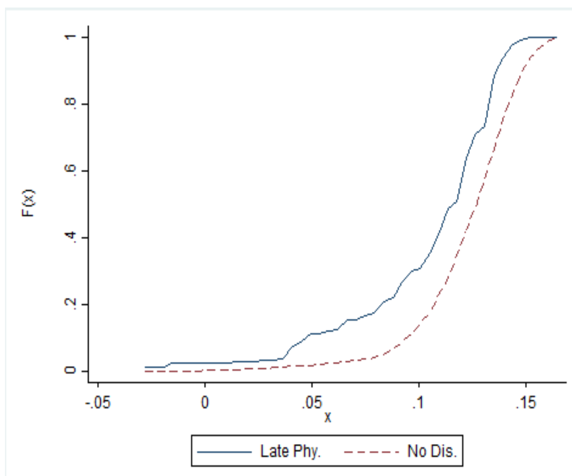
Figure 3: Cumulative Distribution Functions of Returns to Education between Non-Disable and Disable Workers (with Arthritis)



(a) 2008

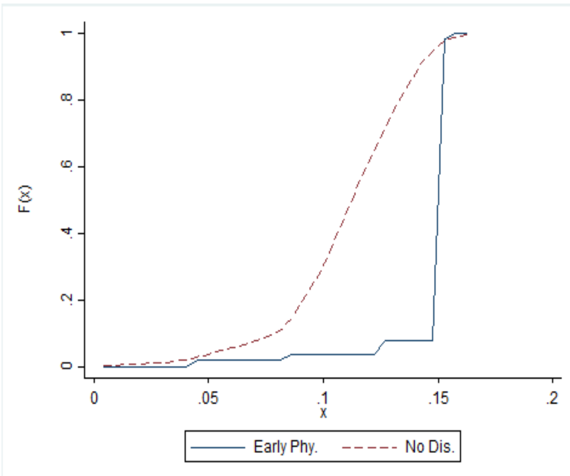


(b) 2008

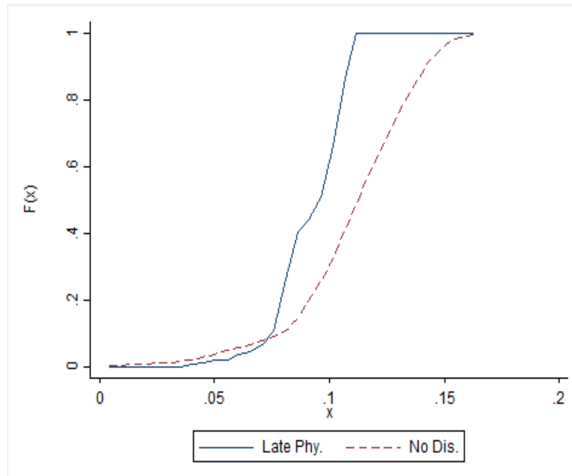


(c) 2008

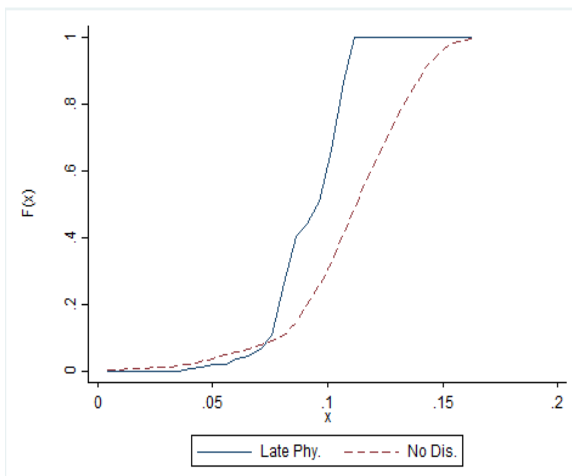
Figure 4: Cumulative Distribution Functions of Returns to Education between Non-Disable and Disable Workers (with Arthritis)



(a) 2001

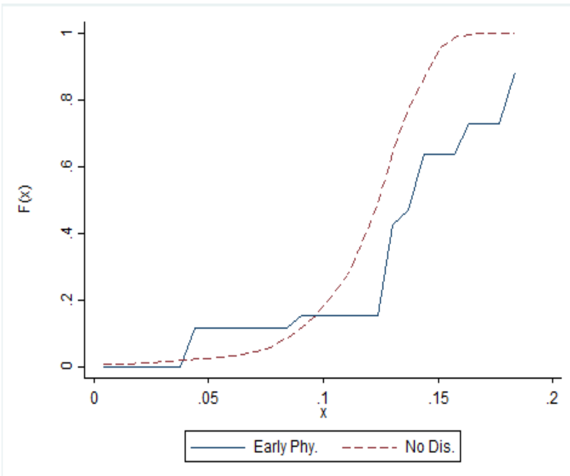


(b) 2001

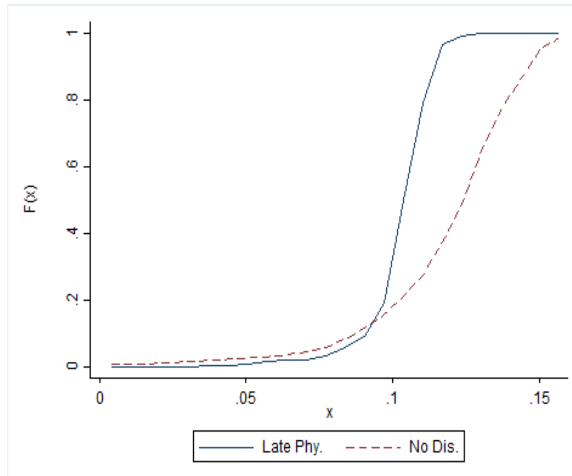


(c) 2001

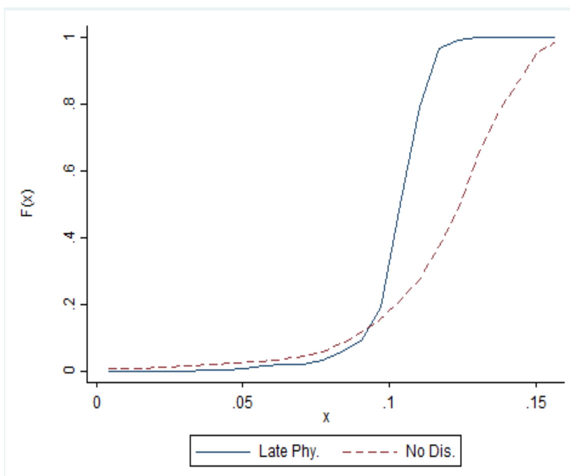
Figure 5: Cumulative Distribution Functions of Returns to Education between Non-Disable and Disable Workers (with Backs)



(a) 2004

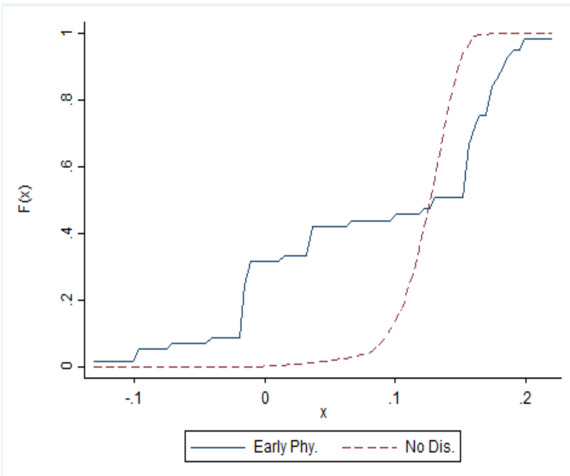


(b) 2004

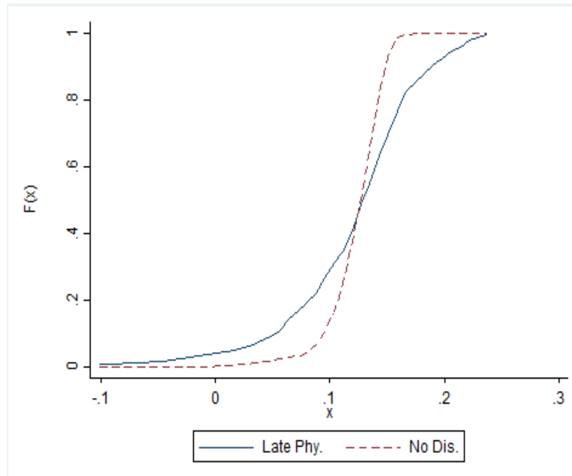


(c) 2004

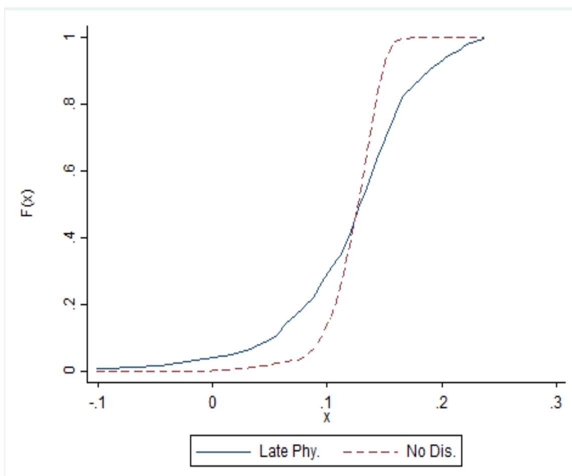
Figure 6: Cumulative Distribution Functions of Returns to Education between Non-Disable and Disable Workers (with Arthritis)



(a) 2008



(b) 2008



(c) 2008

Figure 7: Cumulative Distribution Functions of Returns to Education between Non-Disable and Disable Workers (with Arthritis)