Work limitations and Intergenerational Mobility*

Katie M Jajtner

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Abstract

This paper seeks to determine the degree to which economic disadvantages associated with work-limiting disability may be transmitted to subsequent generations. Persons with work-limitations typically face higher levels of economic disadvantage, including lower earnings, higher expenses, and greater poverty. The United States also tends to have relatively low intergenerational mobility when compared to peer nations. This is important because the Social Security Administration estimates that approximately 25% of new labor market entrants will experience a work-limiting condition at some point in his/her labor market career. Data comes from the Panel Study of Income Dynamics (PSID), and matches 1,128 parent-child pairs from the 1972-1982 birth cohorts. A common measure for intergenerational mobility (the intergenerational elasticity) is estimated for children from households where at least one parent reports a work-limiting disability vis-à-vis children whose parents never report a limitation. Results suggest that children from households with a work-limited parent may experience lower income in their adult years, as well as statistically lower intergenerational economic mobility. Those parent-child pairs classified as the most chronic and/or severely limited are likely driving these results. The analysis is robust to a series of sensitivity tests including the definition of parent disability and income, initial socioeconomic status, as well as child's income, gender, and disability status. As a means of disentangling the multiple channels that may lead to this result, an empirical model of the child's education enrollment from the ages of 15-22 is also estimated. This exercise reveals an increased probability of school exit associated with parent's worsening work-limitations, while an improvement of a work-limitation is associated with lower probability of school exit.

1 Introduction

In the United States, inequality has been rising since the 1980s, and intergenerational economic mobility (or equality of opportunity) lags behind other wealthy nations (Corak 2013; Solon 2002). Within the relatively immobile environment, research has explored how economic disadvantages associated with race (Collins and Wanamaker 2017; Hertz 2005) and geography (Chetty et al. 2014b; Hertz 2008) can persist through the generations. Notably absent from the discussion so far is the health of parents and its association with intergenerational mobility. This paper aims to address this gap and finds that a parent's work-limiting disability may decrease a common measure of intergenerational economic mobility, the elasticity of income.

Disability overall, and work limitations in particular, are not uncommon in the United States. Approximately 12.6% of the non-institutionalized U.S. population is estimated to report vision, hearing, ambulatory, cognitive, independent living, or self-care difficulties according to data from the American Community Survey (Lauer and Houtenville 2017). The Social Security Administration also estimates that a person entering the labor market at age twenty has a 25% probability of experiencing a disability during his/her working-age career (SSA 2017). Other research suggests that eventually 6.5% of the U.S. population will be on Social Security Disability Insurance (Autor and Duggan 2006); and by age 50, 36% of workers will have experienced some work-limiting condition, 9% will have begun a chronic and severe limitation (Meyer and Mok 2013). These statistics highlight the fact that persons with work limitations represent a sizable population, and that disadvantages associated with work limitations can impact many Americans.

Disadvantages associated with work limitations are well documented. Individuals can face lower income, earnings, employment, educational attainment, as well as higher costs of living and poverty(Lauer and Houtenville 2017; Ryan and Bauman 2016; Brucker et al. 2015; Meyer and Mok 2013; She and Livermore 2007). These characteristics help shape an individual's socioeconomic status and standard of living, which can readily be passed on to subsequent generations in a relatively immobile environment. While there is no single causal mechanism for intergenerational mobility, there are a number of factors that can influence a child's outcome later in life such as income, education, employment, and neighborhood effects. Notably, persons with work limitations tend to face disadvantages with respect to many of these characteristics.

As research considering the underpinnings of economic mobility and opportunity expands, it is imperative to explore the intergenerational implications of disadvantages specifically for this population. To the best of the author's knowledge, relatively little literature has considered the role of parental disability in child outcomes, and no attempt has been made to estimate intergenerational mobility. Due to average lower income, earnings, education, employment, and higher medical expenses and poverty among the population with work limitations, it is unlikely that economic disadvantages associated with disability are immune from transfer to subsequent generations. At the very least, one should expect lower average income among children from households with parents with disabilities simply due to generally lower mobility in the United States. One could also imagine that with increased prevalence of poverty, higher expenditures and/or time commitments for self-care, persons with work limitations may be less able to invest in the subsequent generation with finances and/or time thereby increasing the persistence of socioeconomic status specifically within this group. However, it is also reasonable to suppose that public policies aimed at reducing poverty and deprivation among the population (e.g. Supplemental Security Income, Social Security Disability Insurance) could help mitigate lower mobility.

The remainder of the paper will review the literature (Section 2), describe the data and methodology (Section 3), and present results (Section 4). These results are scrutinized further with a variety of sensitivity analyses (Section 5), and an extension to examine the educational attainment channel specifically (Section 6). Limitations and discussion of key results (Section 7) put the findings in perspective prior to concluding (Section 8).

2 Literature Review

Intergenerational economic mobility in the United States is relatively low compared to other wealthy nations. Most estimates for Intergenerational Elasticity of Income (IGE) are between 0.3 and 0.5 for the US (Lee and Solon 2009; Aaronson and Mazumder 2008; Corak 2013; Eberharter 2013; Chetty et al. 2014b), where lower measures indicate more mobility. While cross-sectional comparison is challenging, Corak (2013) finds Canadian IGE to be approximately half the US measure, and Eberharter (2013) finds an IGE of 0.678 for the US, relative to 0.484, and 0.504 for Germany and the UK respectively. Solon (2002) reviews many studies across nations, and the general evidence suggests that the United States is relatively immobile (Solon 2002).

Within the United States, recent literature has begun to examine the role of heterogeneous outcomes within the population. Geography appears to be associated with mobility, where certain regions or spatial clusters experience more or less mobility. Intergenerational persistence in the South is found to be greater than in regions such as the West (Hertz 2008). Using tax data, Chetty et al. (2014b) can be a little more specific, finding that 12.9% of children born into the poorest quintile in San Jose, CA will find their way to the top quintile of the income distribution. Meanwhile, children in Charlotte, NC, are far less mobile - with only 4.4% accomplishing the feat (Chetty et al. 2014b). Park and Myers (2010) considers differentiated mobility by gender and ethnicity for immigrant groups. While they find significant heterogeneity in mobility across ethnic groups depending on the outcome measure, women tended to have higher mobility than male immigrants across ethnic categories (Park and Myers 2010). Heterogeneous mobility outcomes by race are among the most common partitions in the intergenerational mobility literature. From a variety of datasets and time periods, Black Americans consistently experience lower mobility than their White counterparts (Hertz 2005; Collins and Wanamaker 2017), and as Hertz (2008) points out, this is in part due to persistent inequality in average outcomes. When both within and between group mobility is considered, intergenerational persistence among Blacks in the United States is nearly four times greater than for Whites (Hertz 2008).

What is notably absent in the U.S. literature however, is the differentiation of mobility by parental health, and this paper begins to address that gap. Within the documented heterogeneous and low mobility environment in the United States, it is important to consider outcomes of other traditionally disadvantaged groups. This study in particular addresses the prospect of passing disadvantages associated with work-limiting disability on to subsequent generations. Studies have shown that persons with disabilities tend to experience many economic disadvantages including lower income, education, as well as higher non-employment and rates of poverty. In Canada, which is generally a higher-mobility environment (Corak 2013), there is some evidence to suggest that children with parents with disabilities may experience worse outcomes including lower standardized math scores, higher hyperactivity, and higher anxiety scores (Chen, Osberg, and Phipps 2015). Although there is currently little evidence to support the hypothesis of lower economic mobility for this population in the United States, this paper aims to help fill the gap in the literature.

There are a number of key disadvantages persons with disability in general, and work limitations in particular, face that are directly pertinent to intergenerational mobility. First, lower income and earnings, as well as higher rates of poverty, are often observed in this population. However, these deprivations are strongly heterogeneous based on the individual's specific condition. Meyer and Mok (2013) finds that individuals with work-limiting disability experience lower income and earnings up to ten years after disability onset. In the case of income, they find the average work-limited male saw his income drop by about 13% ten years after disability onset, while the "one-time" and "temporary" disability categories experienced a drop of 1.5% and 10% respectively. The "chronic-severe" group saw income declines of over 50% by the tenth year after disability onset (Meyer and Mok 2013). Similar conclusions are reflected in a similar sample of women with disabilities in Meyer and Mok (2014). Brucker et al. (2015) estimated the poverty rate to be three times higher for persons with work limitations across multiple definitions of poverty (Brucker et al. 2015, Appendix table C1). Brault (2008) also estimates the poverty rate among those with severe disabilities at 27%, higher than persons with non-severe disabilities (12%), or no reported disability (9%) in Census data[1].

[1]Note Brault (2008) uses a functional-limitations measure of disability as opposed to a work-limitations measure, yet the main results of higher poverty rates, and heterogeneity among the population hold.

Educational attainment also tends to be lower for persons with disabilities. While over 60% of the U.S. population without disabilities attended some college, only about 40% of the population with disabilities did so (Ryan and Bauman 2016, Table 1). This observation of lower educational attainment is broadly consistent with a number of other studies (Meyer and Mok 2013; Kavanagh et al. 2015). A traditional vector for improving outcomes in subsequent generations in the United States has been through education (Goldin and Katz 2009). However, Corak (2013) suggests that, "(t)he American education system does not promote mobility to the extent that it could because educational spending is more likely to benefit the relatively well-to-do" (Corak 2013, pg 96). Education is so closely tied to economic opportunity and outcomes that some studies also substitute education as a proxy for income in estimating intergenerational mobility when income information is unavailable (e.g. Chetty et al. (2014a)).

Another key disadvantage is relatively higher financial and time-related costs to health care among persons with disabilities that could limit investment in subsequent generations. Mitra, Findley, and Sambamoorthi (2009) found median out-of-pocket expenditures for persons with activity-limiting disabilities are approximately $703 versus $208 for the rest of the population in 2004 (Mitra, Findley, and Sambamoorthi 2009). Olin and Dougherty (2006) also estimated that average medical expenditures of persons with disabilities were much higher than those without disabilities, depending on the severity of their condition. For example, 18-49 year olds with no functional limitations experienced per person average expenditures just over $2,000 dollars while those with physical limitations experienced expenditures over $7,000, and those with Activities of Daily Living (ADL) limitations had expenditures over $17,000. The corresponding percentages of expenses covered by the individual were approximately 25%, 18%, and 9% (Olin and Dougherty 2006, Table 3). Theoretically, such higher expenditures can constrain the family budget, and decrease optimal investment in the subsequent generation in a human-capital model such as Solon (2004).

Del Boca, Flinn, and Wiswall (2013) suggest that time investments in children are more important for their development than financial investments, particularly at younger ages. Research has shown that higher-income and higher-educated parents also tend to invest more time in their children (Phillips 2011; Guryan, Hurst, and Kearney 2008). Given lower educational attainment and income on average for persons with disability, this suggests they might spend less time with children all else equal. They also spend approximately four times as much time as their counterparts without disabilities seeking medical attention (Meyer and Mok 2013[2]). On the other hand, persons with disabilities have lower employment rates (Lauer and Houtenville 2017), which presumably increases available time to invest in children's human capital formation. One study suggests unemployed persons tend to spend *more* time with their children; however, it does not appear that one's labor market status ultimately impacts children's test scores (Levine 2011). Therefore, it is unclear exactly how the time-use channel ultimately impacts child development among persons with disabilities.

Some research suggests onset of a work-limitation is associated with lower marriage rates and increased probability of marriage dissolution (Singleton 2012; Meyer and Mok 2013, 2014[3]), while other research suggests there is no such link (Charles and Stephens 2004). Furthermore, persons married to partners with disabilities do not appear to alter labor supply (Meyer and Mok 2013, 2014). This paper is less concerned with the family structure per se so much as the family resources available. If there is in fact some differential marriage

[2]See Meyer and Mok (2013)'s online Appendix Table 15.

[3]Meyer and Mok (2013, 2014) suggest the estimates can be impresice.

patterns, this can translate into lower household resources given a partner without work-limitations that may not alter his/her labor supply. Furthermore, Chetty et al. (2014b) suggests that one of the most robust correlates of lower mobility in the United States is the fraction of single-parent homes. Even children in two-parent homes residing in neighborhoods with a high portion of single-parents experience less mobility (Chetty et al. 2014b).

While so far there has not been any known attempt to separately estimate mobility for children from households with and without work-limitations, based on the literature presented here, one could expect lower mobility for children with parents with disabilities. While theoretically the time-use channel could prove an advantage to the population, the other deleterious effects likely outweigh any advantage that may be gained in time-use. Therefore, this study expects to find higher persistence rates among the population experiencing work-limiting disability. The main contribution this study makes is to both the mobility and disability literatures. It builds on the literature of heterogeneous mobility by parent health status, and extends the literature on disability and wellbeing to consider the multi-generational consequences of work-limitations.

3 Methods and Data

3.1 Theoretical transmission of socio-economic status in a utility-maximizing framework

One way to consider the transmission of socio-economic status between generations is within a utility-maximizing framework. Becker and Tomes (1979, 1986) form the basic theoretical framework, and Solon (2004, 2014) extend the model to justify the log-log framework so commonly used in applied research. It is from the latter point that this paper departs justifying the potential for particularly persistent socio-economic status within the population experiencing work-limiting disability. For the present research, the framework largely follows Solon (2004, 2014), and makes a single adjustment in the budget constraint such that intergenerational mobility within subpopulations with varying work-limitation statuses could be heterogeneous. His budget constraint is:

$$y_{i,t-1} = C_{i,t-1} + I_{i,t-1} \tag{1}$$

Becker and Tomes (1986) recognized that poor families are more constrained in their ability to invest in the subsequent generation due to the inability to borrow against the child's future human capital. It is also clear that, persons with work-limiting disability tend to have higher out-of-pocket medical expenditures relative to income than non-limited counterparts (Mitra, Findley, and Sambamoorthi 2009). Within this context, it is reasonable to suspect that parents with work-limiting conditions could face an additional constraint on their budget as in equation (2) which would further reduce feasible investment in the child.

$$y_{i,t-1} = C_{i,t-1} + I_{i,t-1} + M_{i,t-1} \tag{2}$$

As in Solon (2004, 2014), $y_{i,t-1}$ is the parent's lifetime earnings, $C_{i,t-1}$ is their consumption, and $I_{i,t-1}$ their investment in the subsequent generation. In this context, this investment is viewed through the lens of human capital formation for the child (Solon 2014). $M_{i,t-1}$ is the addition to the budget constraint (equation (2)) that should be viewed as *additional or extra* medical expenditures associated with work-limiting disability that applies only to that particular sub-population. While all persons have medical expenditures, we can without loss of generality assume these are part of the consumption component, and allow $M_{i,t-1}$ to only represent expenditures that are additional.

The following equations (3) - (6) correspond exactly to equations (2) - (5) in Solon (2004, 2014). Equation (3) is the child's human capital formation ($h_{i,t}$) as a function of parent investment ($I_{i,t-1}$). $\theta > 0$ is the marginal product of human capital, and $e_{i,t}$ is the child's endowment.

$$h_{i,t} = \theta \ln(I_{i,t-1}) + e_{i,t} \tag{3}$$

The child's endowment, equation (4), includes many aspects of nature and nurture that ultimately impact human capital formation outside the direct investment channel such as race, family culture, and characteristics (Becker and Tomes 1979). Within the modeling framework, these characteristics are assumed to be correlated across generations, following an AR(1) process as in equation (4) with v_{it} a white-noise error. λ_t is viewed as the degree of heritability from one generation to the next (Solon 2004).

$$e_{i,t} = \delta + \lambda e_{i,t-1} + v_{i,t} \tag{4}$$

The child's log lifetime earnings in turn are determined by their human capital (which is a function of parental investment and inherited endowment) as in equation (5).

$$\ln y_{i,t} = \mu + p h_{i,t} \tag{5}$$

Finally, parents maximize their own utility with an eye to the future as in equation (6). They care not only about their own consumption ($C_{i,t-1}$), but also the well-being of their child as represented by his/her lifetime earnings ($y_{i,t}$). If utility is Cobb-Douglas, with α representing the degree of altruism the parent has for the child, parent utility takes the following form:

$$U_i = (1-\alpha)\ln C_{i,t-1} + \alpha \ln y_{i,t} \tag{6}$$

Solving the model for parental optimal investment, one arrives at equation (7)[4].

$$I_{i,t-1} = \left(\frac{\alpha p \theta}{1-\alpha+\alpha p \theta}\right)[y_{i,t-1} - M_{i,t-1}] \tag{7}$$

The key difference from the Solon (2014) model appears in equation (7) as $M_{i,t-1}$, indicating that higher additional medical expenses are associated with lower optimal investment in the subsequent generation if these expenses constrain the parent's budget. After substituting the parent's optimal investment into the child's earnings function (equation (5)) and simplifying the equation, one arrives at equation (8) below:

$$\ln y_{i,t} = \mu + p\theta \ln\left(\frac{\alpha p \theta}{1-\alpha+\alpha p \theta}\right) + p\theta \ln(y_{i,t-1}) + p\theta \ln\left(1 - \frac{M_{i,t-1}}{y_{i,t-1}}\right) + p e_{i,t} \tag{8}$$

[4]This corresponds to Solon (2014)'s equation (9).

It is reasonable to assume that a first-order Maclaurin approximation of the term $\ln\left(1 - \frac{M_{i,t-1}}{y_{i,t-1}}\right)$ is sufficient to estimate the intergenerational persistence. Mitra, Findley, and Sambamoorthi (2009)'s estimate the ratio of out-of-pocket expenditures relative to income for persons with activity limitations was approximately 4.4% vis-à-vis approximately 1% for persons without limitations. Using these numbers, $\frac{M_{i,t-1}}{y_{i,t-1}}$ in this context should be approximately 3.5%. Since this value is near zero, a first-order approximation is sufficient and $\ln\left(1 - \frac{M_{i,t-1}}{y_{i,t-1}}\right) \approx -\frac{M_{i,t-1}}{y_{i,t-1}}$.

Further assume that $\frac{M_{i,t-1}}{y_{i,t-1}}$ takes on the functional form: $\frac{M_{i,t-1}}{y_{i,t-1}} = \eta - \omega \ln y_{i,t-1}$. The assumed functional form for government expenditures to lifetime earnings in Solon (2004) is of similar form, and also has a number of desirable properties for the present context of medical expenditures relative to lifetime earnings. For the population without work limitations, $\frac{M_{i,t-1}}{y_{i,t-1}} \equiv 0$, which implies either $\eta = 0$ and $\omega = 0$; or that $\eta = \omega \ln y_{i,t-1}$. Since the latter is not feasible for all values of $\ln y_{i,t-1}$, one can proceed under the assumption that $\eta = \omega = 0$ for all agents without work limitations. For those experiencing a work limitation, one can assume $\frac{M_{i,t-1}}{y_{i,t-1}} > 0$, which implies that $\eta > \omega \ln y_{i,t-1}$ for all values of $\ln y_{i,t-1}$. Higher incomes yield lower medical expenditures to income ratios as expected. and lower incomes yield higher ratios. The key though is that $\eta \neq 0, \omega \neq 0$. If higher incomes will be associated with lower medical expenditures to income ratios (and vice versa), then it is further determined that $\omega > 0$ for all individuals experiencing a work-limitation requiring increased medical expenditures.

Plugging these approximations and assumptions into equation (8), equation (9) follows:

$$\ln y_{i,t} = \mu + p\theta \ln\left(\frac{\alpha p\theta}{1-\alpha+\alpha p\theta}\right) - p\theta\eta + (1+\omega)p\theta \ln(y_{i,t-1}) + pe_{i,t} \tag{9}$$

As Solon (2004, 2014) points out, $(1+\omega)p\theta$ cannot be the empirically estimated persistence from one generation to the next because the final term $pe_{i,t}$ is not a proper error term (Solon 2004, 2014). $e_{i,t}$ is itself autoregressive, and therefore the combination of the two autoregressive parameters ($(1+\omega)p\theta$ and λ_t) yields the following coefficient for the $\ln(y_{i,t-1})$ term, representing the persistence (β_1) of socio-economic status from one generation to the next:

$$\beta_1 \simeq \left(\frac{\lambda_t + (1+\omega)p\theta}{1 + \lambda_t(1+\omega)p\theta} \right) \tag{10}$$

Notably for the present study, $\omega > 0$ will increase β_1, which is associated with less intergenerational mobility. It is imperative to note that this is a single potential transmission channel that could influence mobility. There are in reality many channels that could influence mobility; however, this is a minor and intuitive extension of the theoretical model within a utility-maximizing framework that considers heterogeneous mobility due to parental health status.

3.2 How is intergenerational mobility measured?

The intergenerational elasticity of income (IGE) is one of the most common statistics used to estimate intergenerational mobility. It is defined as the percent change in the child's permanent income or earnings relative a percentage point change in the parent's income or earnings as in equation (11).

$$IGE = \frac{\%\Delta y_{child}}{\%\Delta y_{parent}} \tag{11}$$

A standard technique to estimate the IGE in a given population is an uncontrolled log-log Ordinary Least Squares regression comparing the parent's permanent income with the child's permanent income (or earnings) as in equation (12) where y_c and y_p represent child's and parent's log income respectively, and β_1 is the IGE.

$$y_c = \beta_0 + \beta_1 y_p + \epsilon \tag{12}$$

It is important to note that the specification is purposefully uncontrolled (with the notable exception of life-cycle controls, discussed more fully below) so that the single descriptive statistic acts as a summary statistic capturing persistence of a parent's socioeconomic status relative to their child's status (Mazumder 2005; Aaronson and Mazumder 2008). The remaining econometric concerns surrounding IGE estimation are attenuation and life-cycle bias (Chetty et al. 2014b; Hertz 2007; Grawe 2006; Solon 1992).

Attenuation bias results from short-term approximations of permanent income or earnings. Recall that the IGE measures the persistence of *permanent* income or earnings from one generation to the next. This data is unfortunately unavailable today in any major longitudinal dataset. The Panel Study of Income Dynamics (PSID) has longitudinal data on family dynasties dating back to 1968; however, even this history approaching half a century is insufficient to fully measure a lifetime of income in two successive generations. Therefore, out of necessity, research utilizes short-term approximations of permanent income as in the following:

$$y_{it} = \lambda_t y_i + v_{it} \tag{13}$$

Equation (13) details the expected relationship of permanent and current income for each generation. y_{it} is the current log income of individual i at time t, while y_i is the permanent income for individual i. λ_t is the portion of permanent income typically accruing to an individual at a particular point in time in the life-cycle. In discussing attenuation bias, assume $\lambda_t = 1$. Finally, v_{it} is the transitory component of income. Solon (1992) shows that using short-term proxies of income for permanent income results in a downward bias of β_1. The downward bias can be mitigated by using multiple-year averages of income to reduce transitory fluctuations (Solon 1992). For this reason, specifications for IGE estimation often include multi-year averages of income in both generations (Lee and Solon 2009; Haider and Solon 2006; Mazumder 2005). Although this practice does not eliminate attenuation bias, it is mitigated. For the purposes of the present analysis, this bias is assumed to be equally present for all subpopulations of interest. While it could be argued that the transitory component of permanent income for persons with work-limiting disability could be higher relative to persons who never experience a work-limitation, it would induce additional downward bias in the statistic of interest (the IGE). Therefore, any observed differences in estimated IGE for the populations of interest could be a low-end estimate.

The point in time that one measures short-run income matters for the resulting IGE estimate. This life-cycle bias is conceptualized by allowing λ_t in equation (13) to fluctuate over time, or that transitory "shocks" to permanent income follow a time-dependent path. Haider and Solon (2006) demonstrate that this bias conceptually results in a downward-inconsistent estimator of β_1 when early-life estimates of permanent income are used. Importantly, while typical econometric models suggest that errors in the dependent variable measurement does not bias the estimator, in this case, early life measurement does (Haider and Solon 2006). Haider and Solon (2006) suggest this bias is minimized around age 32 for the child and remains minimal throughout the thirties into their forties. Similarly, the life-cycle bias in the parent's generation is minimized in mid-life, about late twenties to mid-forties (Haider and Solon 2006). Grawe (2006) examines the impact of life-cycle bias on resulting IGE estimates in the literature and finds that the father's age explains approximately 20% of the variance in IGE estimates across studies, with older (younger) ages associated with higher (lower) IGE estimates (Grawe 2006). More recently, Chetty et al. (2014b) corroborate these findings and suggest that IGE estimates are largely stable when parent income is observed in the range of 30-55 and if child' income is measured at least in the late twenties (Chetty et al. 2014b).

3.3 Data and sample

The Panel Study of Income Dynamics (PSID) is a dataset that is uniquely suited to address intergenerational mobility in the United States. PSID began in 1968 with a sample of approximately 5,000 U.S. families and the individuals residing in those family units. Since then, the study continues to survey most decedents of the original sample along with those who live with them[5]. The present analysis takes advantage of this unique intergenerational link to match children and parents from birth cohorts in the 1970s and early 1980s to determine the estimated level of persistence of socioeconomic status from one generation to the next conditioning on a parent's work-limitation status.

[5] *Panel Study of Income Dynamics, public use dataset. Produced and distributed by the Survey Research Center, Institute for Social Research, University of Michigan, Ann Arbor, MI* 2016.

In order to proceed, this study in particular must first identify the degree of work-limitation in the parent's generation. This is accomplished using a series of questions from annual PSID waves from 1981-1996[6]. The three questions are: (1) "Do you have any physical or nervous condition that limits the type of work or the amount of work you can do?", and in the event this first question is answered in the affirmative, (2) "Does this condition keep you from doing some types of work?" and (3) "For work you can do, how much does it limit the amount of work you can do–a lot, somewhat, or just a little?"

If the first question is answered "no", then the individual is classified without limitations in that year. Conversely if the first question is answered "yes", the individual is deemed limited to some degree in that year. For those who are limited, if they indicate the work limitation is "a lot" or that they "can do nothing" in the follow up questions (questions (2) and (3) above), they will be classified as having a severe work-limitation for that year. Minor limitations are classified as individuals who report their limitation interferes "not at all" or "just a little" with work; and moderate limitations are categorized as individuals who report the condition hinders work "somewhat".

Under a discrete categorization of work-limitation status, parents in this study are partitioned into four mutually exclusive groups in the spirit of Meyer and Mok (2013). Those (1) never reporting a work-limitation, (2) experiencing a temporary work-limitation (1-2 reports of any severity level), (3 & 4) experiencing a chronic work-limitation (3+ reports of various severity levels). Due to significant heterogeneity in severity of conditions, individuals who report three or more years of work limitations are further disaggregated by severity level over the course of the years they report a work-limitation. Those who are ultimately classi-

[6]Because PSID only began asking about the spouse's work-limitation condition in 1981, this analysis elects to discard information from 1968-1980 regarding the Head's work-limitation status, which is in practice a sample of only men and unmarried women.

fied as experiencing severe (non-severe) limitations experience a severe (mild or moderate) condition half the time they report a limitation. If the reports are exactly half severe and half non-severe, the first limitation report is used as a tie-breaker following Meyer and Mok (2013).

An alternative continuous specification of work-limitations allows more flexibility in reports. Utilizing the same annualized work-limitation classifications (none, mild, moderate, severe), individuals are assigned a "score" for their work-limitation from zero (non-limited) to three (severe limit) each year (mild conditions are scored as one point, and moderate is scored as two points). The individual's total sum of "points" divided by the maximum possible of points (severe reports each year) represents the individual's work-limitation index as in equation (14). The advantage of this formulation is its continuous nature and the ability to parse out severity reports.

$$Index = \frac{\sum_{k=1}^{K} pts_k}{3 \times K} \tag{14}$$

In two-parent homes, "parent" work-limitation status represents the most severely limited parent with whom the child resides at age 14 (13 if he/she does not reside with either parent at age 14). Work-limitation data at the household level is treated as missing if, and only if, it is missing for both parents. In two-parent homes where only one parent has a reported limitation status, the household takes on the limitation status of the observed parent. This essentially treats the missing-data parent as never limited. In robustness checks, secondary work-limitation definitions observe the parent over three and nine years, as well as six years when the child is 12-17 years old.

Given the longitudinal nature of the study, the duration of observation for a particular individual's work-limitation status materially changes his/her classification (discrete) or index-score (continuous). Cross-sectional estimates of work-limitation reports from the National Health Interview Survey (NHIS) suggest approximately 10% of the population report a work-limiting condition in any given year, or 7.5%-8% of the population in the Current Population Survey (CPS) (Burkhauser et al. 2002). However, cross-section reports capture both temporary and chronic conditions. Naturally, the duration of observation then in a longitudinal study is key to estimating prevalence of work-limitations in the population. Longer observation windows increases the overall prevalence of work-limitation reports, but one should observe fewer chronic conditions than in the cross-section. In this paper's PSID sample, approximately 25% of parents report some level of work-limitations at least once over the course of three years, and this number increases to 33% and 40% over six and nine years respectively. Unsurprisingly, chronic conditions (defined as at least three positive work-limitation reports over the course of observation) are less common, but still somewhat prevalent in the sample. Nearly 8% of the sample reports chronic conditions under a three-year observation (work-limitations are identified in each year of observation), and this number increases to 12% and 17% under longer observation windows.

Longer observation windows are arguably more inclusive of persons who experience work-limitations, as the disadvantages associated with work-limitations can linger years after onset (Meyer and Mok 2013). However, practical implementation poses some concerns within the PSID framework. 1981 is the earliest work-limitations observation year for a full set of parents. Prior to that wave, work-limitation questions were not asked of married mothers. Therefore, in order to include the work-limitation status of mothers in the sample, one cannot draw data prior to 1981. The multi-generational framework poses an additional constraint on the other end of the observation window. Literature advises against observing child's earnings at too young an age (Chetty et al. 2014b; Haider and Solon 2006; Grawe 2006). Therefore, the natural termination period for observing parents' work-limitation status corresponds to final year of feasible income observation. In order to ensure children are at least thirty by the time income is observed in the subsequent generation, the final income report for parents is in 1997. This corresponds to a final work-limitation report in the parent's generation in 1996, or 16 total years of feasible observation[7].

Ideally, one would prefer to observe work-limitations over a long period and with a large sample. However, given the constraints noted above, this is not feasible. There is a trade-off between the number of cohorts (sample size) and duration of work-limitation observation. For example, if three years are used to observe work-limitations, it is feasible to observe 14 birth cohorts. If the observation window is six years, the number of feasible cohorts drops to 11. Observing work-limitations over nine years further reduces the number of cohorts to eight. This study elects to use a six-year observation period for work-limitations, and uses the alternative observation windows as robustness checks.

The eleven cohorts this study elects to follow are the 1972-1982 birth cohorts with a total sample size of 1,128. This balances concerns with observing child income in the subsequent generation at too young an age (making observation of later cohorts challenging), as well as observing the parent's socio-economic status at younger ages. Grawe (2006) and Haider and Solon (2006) suggest income reports are least biased when taken from around a parent's mid-life. Birth cohorts 1972-1982 have an average (unweighted) parent age of 39.67 years ranging from 28 to 61. 98.7% of parents fall within Chetty et al. (2014b)'s suggested range of 30-55 when income is consistently measured at the child's age 12 to 14. Alternatively, birth cohorts 1969-1979 are also feasible within the work-limitation observation parameters

[7]PSID income observations are self-reports about the previous calendar year's income

if parent's income is observed when the child is aged 14-17. In this case parent's unweighted average age is 42.45, but ranges from 31 to 71. 97.8% of the sample still falls within Chetty et al. (2014b)'s suggested range; however, the overall sample size drops from 1,128 to 997 because earlier cohorts tend to have fewer matches. With this in mind, the main specification utilizes cohorts 1972-1982. However, cohorts 1969-1979 are also analyzed in robustness checks. Unless otherwise noted, all estimates and results are adjusted for the PSID complex survey design using PSID cluster, strata, and an average of individual cross-sectional weights from the waves in which the child's outcome is observed[8].

3.4 Empirical estimation of socio-economic persistence within sub-populations

The main specification for estimating the IGE is a log-log uncontrolled Ordinary Least Squares (OLS) regression (Chadwick and Solon 2002; Mazumder 2005; Aaronson and Mazumder 2008; Lee and Solon 2009; Chetty et al. 2014b)[9], and this study follows that convention. Recall that the estimated statistic does not have a causal interpretation, rather it should be viewed as a summary statistic (Mazumder 2005). Theoretical research (i.e. Becker and Tomes 1979, 1986; Solon 2004, 2014) relies on earnings as opposed to income to estimate the persistence of socioeconomic status between generations. However, within the parent's budget constraint in Solon (2004, 2014), one can conceptualize the theory in terms of permanent income. Many applied researchers opt for estimating the IGE with income proxies as opposed to earnings (e.g. Chadwick and Solon 2002; Aaronson and Mazumder 2008; Lee and Solon 2009), and Mazumder (2005) suggests that although the theoretical underpinnings are not primarily based on income, it can provide information on the available resources while

[8] See Heeringa, Berglund, and Khan (2011) for more information on PSID design specifications, cluster and strata.

[9] Mazumder (2005) also uses a Tobit framework for dealing with particularly low or high earnings.

the child is growing up, may be less prone to transitory shocks, and may be particularly useful in estimating persistence among lower socioeconomic statuses who rely more heavily on transfer income (Mazumder 2005). One drawback of family income proxies in the child's generation is the implications of assortative mating that it necessarily raises (Chadwick and Solon 2002). Specifications including a mix of income and earnings are less common[10], and not in the strictest sense the IGE estimate itself but nonetheless are of great interest and still informative on persistence of socio-economic status (Mazumder 2005).

This study elects to follow the approach of estimating intergenerational persistence using an income-earnings formulation as its main specification. First, this research is particularly interested with the comparison of mobility sub-setting the population by a parent's work-limitation status. Previous literature is clear that apart from lower earnings (Meyer and Mok 2013, 2014), one observes higher prevalence of non-employment (Lauer and Houtenville 2017; Meyer and Mok 2013) among persons with disabilities or work limitations, which will make earnings measurement infeasible and ill advised for this particular application. Second, using PSID it is impossible to observe the work-limitation status of the non-PSID sample[11] spouse. Therefore, utilizing the income and earnings that he/she adds to the Family Unit (as well as Other Family Unit Members) dilutes the portion of the observed socio-economic outcome in the child's generation that can be readily associated with observed parental work-limitation status. In other words, one should expect that parent-child pairs categorized as "non-limited" also include child-generation outcomes (the Family Unit income) reflecting

[10]See Chadwick and Solon (2002), Mazumder (2005) Chetty et al. (2014b) for examples of income-earnings specifications in some capacity. See Table 9 in Mazumder (2005) In Chetty et al. (2014b), a rank-rank estimate using parent family income with child's earnings reveals an estimate that is similar in magnitude to an estimate using child's individual income and slightly lower than one using child's family income.

[11]"PSID sample" is distinct from the sample employed in this study. It identifies individuals who are part of the PSID pool: these are in this case original PSID family members and their decedents. See https://psidonline.isr.umich.edu for more information on PSID generational following rules and sample design.

unobserved parent work-limitations. Due to the non-standard income-earnings specification, in sensitivity analysis the Family Unit income of the child is nevertheless substituted for earnings, with no major change to results.

Attenuation and life-cycle bias are always a concern in IGE estimation. In this study, attenuation bias is mitigated by using a three-year moving average of parent income, and a two-wave moving average of child's earnings. Assuming that using income as opposed to earnings does not fully address the issue of transitory shocks[12], as discussed in section 3.2, one could reasonably expect greater transitory income shocks among those experiencing a work-limitation. In this case, the attenuation bias would be greater among the populations identified as work-limited. Any inferences regarding the differences between the work-limited and non-limited subpopulations should be viewed as minimum estimates. On the other hand, life-cycle bias is mitigated in the child's generation by consistently observing child's income between the ages of 30 - 33[13]. Parent income is consistently observed at the child's age 12-14[14]. Parent ages in the main sample are between 28 and 61, with 98.7% between the ages of 30 and 55[15]. The main specification includes a flexible parent age control to help adjust for the range of ages following the examples of Lee and Solon (2009) and Aaronson and Mazumder (2008). Therefore, the main estimated equation takes the following form:

$$\ln e_c = \beta_0 + \beta_1 \ln y_p + \beta_2(age_p) + \beta_3(age_p)^2 + \beta_4(age_p)^3 + \beta_5(age_p)^4 + \epsilon \tag{15}$$

[12]See Mazumder (2005) for why income could possibly mitigate transitory shocks.

[13]Due to the biannual nature of PSID later survey waves, approximately half the sample observes income at age 30 and 32 and the other half observes income at ages 31 and 33.

[14]Hertz (2007) suggests that holding constant the child's age during parent's income observation is generally sufficient to mitigate life-cycle bias.

[15]Chetty et al. (2014b) suggests IGE estimates are largely insensitive for parent age observed within this range.

Logged parent income is represented by $\ln y_p$ in equation (15) and is measured by a three-year moving average consistently observed at the time the child is age 12-14[16]. Child's earnings ($\ln e_c$) is a logged 3-year (2-wave) moving average of the child's individual labor earnings when the child is 30-33 years old[17]. All income and earnings are normalized to 2014 dollars. Parent age (age) is the average parent age. All parent variables are assigned based on the parent(s) the child lived with at age fourteen. In the event the child did not reside with either biological or adoptive parent at age fourteen, the parent with whom he/she resided at age thirteen is substituted[18]. Sons and daughters were pooled to maintain a high sample size and drawing on previous literature suggesting estimates for sons and daughters are similar and/or statistically non-differentiated (Chetty et al. 2014b; Lee and Solon 2009). Finally, successive birth cohorts were pooled again to maintain a high sample size and based on a growing literature suggesting there is no statistical trend in intergenerational mobility in the United States (Chetty et al. 2014a; Lee and Solon 2009)[19].

The main specification for this study separately estimates equation (15) for mutually exclusive subpopulations by the parent's work-limitation status with β_1 the key estimate of interest. In the spirit of Meyer and Mok (2013), one formulation includes discretized work-limitation categories of non-limited and any limitation. Those with any limitation are further disaggregated into temporary and chronic; and within the chronic category: not-severe and severe. Additionally, the work-limitation index is binned into thirds and fourths to disaggregate the experience of work-limitations (see section 3.3 for more details). In all cases, the reference population is the non-limited parent-child pairs and uses a Chi Squared

[16] Note that this corresponds to collecting income from the waves in which the child was 13-15.

[17] Recall only two waves are observed for a three-year moving average due to biannual waves in later years of PSID.

[18] This represents 13 cases in the main sample

[19] Aaronson and Mazumder (2008) suggests that there is a long-run trend of decreased mobility in the U.S.; however, as this study is only considering recent birth cohorts it does not apply.

Test to determine if mobility estimates are statistically different. All reported statistics and estimates are adjusted for the PSID complex survey design using provided stratum, cluster, and an average of cross-sectional weights from the wave in which child's earnings are observed.

4 Results

Tables 1 and 2 demonstrate that the sample of work-limited parents in this study is consistent with expectations of disadvantage. Table 1 disaggregates parent work-limitation by discrete categories and table 2 breaks up the work-limited sample by thirds according to the parent's (continuous) work-limitation index[20]. In both cases, those who experience more chronic and/or severe conditions face greater disadvantage. This sample observes lower income, employment and educational attainment among severe and/or chronic work-limitation conditions. There is also a higher proportion of parents reporting disability for more severe and/or chronic conditions.

Table 1: Parent's descriptive statistics by discrete work-limitation status

	N	Income		Age	Employment		Disability (n.l.f.)		Married (N=1,125)	Education (N=1,113)	
Non-Limited	753	$103,463		40.66	0.81		0.00		0.79	13.60	
Any Limitation	375	$ 87,545	*	41.36	0.72	***	0.02	***	0.84	13.15	**
Temporary	234	$ 96,874		41.07	0.77		0.00	*	0.84	13.29	
All Chronic	141	$ 71,127	***	41.88	0.64	***	0.06	***	0.83	12.92	**
Chronic-Not Severe	105	$ 77,583	***	41.90	0.73	**	0.02		0.85	13.19	
Chronic-Severe	36	$ 54,101	***	41.82	0.40	***	0.16	***	0.79	12.20	***

Source: Author's calculations using PSID (N=1,128)
Notes: Estimates are adjusted for survey design using PSID cross section weights & linearized s.e.
Income & earnings adjusted for inflation and represents 2014 USD
"Disability (n.l.f.)" represents individuals reporting not being in the labor force due to disability
$***p < 0.01, **p < 0.05, *p < 0.1$ (reference = Non-Limited)

[20] See table A1 in the Appendis for disaggregation of the work-limitation index by quartiles. These statistics follow similar patterns to those described for the partition by thirds, but have significantly smaller samples.

Table 2: Parent's descriptive statistics by thirds of work-limitation index

	N	Income		Age	Employment		Disability (n.l.f.)		Married (N=1,125)		Education (N=1,113)	
Non-Limited	753	$103,463		40.66	0.81		0.00		0.79		13.60	
Bottom Third	142	$106,039		41.34	0.79		0.00		0.94	***	13.38	
Middle Third	120	$ 89,337	*	41.06	0.79		0.01		0.83		13.23	
Top Third	113	$ 58,366	***	41.71	0.56	***	0.07	***	0.69	*	12.73	**

Source: Author's calculations using PSID (N=1,128)
Notes from Table 1 apply.

In the child's generation, one can observe a marked decrease in mean earnings and income by parent's work-limitation status (tables 3 and 4). Earnings are not statistically different from the non-limited category. The lack of significance is in part due to large standard errors, and if parent's work limitations are disaggregated by quartiles of the work-limitation index, children of parents with the 25% most chronic and severe limitations do observe statistically lower earnings (see table A2 in the Appendix). Income is consistently statistically lower for children of work-limited parents. Additionally, one observes less employment and lower educational attainment in the child's generation among those with chronic and/or severely limited parents.

Table 3: Child's descriptive statistics by parent's discrete work-limitation status

	N	Earnings	Income		Female	Employment		Education (N=1,102)	
Non-Limited	753	$54,734	$91,188		0.46	0.93		14.55	
Any Limitation	375	$47,270	$74,904	**	0.48	0.88	**	14.44	
Temporary	234	$47,293	$73,389	**	0.47	0.89		14.49	
All Chronic	141	$47,229	$77,569		0.49	0.87	**	14.34	
Chronic-Not Severe	105	$49,960	$82,779		0.51	0.89		14.69	
Chronic-Severe	36	$40,026	$63,828	**	0.46	0.80	**	13.44	**

Source: Author's calculations using PSID (N=1,128)
Notes: Estimates are adjusted for survey design using PSID cross section weights & linearized s.e.
Income & earnings adjusted for inflation and represents 2014 USD
$***p < 0.01, **p < 0.05, *p < 0.1$ (reference = Non-Limited)

Table 4: Child's descriptive statistics by thirds of parent work-limitation index

	N	Earnings	Income		Female	Employment		Education (N=1,102)	
Non-Limited	753	$54,734	$91,188		0.46	0.93		14.55	
Bottom Third	142	$47,216	$74,195	**	0.45	0.89		14.52	
Middle Third	120	$50,367	$78,885	*	0.51	0.88	*	14.84	
Top Third	113	$44,170	$71,864	*	0.49	0.87	*	13.90	**

Source: Author's calculations using PSID (N=1,128)
Notes from Table 3 apply.

Separate estimation of intergenerational mobility within subpopulations reveals statistically less mobility (higher IGE estimate) for parent-child pairs identified as work-limited in the parent's generation. From figures 1 and 2 it is clear that the bulk of these results are driven by parents with severe and/or chronic conditions. While the "Any" work-limitation category is statistically different than the non-limited category at the 10% level in figure 1, when this category is disaggregated into temporary and chronic or temporary, chronic-not-severe and chronic-severe, it is only the chronic-severe category that remains statistically different from the non-limited category. Similarly in figure 2, the bottom and middle third of parent work-limitation indexes do not experience statistically lower mobility. It is only the top third where one observes statistically lower mobility (see figure 3 in the Appendix for an analogous comparison of the work-limitation index by quartiles.).

IGE estimates do not differentiate between upward and downward mobility, nor do they inform on the mobility of sample members between work-limitation classifications. Therefore, transition matrices are included to fill this void. The transition matrix is limited only to quartiles of the weighted PSID distribution by thirds of parent's work-limitation index due to sample size. Consistent with earlier findings, transition matrices observe relatively fewer children of severe/chronically work-limited parents in the top of the earnings distri-

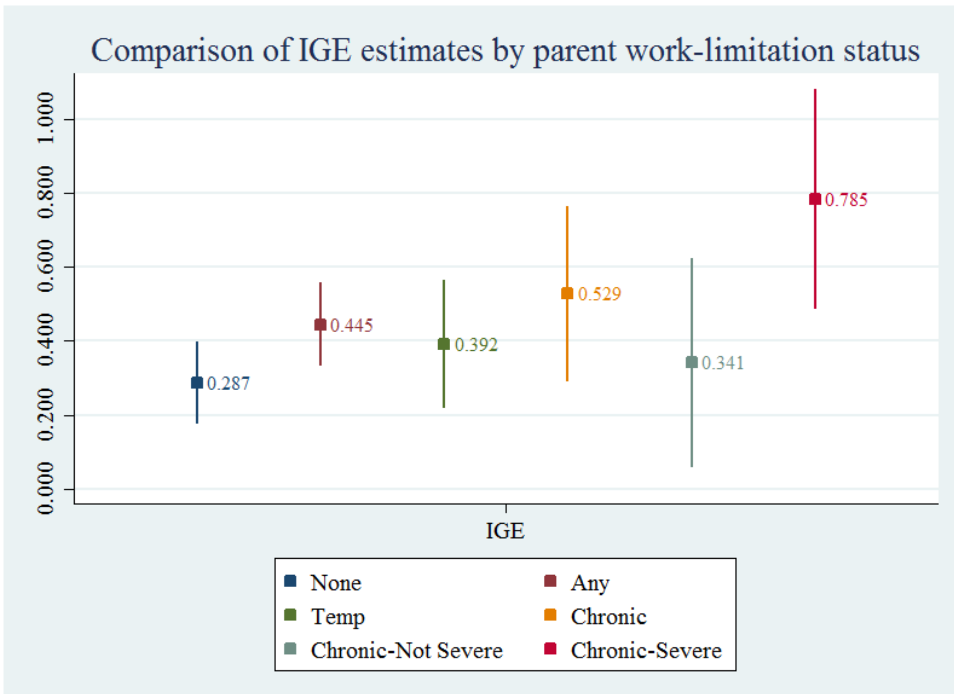

Figure 1: Mobility estimates for the full sample of six-years disability observation by parent's discrete work-limitation status.

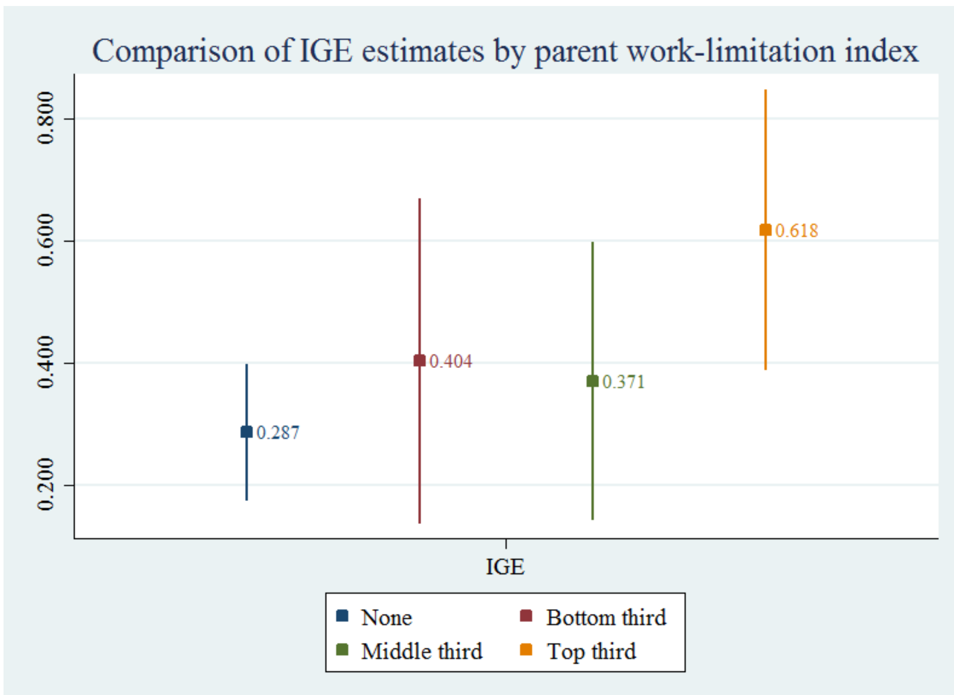

Figure 2: Mobility estimates for the full sample of six-years disability observation by thirds of parent's work-limitation index.

bution and relatively more in the bottom (see table 5). Among the work-limited sample, there appears to be more persistence in parent-child quartiles in the bottom half and a little less persistence in the top. If upward (downward) mobility is defined to be a child achieving any quartile greater (less) than his/her parent, and stationary status is persistence in the same quartile, there is perhaps some evidence of greater downward mobility among the work-limited and decreased upward mobility (see table 6). This is especially true among the most severe/chronic conditions; however, it is imperative to note the extremely small number of observations in each cell when work-limitations are disaggregated.

5 Sensitivity and Robustness

The results presented in section 4 are for the most part robust to various sensitivity tests. In particular, longer and shorter observation periods for work limitations produce similar inferences for mobility of children from work-limited homes depending on the categorization of parent work-limitation status. More importantly, due to the non-linearities in IGE estimation (Chetty et al. 2014b) and selection bias in group assignments, the results are not sensitive to selecting a sample of non-limited parent-child pairs that mimic the limited sub-sample's characteristics such as lower income and educational attainment. Many of the sensitivity results are available in tables 7 and 8[21]. Main results are the first row of each table as a reference for the sensitivity analysis.

[21] Sensitivity by quarters of parent's work-limitation status is available in the Appendix table A3

Table 5: Transition matrices by thirds of parent work-limitation index

Total sample

Parent Income	Child's Earnings 1	2	3	4
1	63.57	20.54	13.18	2.71
2	34.31	33.89	19.67	12.13
3	23.82	31.66	24.14	20.38
4	15.20	19.45	28.88	36.47
Total	32.49	26.11	22.10	19.30

Work-Limited sample

Parent Income	Child's Earnings 1	2	3	4
1	67.62	17.14	11.43	3.81
2	34.78	35.87	21.74	7.61
3	22.22	34.26	25.93	17.59
4	11.69	28.57	28.57	31.17
Total	35.60	28.80	21.47	14.14

No Limitations

Parent Income	Child's Earnings 1	2	3	4
1	60.78	22.88	14.38	1.96
2	34.01	32.65	18.37	14.97
3	24.64	30.33	23.22	21.80
4	16.27	16.67	28.97	38.10
Total	30.93	24.77	22.41	21.89

Bottom Third

Parent Income	Child's Earnings 1	2	3	4
1	69.57	17.39	13.04	0.00
2	30.56	38.89	25.00	5.56
3	24.44	33.33	26.67	15.56
4	15.38	30.77	20.51	33.33
Total	30.77	31.47	22.38	15.38

Middle Third

Parent Income	Child's Earnings 1	2	3	4
1	62.5	18.8	15.6	3.1
2	29.2	37.5	29.2	4.2
3	17.5	35.0	30.0	17.5
4	3.9	30.8	30.8	34.6
Total	28.7	30.3	26.2	14.8

Top Third

Parent Income	Child's Earnings 1	2	3	4
1	70.00	16.00	8.00	6.00
2	43.75	31.25	12.50	12.50
3	26.09	34.78	17.39	21.74
4	16.67	16.67	50.00	16.67
Total	48.72	23.93	15.38	11.97

Notes: Sample includes outliers, but not students,homemakers, or children who did not reside with parent at age 14. All cells $\leq$ 20 obs. for all disaggregated limited categories (exception: cell(1,1) of top third). N= 1,145; Percentages sum to 100 by row.

Table 6: Aggregate upward and downward mobility

	Lower	Stationary	Higher
Full sample	0.38	0.40	0.22
Non-limited	0.38	0.39	0.24
Any limited	0.40	0.40	0.20
Bottom Third	0.39	0.42	0.19
Middle Third	0.37	0.41	0.22
Top Third	0.47	0.34	0.19

Notes: See notes table 5
Rows sum to 100%

Rows 2 and 3 of tables 7, 8, and A3 present the results if work-limitation status were observed over three and nine years respectively. The attractive aspect of the three-year observation window is the larger sample size which can allow more precise estimation. However, it also obscures work-limitation duration as many "non-limited" observations do experience work-limitations over longer observation periods. Additionally, parent income information is only observed exactly during the time frame of observed work-limitation status, implying there could be a more direct relationship between categorization on income levels. In spite of these shortcomings, results suggest that more chronic and severe conditions (as measured discretely or by quarters of the work-limitation index) experience less mobility.

Under a nine-year observation window one can observe work-limitations for longer durations and capture more of the group that experiences disadvantage. Due to data collection restrictions three additional birth cohorts must be excluded leaving a sample of only 840. Given the smaller samples, it is unsurprising that the standard errors generally increase, and some of the significance is lost. However, with discrete work-limitation status (table 7), there is still evidence of lower mobility for the chronic-severe parent-child pairs.

Table 7: Sensitivity by parent's discrete work-limitation status

	N	Non-Limited	Any Limit	Temporary	Chronic	Chronic, not severe	Chronic, severe
Main Results	1128	0.287	0.445 *	0.393	0.528	0.341	0.785 **
		(0.0546)	(0.0558)	(0.0853)	(0.116)	(0.138)	(0.144)
3yr work limit	1441	0.315	0.450	0.346	0.675 **	0.537	0.724 *
		(0.0519)	(0.0642)	(0.079)	(0.118)	(0.182)	(0.179)
9yr work limit	840	0.315	0.447	0.431	0.425	0.268	0.825 **
		(0.0709)	(0.076)	(0.0929)	(0.122)	(0.0918)	(0.204)
Child FU income	1234	0.358	0.370	0.282	0.531	0.390	0.740 *
		(0.0496)	(.0671)	(0.0693)	(0.129)	(0.153)	(0.191)
Sons	551	0.302	0.368	0.319	0.713 *	0.366	0.928 **
		(0.0608)	(0.117)	(0.123)	(0.196)	(0.23)	(0.258)
Daughters	577	0.276	0.512 **	0.503 **	0.515 **	0.663	0.479
		(0.0788)	(.0679)	(-0.092)	(.0726)	(-0.227)	(0.143)
Remove SEO	791	0.263	0.439	0.386	0.485	0.202	0.839 ***
		(0.0679)	(.0631)	(0.0945)	(0.141)	(0.127)	(0.143)
Remove 1975&1977	930	0.295	0.430	0.380	0.481	0.298	0.682
		(0.0617)	(.0714)	(0.109)	(0.113)	(0.145)	(0.21)
Remove work-limited children	964	0.269	0.440 *	0.387	0.542	0.353	0.825 ***
		(-0.06)	(0.057)	(0.088)	(0.134)	(0.145)	(0.143)
Parent income, child's age 17	997	0.303	0.279	0.339			
		(0.0805)	(0.0773)	(0.0772)			
4-5 years parent income	1130	0.314	0.449	0.395	0.544	0.399	0.792 **
		(0.0608)	(0.0638)	(0.088)	(0.115)	(0.141)	(0.176)
Trim child earnings < $125,000	1086	0.213	0.423 **	0.375 *	0.491 *	0.305	0.747 ***
		(0.0523)	(0.0583)	(0.0858)	(0.117)	(0.136)	(0.148)
Matched income	750	0.314	0.445	0.393	0.528	0.341	0.785 **
		(0.0797)	(0.0558)	(0.0853)	(0.116)	(0.138)	(0.144)
Matched education	743	0.241	0.445	0.393	0.528	0.341	0.785 **
		(0.0894)	(0.0558)	(0.0853)	(0.116)	(0.138)	(0.144)
Matched income & education	743	0.230	0.445 *	0.393	0.528 *	0.341	0.785 ***
		(0.0786)	(0.0558)	(0.0853)	(0.116)	(0.138)	(0.144)
1 child/ unique "family"	899	0.274	0.424	0.335	0.566 *	0.426	0.752 **
		(0.0641)	(.0685)	(0.0961)	(0.124)	(0.151)	(0.186)
2 parent homes	738	0.412	0.310	0.367			0.438
		(0.0951)	(.0718)	(0.113)			(0.147)
Single parents	390		0.631	0.570	0.775	0.467	1.206
			(0.119)	(0.135)	(0.149)	(0.361)	(0.108)
Unweighted	1128	0.335	0.421	0.399	0.472	0.422	0.607
		(0.0411)	(0.056)	(0.0629)	(0.112)	(0.146)	(0.181)
Rank-rank (weighted dist., unweighted est.)	1100	0.287	0.368	0.377	0.363	0.357	0.359
		(0.0331)	(0.0414)	(0.0498)	(.0751)	(.0982)	(0.123)
Rank-rank (PSID sample, unweighted)	1146	0.369	0.512 **	0.520 **	0.514	0.505	0.549
		(0.0391)	(0.0516)	(0.0615)	(.0952)	(0.122)	(0.16)
Rank-rank (PSID sample, weighted)	1146	0.344	0.488 *	0.476	0.480	0.468	0.597
		(0.0343)	(0.0718)	(0.0891)	(0.111)	(0.138)	(0.188)
Rank-rank (PSID pop, weighted)	1100	0.230	0.344	0.305	0.395	0.314	0.516 **
		(0.037)	(0.0608)	(0.079)	(0.0972)	(0.124)	(0.132)

Source: Author's calculations using PSID
Notes: Estimates adjusted for survey design using PSID cross section weights & linearized s.e. unless otherwise noted.
IGE estimates not statistically non-zero (5% level) are omitted
$***p < 0.01, **p < 0.05, *p < 0.1$ (reference = Non-Limited)

Table 8: Sensitivity by thirds of parent's work limitation index

	N	Non-Limited	Bottom Third	Middle Third	Top Third	
Main Results	1128	0.287	0.404	0.371	0.617	**
		(0.0546)	(0.13)	(0.111)	(0.113)	
3yr work limit	1441	0.315	0.315	0.507	0.593	
		(0.0519)	(0.0971)	(0.12)	(0.139)	
9yr work limit	840	0.315	0.400	0.339	0.574	
		(0.0709)	(0.146)	(0.117)	(0.169)	
Child FU income	1234	0.358	0.303	0.356	0.532	
		(0.0496)	(.0988)	(0.101)	(0.137)	
Sons	551	0.302	0.333	0.390	0.758	*
		(0.0608)	(0.133)	(0.16)	(0.23)	
Daughters	577	0.276	0.540	0.473	0.449	
		(0.0788)	(0.205)	(0.102)	(0.131)	
Remove SEO	791	0.263	0.404	0.330	0.626	*
		(0.0679)	(0.142)	(0.116)	(0.141)	
Remove 1975&1977	930	0.295	0.421	0.357	0.448	
		(0.0617)	(0.154)	(0.122)	(0.167)	
Remove work-limited children	964	0.269	0.397	0.356	0.659	**
		(0.06)	(0.139)	(0.113)	(0.117)	
Parent income, child's age 17	997	0.303	0.464	0.279	0.302	
		(0.0805)	(.0932)	(0.121)	(0.147)	
4-5 years parent income	1130	0.314	0.339	0.444	0.589	*
		(0.0608)	(0.125)	(0.11)	(0.12)	
Trim child earnings < $125,000	1086	0.213	0.341	0.364	0.589	**
		(0.0523)	(0.123)	(0.111)	(0.113)	
Matched income	750	0.314	0.404	0.371	0.617	**
		(0.0797)	(0.13)	(0.111)	(0.113)	
Matched education	743	0.241	0.404	0.371	0.617	**
		(0.0894)	(0.13)	(0.111)	(0.113)	
Matched income & education	743	0.230	0.404	0.371	0.617	**
		(0.0786)	(0.13)	(0.111)	(0.113)	
1 child/ unique "family"	899	0.274	0.291	0.376	0.691	**
		(0.0641)	(.131)	(0.119)	(0.115)	
2 parent homes	738	0.412	0.403			
		(0.0951)	(0.152)			
Single parents	390		0.391	0.497	0.833	
			(0.174)	(0.124)	(0.141)	
Unweighted	1128	0.335	0.415	0.405	0.438	
		(0.0411)	(.0876)	(0.083)	(0.134)	
Rank-rank (weighted dist., unweighted est.)	1100	0.287	0.377	0.368	0.366	
		(0.0331)	(.0711)	(0.0696)	(0.0853)	
Rank-rank (PSID sample, unweighted)	1146	0.369	0.494	0.495	0.560	*
		(0.0391)	(0.0848)	(0.0889)	(0.112)	
Rank-rank (PSID sample, weighted)	1146	0.344	0.433	0.462	0.598	**
		(0.0343)	(0.126)	(0.142)	(0.103)	
Rank-rank (PSID pop, weighted)	1100	0.230	0.216	0.356	0.475	**
		(0.037)	(0.114)	(0.132)	(0.0913)	

Source: Author's calculations using PSID
Notes: Estimates adjusted for survey design using PSID cross section weights & linearized s.e. unless otherwise noted. IGE estimates not statistically non-zero (5% level) are omitted
$***p < 0.01, **p < 0.05, *p < 0.1$ (reference = Non-Limited)

Row 4 of the sensitivity tables (7, 8, and A3) replaces child's individual earnings with child's family unit income. This modification is arguably closer to the literature where parent and child's socioeconomic status is measured by the same indicators. Sample sizes increase as students and homemakers are no longer excluded. Family unit income appears to mute differences between groups. This could be due to non-perfect assortative mating as well as the fact that one can only observe the work-limitation status of one of the income-earners in the family unit (the PSID sample member). Therefore, IGE estimates should be higher for the non-limited classification not only due to measurement with family unit income[22], but also because there are likely unobserved work-limited observations in that classification from the non-PSID sample partner. Nevertheless, there continues to be a statistical difference between the chronic-severe group and non-limited group at the 10% level, although this does not hold for partitions of the work-limitation index.

Rows 5 and 6 split the sample by sons and daughters. Results are fairly similar across genders with the exception of the IGE estimate for the most chronic and/or severe limitation categories where the daughters' estimate is lower. While this observation is intriguing, without larger samples (and smaller standard errors), it is difficult to suggest that there is any difference by gender. This coincides with previous literature suggesting IGE estimates are similar across genders (Chetty et al. 2014b; Lee and Solon 2009). For both genders taken independently, there continues to be suggestive evidence of decreased mobility for the work-limited population.

[22]See Chetty et al. (2014b) and Mazumder (2005)

Row 7 removes all observations associated with the Survey of Economic Opportunity (SEO) sample of PSID. This sub-sample suffers from some irregularities at the design phase in the initial selection probability (Brown 1996). As the SEO was a low-income target sample, it is unsurprising that some IGE estimates decrease slightly; however, the main results remain unaltered.

The 1975 and 1977 birth cohorts observe curiously higher prevalence of work limitations (not pictured in descriptive statistics). In both cases, approximately 43% of the birth cohort falls into one of the limited categories versus a more typical range of 25-35%. Additionally, many of these reports are chronic in nature (19.5% and 24% respectively)[23]. There is no immediate rationale for increased reports for these cohorts given that the 1976 cohort appears unaffected. However, it is noted that in particular parents of the 1975 birth cohort experienced high unemployment in the years leading up to the six-year work-limitation observation (approximately 9.6% per estimates from the Bureau of Labor Statistics in 1982 and 1983). Given this observation, row 8 removes the affected cohorts. Results are somewhat sensitive to this alteration, with only the quarter-partition of work-limitation status retaining any statistical significant differences. However, given that a number of these observations account for the most chronic and severe reports, it is unsurprising to see higher standard errors and decreased significance when they are removed.

Another source of unobserved heterogeneity that could confound results is the work-limitation status of the children. It is feasible to consider some work-limiting conditions may be genetically transmitted, so this analysis removes children who also report any work-limitation from approximately ages 27-34. Although in this sample there is little evidence to

[23] 1978 also experiences high prevalence of work-limitations (40%); however it is mostly driven by temporary reports (29%) rather than chronic reports as with the 1975 and 1977 birth cohorts.

suggest that children of work-limited parents tend to experience work-limitations as adults. In fact, for the weighted sample approximately 15% of non-limited parent-child pairs observe a work-limitation in the child's generation relative to 12.5% of limited parent-child pairs. With this in mind, it is unsurprising that the main impact on results from removing children who self-report work-limitations in the 4 waves up to (and including) earnings observations is higher standard errors, but no impact on observed lower mobility for traditionally disadvantaged groups.

As noted in section 3.3, the selection to follow birth cohorts 1972-1982 is at least partially arbitrary. Under a six-year observation window for work-limitations, it is also feasible to consider observing parent income slightly later and consider birth cohorts 1969-1979. Unfortunately, the decreased sample sizes make IGE estimates often imprecise (see row 10 of tables 7 and A3 in particular).

Attenuation bias is one of the main econometric concerns with IGE estimation (Haider and Solon 2006; Solon 1992). As noted previously, this study attempts to mitigate these concerns by utilizing multi-year averages of observed income and earnings. Theory and empirical work suggests that observing income or earnings over longer periods should give more precise, and generally *higher* IGE estimates (Haider and Solon 2006). While that observation appears to generally hold in this sample, it curiously does not hold for some of the groups for the work-limitation index disaggregation (see tables 8 and A3). Nevertheless, the IGE estimate for chronic and/or severely limited groups remains statistically higher than the non-limited group suggesting lower mobility.

The procedure for trimming earnings followed in this study was to simply half the family unit income trim (adjusted for inflation) from the Lee and Solon (2009) study. This retains all earnings less than approximately $530,000, which could be arguably high. Therefore, a more aggressive child earnings trim to $125,000 drops 42 observations, generally decreases IGE estimates, but does not ultimately alter inferences.

The next series of sensitivity tests consider different demographic characteristics that could result in selection bias into one of the work-limited categories. Persons with work-limitations tend to have lower income and earnings (e.g. Meyer and Mok 2013) as well as educational attainment (Ryan and Bauman 2016). Lower educational attainment is generally associated with lower earnings, and lower earnings themselves also can produce higher IGE estimates due to non-linearities in the statistic (Chetty et al. 2014b). Therefore, it is imperative to determine if observed lower mobility among disadvantaged groups may be due to one of these characteristics. These characteristics are not included as controls in the main specification due to concerns of endogeneity with income. In rows 13-16 of tables 7, 8, and A3 IGE estimates are reported for samples of non-limited parent-child pairs matching on observed characteristics of the limited sample. The matching procedure employs a nearest-neighbor approach without replacement to select a sub-sample from the non-limited group that best mirrors the income (row 13), education (row 14), and both income and education (row 15) of the work-limited sample. As expected, IGE estimates for the non-limited sub-sample increase when matched on income reflecting the documented non-linearities of the statistic (Chetty et al. 2014b). In spite of observed lower mobility among the low-income subsample, those with severe and/or chronic conditions continue to experience statistically lower mobility. When matching on education, there appears to be higher mobility for lower educational attainment categories if the parents do not experience work-limitations, amplifying differences with the work-limited sample. Matching on both income and education suggests greater mobility for the non-limited sample.

There also may be some concerns of homogeneity among observations from the same family unit. As standard errors already include clustered effects for primary stage units within the PSID sample design, another sensitivity test examines IGE estimates if a single (randomly chosen) child is observed from each unique parent set (row 16)[24]. Again, one continues to observe lower mobility among the most disadvantaged work-limitation groups.

The sample is then split into two-parent and single-parent homes. Although this sample does not suggest there is any difference in marital rates (see tables 1 and 2), in using family unit income, this characteristic could theoretically play a role. Row 17 considers two-parent homes and row 18 considers single-parent homes. It is difficult to draw much inference from this exercise due to small sample sizes and imprecise estimation. Even the non-limited category of single-parents does not have an IGE estimate that is statistically different from zero at any conventional level. Among two-parent homes, IGE estimates for the most disadvantaged appear to be much more similar to the non-limited population. While this could be a potential source of heterogeneity in observed intergenerational elasticity, it is difficult to infer much due to high standard errors are high.

A rank-rank specification is thought to perhaps be more insulated from changes in the underlying income distribution (Aaronson and Mazumder 2008) and can allow for a larger sample that is unburdened by trimming outliers and/or negative/zero income observations (Chetty et al. 2014b). The alteration here amounts to replacing child's earnings with the

[24]The sample comprises all only-children plus a randomly selected child from any parenting set.

child's rank in the earnings distribution, and replacing parent's income with parent's rank in the income distribution in equation (15). There are four rank-rank specifications for sensitivity analysis (rows 20-23 in tables 7, 8, and A3). The first weights quantiles according to longitudinal family weights in each generation using the final wave-weight from which data is obtained[25][26], and no additional weighting is employed in estimating the IGE. In the second rank-rank specification, no weighting is used at any stage and ranks are determined only among parent-child pairs from this study. The third specification applies the sample weights and complex survey design attributes to estimate the rank-rank slope among parent-child pairs in this study. Finally, the last specification ranks among the full PSID sample (as opposed to only parent-child pairs in this study), and again applies adjustments for survey design. A rank-rank specification is not the preferred specification in this study due to the inconsistencies and non-comparability of ranks and weights across waves. However, in spite of the shortcomings there remains evidence of lower mobility among the most disadvantaged (see tables 8 and A3 in particular).

6 The Education Channel

Previous results suggest children whose parents experience a work-limiting condition tend to face more persistence, or less intergenerational mobility, than their peers whose parents do not report limitations. This section begins to address one potential avenue that may contribute to greater persistence, or lower socio-economic status in the child's generation:

[25] Due to inconsistencies in weights across waves (see variables V21547 and V23361 for examples as well as the accompanying documentation at https://psidonline.isr.umich.edu/), when weights are applied in estimating quantiles, each cohort is ranked specifically only among PSID sample members in the years from which data is obtained as opposed to a full sample weighting scheme

[26] In order to ensure a single observation per household, only Heads are part of the ranking. There are a few PSID-sample Spouse/"Spouse" observations where the Head has missing moving average income in the wave corresponding to the child's age 15. In these cases, the Spouse/"Spouse" is ranked instead of the Head to maintain one observation per family unit in the ranking distribution.

post-secondary education. Descriptive statistics from table 3 and 4 show evidence of lower educational attainment among children whose parents experience the most chronic and/or severe work limitations. This section estimates an empirical model of the child's education enrollment and school exit relative to parent's health status, as measured by work-limitations.

Data still comes from the PSID, although it takes advantage of later birth cohorts (1985-1992) with richer covariate data in the parent's generation. More importantly, the later-cohort data allows the use of the PSID's Transition to Adulthood (TA) survey that provides detailed information on the child's (age 18+) enrollment status both currently and retrospectively until age 28. This allows constructing a full time-series of the child's educational history from secondary school on to post-secondary education (when applicable). The sample is restricted to only children who report terminating secondary education between the ages of 16 and 19. Therefore, the entire sample begins in school at the ages of 15 or 16[27]. Parent characteristics are adopted for all children who live with either biological parent at age 14 or 15, and parental covariates are generally an average over observed biological parents (e.g. age at the child's birth, educational attainment, marital status over the child's lifetime, and family-unit real income over the child's lifetime). When blue-collar employment, unemployment, and work-limitations are observed for both biological parents, the most severe report is adopted.

[27]Due to the biannual wave structure of the PSID and TA, in regression analysis odd birth cohorts (1985, 1987, 1989, 1991) observe parent covariates and child outcomes only at the child's even ages (16, 18, 20, 22); while even birth cohorts (1986, 1988, 1990, and 1992) observe data at the child's odd ages (15, 17, 19, 21). In the child's descriptive statistics however, the educational enrollment status at each age reflects the entire sample as enrollment is observed at all ages for each sample child.

The empirical strategy uses a static model for child's school enrollment, and the estimation equation takes the following form:

$$\begin{aligned} y_{it} =& \alpha + \beta_1 mildlmt_{it} + \beta_2 modlmt_{it} + \beta_3 sevlmt_{it} \\ &+ \sum_{p=1} \eta_p X_{itp} + \sum_{p=1} \gamma_p Z_{ip} + \sum_{c=1} \omega_c Z_{ic} + State_{it} + Age_{it} + \epsilon_{it} \end{aligned} \tag{16}$$

where y_{it} is a binary variable indicating whether child i is enrolled ($y_{it} = 0$) or not enrolled ($y_{it} = 1$) at age t[28]. $mildlmt_{it}$, $modlmt_{it}$, and $sevlmt_{it}$ represent a binary indicator for mild, moderate, and severe work limitations respectively. Coefficients β_1, β_2, and β_3 are the coefficients of interest, representing the empirical marginal effect of parental health (in this case, work-limitations) on the child's enrollment. Time-varying parent and child controls are all contained in X_{itp}, and include the parent's unemployment status, participation in blue collar work, marital status, real Family Unit income, and whether the child lives in a metropolitan area. Time-invariant parent controls (Z_{ip}) include the parent's work-limitation status (as measured by the work-limitation index discussed earlier), aggregate unemployment, blue collar occupation participation, marriage status, and real Family Unit income from the child's birth through age 16[29]. Additionally Z_{ip} includes average parental educational attainment (as measured at the child's birth)[30], and an average of parent age and age-squared at the child's birth. Z_{ic} represents observed child time-invariant characteristics such as gender,

[28]For clarity, this does not allow school re-entry, although there are 67 observations of school re-entry in the data. They represent less than 2% of the data, and restrict a first-difference approach to a binary outcome variable representing school exit.

[29]These controls go through age 16 because ages 15 and 16 are not used in estimating the level model because by sample construction all children are in school at these ages, resulting in zero between-individual variation in the dependent variable.

[30]There is likely some measurement error in parental educational attainment. PSID surveyed all Heads and Spouses in 1985 for updated educational attainment; however, in subsequent years through 1992 this data was not re-asked, rather pulled forward for individuals who are not new Heads or Spouses.

race (binary Caucasian formulation), number of siblings, and percentage of waves living in a metropolitan area from birth through age 16. Additional fixed-effects include the state of residence ($State_{it}$) to control for state-specific effects, most notably compulsory education requirements, and an age trend (Age_{it}) to address the natural progression of education. While it may also be important to include birth-cohort fixed effects, most notably to control for the Great Recession's impact on child enrollment decisions, this produces too little variation and multicollinearity in the specification when included with age effects. The first specification adopts a pooled Linear Probability Model (LPM) as in equation (16) with school non-enrollment as the dependent variable. Due to unobserved individual heterogeneity and correlation among various explanatory variables (e.g. Parent's current income and historical income), the estimates are very likely biased.

To begin addressing the issue of endogeneity in the estimation, a first-differenced model is used, which effectively drops all parent and child time-invariant observables from equation (16), resulting in the following specification:

$$\begin{aligned}\Delta y_{it} =& \beta_1 \Delta mild.wklmt_{it} + \beta_2 \Delta moderate.wklmt_{it} + \beta_3 \Delta severe.wklmt_{it} \\ &+ \sum_{p=1} \eta_p \Delta X_{itp} + State_{it} + Age_{it} + \Delta\epsilon_{it}\end{aligned} \tag{17}$$

where Δ represents a change over two years (one wave). In this case, Δy_{it} represents a school exit. More importantly, it also controls for unobserved individual heterogeneity. For this reason, equation (17) has removes all time-invariant characteristics, both observed as in Z_{ip} and Z_{ic}, and unobserved as in α_i. While this improvement makes important steps toward consistency, the estimates of interest (parent work limitation transitions) still obscures the effects of onsets verses recoveries as these are observed as positive or negative one (respectively) in a first-differenced model. As parents transition in and out of each severity of condition, the resulting coefficients of interest in equation (17) are essentially an average of onsets and recoveries.

The third model moves to address that last concern by differentiating static conditions as well as onsets and recoveries of varying degrees[31] in a split first-difference specification as in Mitra and Jones (2017). As with the first-difference model, all time-invariant characteristics are omitted for the same econometric reasons; however, the parent's work-limitation status is further differentiated as in the following:

$$\begin{aligned}\Delta y_{it} = {} & \beta_1 nochange\_mm\_wklmt_{it} + \beta_2 nochange\_sev\_wklmt_{it} + \beta_3 mm\_onset_{it} \\ & + \beta_4 none\_sev\_onset_{it} + \beta_5 mm\_sev\_onset_{it} + \beta_6 mm\_recovery_{it} + \beta_7 sev\_none\_recovery_{it} \\ & + \beta_8 sev\_mm\_recovery_{it} + \sum_{p=1} \eta_p \Delta X_{itp} + State_{it} + Age_{it} + \Delta\epsilon_{it}\end{aligned} \tag{18}$$

where coefficients $\beta_1 ... \beta_8$ are the coefficients of interest. Mild and moderate conditions are grouped for parsimony. $nochange\_mm\_wklmt_{it}$ represents a mild or moderate condition that is consistent over the two observed waves. $nochange\_sev\_wklmt_{it}$ similarly represents a condition that is severe over both waves. mm_onset_{it} is the onset of a mild or moderate condition from observing no limitation in the previous wave. $none\_sev\_onset_{it}$ is the

[31] "Onsets" and "recoveries" are not definitive beginnings or terminations of a work-limitation status. The nature of such limitations is often episodic, where individuals can transition in and out of a limitation status. Particularly in this data, waves are two years apart, allowing for changes in underlying health and circumstances. Over four waves if a parent's work limitation status is non-limited, severely limited, moderately limited, and severely limited, they would experience two severe onsets (one from no limitation, and one from the moderate condition), as well as a partial recovery from the severe limitation to a moderate limitation. Additionally, in two-parent homes, each waves adopts the most severe parent work-limitation report. Therefore, the dynamics of two parents transitioning in and out of work limitations are obscured. If both parents face work-limitations, yet only one recovers to no limitation, the observation will still be coded for a stagnant condition.

onset of a severe condition after an observation of no limitation the previous wave, while $mm\_sev\_onset_{it}$ is a worsening of an existing condition from mild or moderate to severe over two waves. $mm\_recovery_{it}$ represents observing a mild or moderate limitation followed by no limitation the subsequent wave. $sev\_none\_recovery_{it}$ represents observing a severe limitation one wave followed by no limitation the next. Finally, $sev\_mm\_recovery_{it}$ is an improvement of a severe limitation one wave followed by either a moderate or mild limitation the next. While Δ is absent from the specification for the main coefficients of interest, it is implicit in the formulation of the transitions. All results are unweighted because the main source of PSID sample-selection endogeneity (income) is controlled for in estimation (Solon, Haider, and Wooldridge 2015).

6.1 Descriptive statistics

Table 9 shows children of parents with work-limitations tend to experience lower enrollment rates for post-secondary education. Recall that the sample consists of children who report exiting secondary education between the ages of 16-19. While approximately 71% of children whose parents do not experience a work-limitation attend some college at age 20, only 61% of children whose parents experience any limitation do so. This gap is largely attributable to children whose parents experience the most chronic and/or severe limitations as represented by the bottom row, "Top Third" of the parental work-limitation index. These gaps appear to persist and widen at ages 21 and 22[32].

[32]All descriptive statistics are adjusted for the complex survey design. For reference, the sample-specific unadjusted means are also included in the Appendix, table A4. While there continues to be significant gaps in educational attainment, they are smaller likely due to the higher probability of low-income sampling in PSID.

Table 9: Child's descriptive statistics, adjusted for survey design

		Enrollment													Attainment	
	N	Age 17	Age 18		Age 19		Age 20		Age 21		Age 22		Exit Age		(N=1,255)	
Non-limited	828	99.2%	93.1%		79.4%		70.9%		67.3%		59.4%		20.557		13.992	
Any limitation	519	98.6%	88.0%	***	71.1%	***	60.8%	***	52.1%	***	44.1%	***	20.016	***	13.633	**
Bottom third	196	99.6%	91.6%		72.7%		65.1%		58.4%		45.9%	**	20.198		13.881	
Middle third	179	97.0%	88.5%		73.3%		62.5%		49.9%	***	43.1%	***	19.999	**	13.682	
Top third	144	99.0%	82.9%	**	66.4%	**	53.4%	***	46.8%	***	42.9%	**	19.805	***	13.276	***

Notes: Author's calculations using public-use PSID core and TA supplement data.
Estimates are weighted using TA weights and core stratum and clusters
$*p < 0.1 **p < 0.05 *** p < 0.01$

Parental descriptive statistics show the usual expected relationships. One can observe lower education (although not necessarily statistically significant) and income, as well as higher percentage of waves reporting unemployment, blue collar occupations, and age[33]. These statistics largely coincide with the earlier PSID sample from birth cohorts 1972-1982.

Table 10: Parent's descriptive statistics, adjusted for survey design

	N	Education (N=1,109)		Unemployment		Blue Collar		Real Income (N=1,345)		Marriage (N=1,345)		Age (N=1,200)	
Non-limited	828	14.16		6.0%		27.3%		$ 90,864		77.0%		28.77	
Any limitation	519	13.85	*	6.9%		36.1%	**	$ 81,375	**	84.2%	***	29.47	**
Bottom third	196	14.10		5.3%		33.5%		$ 90,281		88.6%	***	29.85	**
Middle third	179	13.79		6.7%		41.2%	**	$ 79,321	**	81.7%		28.37	
Top third	144	13.61	**	9.1%	**	33.8%		$ 72,438	**	81.6%		30.32	**

Notes: Author's calculations using public-use PSID core and TA supplement data.
Estimates are weighted using TA weights and core stratum and clusters
$*p < 0.1 **p < 0.05 *** p < 0.01$

[33]Sample-specific means again show similar, muted patterns and are included for the reader's reference Appendix table A5

6.2 Results

Model 1 of table 11 is a pooled linear probability model estimate[34]. These results suggest Severe work limitations are associated with a significantly lower probability of school enrollment. The linear probability model suggests about 9% increased probability of non-enrollment. Higher family income (both in the current time period and historically) is associated with greater probability of school enrollment, and a history of blue collar work is associated with lower probability of school enrollment. A child with more siblings is less likely to be enrolled, and women are more likely to be enrolled in school (see table A6 in the Appendix). As noted previously, this model presents obvious sources of endogeneity that prevent reliable coefficient estimates. In light of these considerations, there is little reason to suspect these estimates are valid.

Model 2 begins to address the issue of endogeneity by estimating a first-difference model. The coefficient on Severe work limitations is no longer statistically significant; however, the model captures transitions into and out of a Severe work limitation as one or negative one respectively (the interpretation of the mild and moderate coefficients is analogous). Therefore, it is not entirely unsurprising to find a null effect.

The final specification (model 3) addresses the concern of averaged effects in model 2. Transitions in and out of work-limitations are differentiated by onsets, recoveries, or stable conditions, as well as by severity. From this specification, one can observe it is the transitions from mild or moderate conditions to severe (and vice-versa) that are most likely to impact school enrollment. A severe work-limitation onset following a mild or moderate condition in the previous period is associated with a 12% increase in the probability of school exit.

[34]Full estimation results including time-varying and time-invariant covariates is available in the appendix table A6

Meanwhile, a severe condition that improves to mild or moderate is associated with a 8% reduction in the probability of school exit. Stable conditions over two waves, regardless of severity, do not statistically affect the child's probability of school exit; however, the coefficient particularly for a stable severe condition is positive, suggesting there could be some increased probability of school exit.

On the whole, evidence suggests that a parent's work-limitation status can impact the child's enrollment decision. Specifically, a worsening of an existing condition increases the probability of school exit; while an improvement of a severe condition decreases the likelihood of school exit. This buttresses the main results in this paper of higher persistence of socioeconomic status as measured by the IGE among parent-child pairs where the parent experiences chronic and/or severe work limitations. Education is often thought to be a main vector of improving socioeconomic status (e.g. Goldin and Katz 2009), and in intergenerational mobility literature it can serve as an instrument for income when such measures are either unavailable or unreliable (e.g. Chetty et al. (2014a) and Solon (1992)). In this sense, the child's decision to exit school is affected by the parent's health, which helps explain lower average educational attainment for children of parents with more severe/chronic work-limitations as in tables 3, 4, and 9. There are however, important limitations to these results. Endogeneity may still be a problem in the specification. For example, suppose a child's unobserved schooling preference is: $pref_{it} = \nu_i + \delta_{it}$, where ν_i is a time-invariant component and δ_{it} is a time-varying component. If a parent experiences a health shock that changes his/her work-limitation status, there is reason to suspect the child's time-varying school preference could also be affected. Therefore, the parent's health transition may still be correlated with the error. As this research continues to develop, within-model instrumental variables are being considered to help address for this endogeneity.

Table 11: Results for child's enrollment

	(1) Pooled LPM	(2) First Difference	(3) Split First Difference
Mild/Moderate (MM)	-0.00803	-0.0120	
	(0.0215)	(0.0185)	
Severe (S)	0.0796**	0.0387	
	(0.0323)	(0.0304)	
No change MM			0.00741
			(0.0474)
No change S			0.0392
			(0.0268)
None(t-1), MM(t)			-0.0207
			(0.0265)
None(t-1), S(t)			0.0122
			(0.0512)
MM(t-1), S(t)			0.124**
			(0.0601)
MM(t-1), None(t)			-0.0277
			(0.0274)
S(t-1), None(t)			0.0411
			(0.0605)
S(t-1), MM(t)			-0.0804*
			(0.0426)
N	3887	3979	3979
r2	0.319	0.194	0.196

Standard errors in parentheses
Author's calculations using PSID core and TA supplment
All specifications are unweighted, employ state fixed-effects,
and child-clustered robust standard errors
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

7 Discussion

Results and sensitivity analysis presented above suggest that disadvantages associated with work-limitations may not be immune from transfer to subsequent generations. Due to small sample sizes and some sensitivity in results, it is important to stress that further research on the topic is warranted, especially with larger samples. In many of the most important sensitivity exercises however, the main inference of lower observed mobility among the most disadvantaged groups remains intact.

IGE estimates here for the non-limited sample appear to be lower than most of the existing literature. In a U.S. context, the general consensus is that intergenerational elasticity hovers around 0.4 (Lee and Solon 2009; Solon 2002, 1992). Using administrative data, Chetty et al. (2014b) finds elasticity to be closer to 0.34 when excluding zero income as in other studies. The main results of this current study suggest an IGE estimate of 0.287 for the subsample without work limitations which is not statistically different from Chetty et al. (2014b), but that is statistically lower than the general consensus of 0.4 at the 5% level[35]. However, it is important to recall that the sample without work limitations comprises only approximately 65% of the total sample observed here. Among the entire sample IGE is estimated to be 0.342 using earnings and 0.367 using family unit income, neither of which is statistically different from the 0.4 general consensus measure.

This research substantively adds to existing work on both intergenerational mobility and disability. While great care has gone into establishing the best practices to estimate intergenerational mobility (see Haider and Solon 2006; Grawe 2006; Solon 1992 for examples), some recent work has focused on differentiated mobility by observed parent characteristics.

[35]F-statistic from an Adjusted Wald test = 4.29 and p-value of 0.0464.

To the best of the author's knowledge, the vast majority of mobility differentiation work has been along the lines of race (Collins and Wanamaker 2017; Hertz 2008, 2005), and to some extent geography (Chetty et al. 2014b; Hertz 2008) and gender (Lee and Solon 2009; Platt 2005; Chadwick and Solon 2002). Very little work has been done on differentiating mobility by parent's health or inability to actively engage in the labor market[36]. The present study begins to address this knowledge gap by differentiating mobility by parent work-limitation status.

Results from this study also add to the existing knowledge in the disability literature. Work-limitations are a common measure of disability in the literature (Meyer and Mok 2013; She and Livermore 2007; Burkhauser, Houtenville, and Rovba 2005). While the measure typically does not capture the same population with functional limitations (Burkhauser et al. 2002), it nevertheless consistently uncovers similar disadvantages and deprivations in the population[37]. Almost all studies on disability have focused on current, or in rare cases such as Meyer and Mok (2013, 2014), long-term implications of disability *for the individual*. Chen, Osberg, and Phipps (2015) is an example of the exception to this rule of thumb. In that study, the authors discovered that children of parents with disabilities tend to have lower educational achievement, but that the gap lessens with increased disability benefits in Canada (Chen, Osberg, and Phipps 2015). It is in this growing body of literature that the current

[36]There is one unpublished study that suggests the general practice of excluding zero-earners artificially deflates IGE estimates, and that these zero-earners are not evenly distributed across the population. Such earners typically have lower earnings when employed, and tend to have children with higher propensities to experience zero-earnings in their turn (Drewianka and Mercan 2009)

[37]Compare results of studies such as Kavanagh et al. (2015) with functional limitations, and Meyer and Mok (2013) with work-limitations. Also see Brucker et al. (2015), Mitra, Findley, and Sambamoorthi (2009), She and Livermore (2007), and Burkhauser et al. (2002) that include both functional and activity limitations.

study fits, as it is (to the best of the author's knowledge) the first attempt to separately estimate the most common measure of intergenerational mobility for the population with disabilities.

As the United States is a nation with relatively low intergenerational mobility, this study provides preliminary evidence that some of this lower mobility could be attributable to a parent's health status. More specifically, children whose parents experience worsening of an existing condition are more likely to exit school, and children whose parent's work-limitation condition improves (from severe to mild or moderate) are less likely to exit school. These transitions help explain the lower educational attainment of children whose parents experience chronic and/or severe work limitations. Future work needs to focus on the efficacy of specific policies (such as Social Security Disability Insurance) designed to mitigate disadvantages associated with disability to determine whether these policies have any impact on the transmission of disadvantage across generations. While data limitations of the 1972-1982 birth cohorts prevent such analysis in estimating the IGE, focusing only on educational outcomes with younger cohorts may be able to fill the gap in the future and address this pivotal concern in the U.S. context.

It is also important to note key limitations of the results and analysis presented here. The most obvious limitation is that of small sample sizes particularly for IGE estimation. When parents with chronic conditions are further disaggregated by severity, those with both chronic and severe conditions comprise fewer than 40 total observations. While the work-limitation index in part addresses these concerns, the partition by thirds likely still captures heterogeneous conditions within each third. The partition by fourths likely ameliorates the situation, but again begins to have small sample sizes. Therefore, the estimates presented here need to be cautiously interpreted as suggestive evidence pending further research.

The construction of the work-limitation index in equation 14 presents some challenges. PSID increased the number of questions to identify the severity of work-limiting conditions in 1986 from two to three. From 1981-1985 responses to questions (1) and (3) from the series are recorded for Heads and Wives/"Wives"[38]. In 1986 however, question (2) is added, giving respondents a little more flexibility in their answers. From a sample of approximately 10,000 responses in the PSID per year table 12 shows that that in the five years leading up to the switch (1981-1985) there is a notable higher prevalence of severe limitations in the population relative to the five years after. This is important given the observed higher prevalence and severity of limitation reports particularly in birth cohorts 1975 and 1977 coupled with the fact that most of the statistical significance is lost when excluding these cohorts. However, the 1975 birth cohort observes work-limitation status from 1984-1989 while the 1977 birth cohort observes work-limitations from 1986-1991. Additionally, the 1972 birth cohort is the most affected cohort, observing five of six years of data prior to the change, yet the prevalence of work-limitations in that cohort are among the lowest estimated prevalence rates. Therefore, in spite of this minor difference, the results are likely still valid to the shift in questions from 1985-1986.

[38]The question series is as follows: (1) "Do you have any physical or nervous condition that limits the type of work or the amount of work you can do?", and in the event this first question is answered in the affirmative, (2) "Does this condition keep you from doing some types of work?" and (3) "For work you can do, how much does it limit the amount of work you can do–a lot, somewhat, or just a little (or not at all post-1986)?"

Table 12: Comparison of limitation prevalence surrounding the change in work-limitation series questions

	1981-1985	1986-1990
Non-Limited	81.6%	81.7%
Mild Limit	4.5%	5.9%
Moderate Limit	4.3%	5.3%
Severe Limit	9.6%	7.1%

Source: Author's calculations using PSID

A more traditional concern with survey data is the reliability of self-reports. While income reports are certainly not immune to reporting error, multiple year averages should at least mitigate the issue in part. Of more importance for the present study is the classification of work-limitation status by the respondent. There are two sources of bias in the PSID parent generation. First, the PSID Head answers all work-limitation questions about himself (or herself is she is unmarried), and his wife or partner (if married/cohabiting) with the exception of 1985. The second source is various biases that can arise in the reliability of self-reports themselves.

To address the first, in most years Meyer and Mok (2014) find the prevalence of work-limitations is lower among PSID Wives/"Wives" (Heads typically provide a proxy report) relative to female Heads. The gap in their estimated prevalence rates ranges from 1% point to approximately 10% points during the 1981-1996 period with female Heads always having higher prevalence rates. The average is a 4.4% point gap. There is also a severity gap, with on average 6.7% point higher severity prevalence among female Heads in 1981-1985 and 5.6% thereafter[39]. The one exception to this rule of thumb is 1985, when Wives/"Wives" self-reported work-limitations. The prevalence gap is below average (3.3%), suggesting less downward bias in reporting; but the severity gap is above average (11.2%), suggesting there

[39]See Meyer and Mok (2014) table 1 for full details. There is a single year where proxy reports for Wives/"Wives" have higher severity than the self-reported Heads with a gap of 3.9% (1987)

could be some systematic difference between female Heads and Wives. Female Heads are typically single women in PSID, comprising a higher economic responsibility in the financial wellbeing of the household, which means they could be more inclined to report work-limitations all else equal (see the discussion on other reporting biases below). However, proxy reports also likely downward-bias reports. In the current sample, 75% of family units are headed by a male when the child is 14, suggesting that work-limitation reports could be under-reported in this sample.

Work-limitation measures were not initially designed to indicate the presence or absence of disability (Hale 2001). Additionally, self-reports are inherently non-objective with different individuals conceptualizing work-limitations differently. Some suggest that one's exposure to and acquaintance with individuals who qualify for work disability benefits decreases the individual's conceptualized threshold of what constitutes a work-limitation, thereby increasing the propensity to self-report a limitation (Van Soest et al. 2011). Or ordering work-limitations after employment and income (as in the PSID) may prime individuals to justify their non-employment by inflating work-limitation responses (Black, Johnston, and Suziedelyte 2017). Unequivocally, work-limitation and functional-limitation measures capture distinct populations (Burkhauser et al. 2002). However, it is worth repeating that the populations are not mutually exclusive and research often finds similar results when functional-limitations measures are used (Kavanagh et al. 2015; Brucker et al. 2015; Mitra, Findley, and Sambamoorthi 2009; She and Livermore 2007; Burkhauser et al. 2002).

It would be of great interest to consider functional-limitation as an alternative specification for this study; however, the data are simply unavailable. PSID began asking functional limitation questions in 1999, and so in the future it will be feasible to consider this comparison. For the moment, the present study uses work-limitations because it is the only measure available. In spite of its shortcomings, there is evidence to suggest these questions capture health problems. For example, Meyer and Mok (2013) show that in the PSID those self-reporting work-limitations have a higher propensity to face more objective health conditions (e.g. high blood pressure and diabetes), and they also face more activity limitations (e.g. walking, bending, driving) (Meyer and Mok 2013). Van Soest et al. (2011) concur, showing that individuals experiencing conditions such as heart or lung problems, stroke, diabetes, cancer, pain, or emotional problems are more likely to report work-limitations.

8 Conclusion

This paper examined the possibility of passing economic disadvantage associated with work-limiting disability to the next generation in the United States, a relatively immobile environment. On average, persons with disabilities face a number of disadvantages in their lifetimes including lower income, earnings, employment, and higher medical expenditures and poverty rates (Brucker et al. 2015; Meyer and Mok 2013; Mitra, Findley, and Sambamoorthi 2009; She and Livermore 2007). Furthermore, this is not a small minority of the population, with the Social Security Administration estimating that one in four workers entering the workforce at age 20 will experience a work-limitation in his/her working age career. This paper primarily contributes to the mobility literature and studies on disability. Most heterogeneous differentiations of mobility to date have been regarding race (Collins and Wanamaker 2017; Hertz 2005) or geography (Hertz 2008; Chetty et al. 2014b), but little work has been done on examining the association of parental health status with mobility. This research also adds to the growing literature examining child outcomes relative to parent disability status (e.g. Le and Nguyen 2017; Chen, Osberg, and Phipps 2015; Morefield et al. 2010; Frank and Meara 2009).

Empirical estimation of group-specific mobility was estimated with a traditional measure of mobility - the intergenerational elasticity of income using PSID birth cohorts 1972-1982. Results suggest that disadvantages associated with work-limiting disability among parents can be passed on to children when the parent's condition is severe and/or chronic in nature. Children from such families exhibit lower income, as well as lower mobility. These results are robust to a series of sensitivity analysis, most importantly matching the sample of non-limited parent-child pairs in observable characteristics to the limited sample. This exercise indicates that initial socioeconomic status of the parent is not necessarily driving these results. Additionally, transition matrices suggest that there is more upward mobility among the non-work-limited sample populations. The estimates presented here appear robust to a variety of sensitivity tests including definitions of income, disability, and some characteristics of both the parent and child. As an extension, an empirical education enrollment exercise sheds further light on these results by examining the child's school exit relative to changes in the parent's work-limitation status. Those results suggest worsening work-limitations are associated with a higher probability of school exit, while an improvement from a severe to mild or moderate condition may decrease the probability of school exit.

Additional research should be pursued to unpack these results a bit more. One avenue is the impact social programs may have on these results: specifically Social Security Disability Insurance and/or Supplemental Security Insurance. Another important topic to consider is the robustness of results to a functional-limitations definition of disability. Work-limitation measures are common in the literature; however, it is in part due to data availability. Finally, the small sample sizes in this study suggest caution in interpreting results too aggressively. Data with significantly larger samples may prove more enlightening.

9 Appendix

9.1 Intergenerational Mobility Estimates

Table A1: Parent's descriptive statistics by quartiles of work-limitation index

	N	Income		Age	Employment		Disability (n.l.f.)		Married (N=1,125)		Education (N=1,113)	
Non-Limited	753	$103,463		40.66	0.81		0.00		0.79		13.60	
Bottom Fourth	142	$106,039		41.34	0.79		0.00		0.94	***	13.38	
2nd Fourth	64	$ 98,671		41.41	0.80		0.01		0.84		13.62	
3rd Fourth	86	$ 72,576	***	40.99	0.71	**	0.00		0.72		12.89	**
Top Fourth	83	$ 56,584	***	41.70	0.54	***	0.09	***	0.74		12.58	***

Source: Author's calculations using PSID (N=1,128)
Notes from Table 1 apply.

Table A2: Child's descriptive statistics by quartiles of parent work-limitation index

	N	Earnings		Income		Female	Employment		Education (N=1,102)	
Non-Limited	753	$54,734		$91,188		0.46	0.93		14.55	
Bottom Fourth	142	$47,216		$74,195	**	0.45	0.89		14.52	
2nd Fourth	64	$48,865		$74,084	**	0.62	0.89		14.87	
3rd Fourth	86	$52,431		$84,140		0.45	0.89		14.59	
Top Fourth	83	$41,740	*	$68,974	**	0.46	0.86	*	13.81	**

Source: Author's calculations using PSID (N=1,128)
Notes from Table 3 apply.

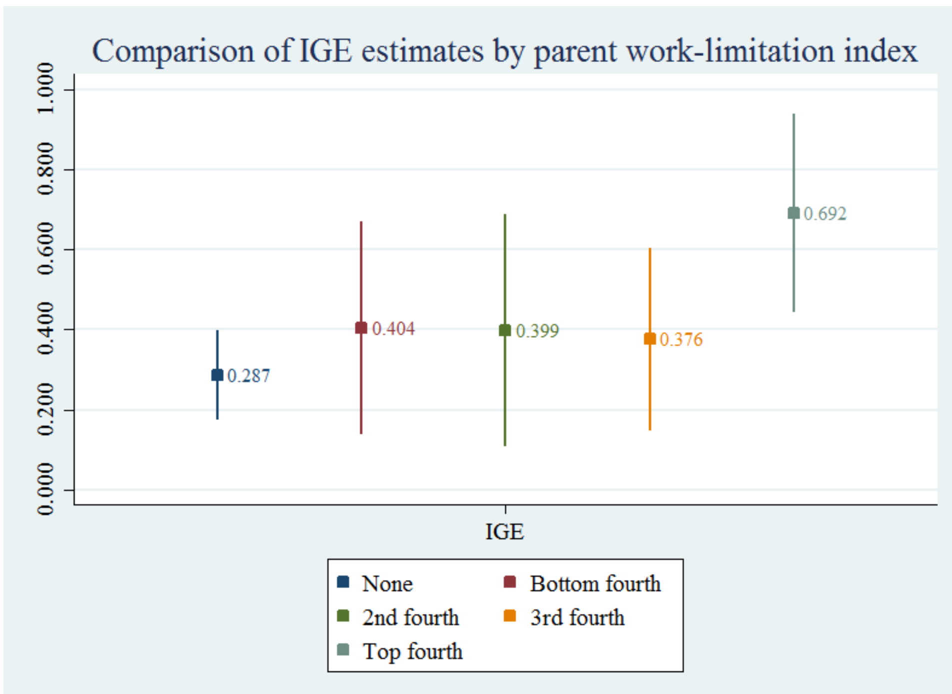

Figure 3: Mobility estimates for the full sample of six-years disability observation by quartiles of parent's work-limitation index.

Table A3: Sensitivity by fourths of parent's work limitation index

	N	Non-Limited	Bottom Fourth	2nd Fourth	3rd Fourth	Top Fourth
Main Results	1128	0.287	0.404	0.399	0.376	0.692 **
		(0.0546)	(0.13)	(0.141)	(0.111)	(0.121)
3yr work limit	1441	0.315	0.315	0.558	0.519	0.630 *
		(0.0519)	(0.0971)	(0.145)	(0.204)	(0.146)
9yr work limit	840	0.315	0.444	0.287	0.488	0.563
		(0.0709)	(0.174)	(0.152)	(0.081)	(0.164)
Child FU income	1234	0.358	0.303	0.177	0.459	0.547
		(0.0496)	(0.0988)	(0.0965)	(0.131)	(0.174)
Sons	551	0.302	0.333		0.377	0.979 **
		(0.0608)	(0.133)		(0.149)	(0.233)
Daughters	577	0.276	0.540	0.502	0.380	0.542 *
		(0.0788)	(0.205)	(0.101)	(0.15)	(0.117)
Remove SEO	791	0.263	0.404	0.372	0.367	0.690 **
		(0.0679)	(0.142)	(0.141)	(0.13)	(0.141)
Remove 1975&1977	930	0.295	0.421	0.355	0.374	0.615 *
		(0.0617)	(0.154)	(0.163)	(0.107)	(-0.15)
Remove work-limited children	964	0.269	0.397	0.371	0.432	0.673 **
		(0.06)	(0.139)	(0.148)	(0.122)	(0.128)
Parent income, child's age 17	997	0.303	0.464	0.510		
		(0.0805)	(0.0932)	(0.112)		
4-5 years parent income	1130	0.314	0.339	0.483	0.457	0.638 *
		(0.0608)	(0.125)	(0.128)	(0.124)	(0.146)
Trim child earnings < \$125,000	1086	0.213	0.341	0.399	0.387	0.646 ***
		(0.0523)	(0.123)	(0.141)	(0.12)	(0.123)
Matched income	750	0.314	0.404	0.399	0.376	0.692 **
		(0.0797)	(0.13)	(0.141)	(0.111)	(0.121)
Matched education	743	0.241	0.404	0.399	0.376	0.692 **
		(0.0894)	(0.13)	(0.141)	(0.111)	(0.121)
Matched income & education	743	0.230	0.404	0.399	0.376	0.692 ***
		(0.0786)	(0.13)	(0.141)	(0.111)	(0.121)
1 child/ unique "family"	899	0.274	0.291	0.381	0.451	0.675 **
		(0.0641)	(0.131)	(0.152)	(0.115)	(0.129)
2 parent homes	738	0.412	0.403	0.192 *		0.369
		(0.0951)	(-0.152)	(0.0837)		(0.159)
Single parents	390		0.391		0.560	0.788
			(0.174)		(0.108)	(0.191)
Unweighted	1128	0.335	0.415	0.347	0.358	0.553
		(0.0411)	(0.0876)	(0.123)	(0.118)	(0.162)
Rank-rank (weighted dist., unweighted est.)	1100	0.287	0.377	0.381	0.317	0.435
		(0.0331)	(0.0711)	(0.102)	(0.0881)	(0.0973)
Rank-rank (PSID sample, unweighted)	1146	0.369	0.494	0.526	0.430	0.658 **
		(0.0391)	(0.0848)	(0.127)	(0.116)	(0.128)
Rank-rank (PSID sample, weighted)	1146	0.344	0.433	0.544	0.418	0.644 **
		(0.0343)	(0.126)	(0.165)	(0.126)	(0.114)
Rank-rank (PSID pop, weighted)	1100	0.230	0.216	0.392	0.347	0.516 **
		(0.037)	(0.114)	(0.132)	(0.129)	(0.1)

Source: Author's calculations using PSID
Notes: Estimates adjusted for survey design using PSID cross section weights & linearized s.e. unless otherwise noted. IGE estimates not statistically non-zero (5% level) are omitted
$***p < 0.01, **p < 0.05, *p < 0.1$ (reference = Non-Limited)

9.2 Education Estimation

Table A4: Child's descriptive statistics, simple sample

		Enrollment														Attainment	
	N	Age 17		Age 18		Age 19		Age 20		Age 21		Age 22		Exit Age		(N=1,364)	
Non-limited	912	98.4%		91.0%		75.3%		64.1%		59.3%		51.8%		20.243		13.692	
Any limitation	555	98.0%		88.6%	*	68.8%	***	59.5%	**	47.9%	***	39.5%	***	19.870	***	13.447	***
Bottom third	198	99.5%		89.9%		68.7%	*	61.6%		50.5%	**	40.4%	***	19.894	**	13.511	
Middle third	185	95.7%	**	87.0%	*	68.6%	*	56.8%	*	43.8%	***	36.8%	***	19.773	***	13.399	*
Top third	172	98.8%		89.0%		69.2%	*	59.9%		49.4%	**	41.3%	**	19.948	*	13.423	*

Notes: Author's calculations using public-use PSID core and TA supplement data.
Reference category is "non-limited" in all cases
* p¡0.1 **p¡0.05 ***p¡0.01

Table A5: Parent's descriptive statistics, simple sample

	N	Education (N=1,212)		Unemployment		Blue Collar		Real Income (N=1,465)		Marriage (N=1,465)		Age (N=1,200)	
Non-limited	912	13.46		0.09		0.32		$ 75,932		0.69		27.69	
Any limitation	555	13.43		0.09		0.37	**	$ 72,230		0.77	***	28.83	***
Bottom third	198	13.76		0.07	*	0.35		$ 80,285		0.81	***	29.05	***
Middle third	185	13.43		0.09		0.38	**	$ 69,493		0.71		28.09	
Top third	172	12.99	**	0.11	**	0.38	**	$ 65,903	**	0.77	**	29.49	***

Notes: Author's calculations using public-use PSID core and TA supplement data.
* p¡0.1 **p¡0.05 ***p¡0.01

Table A6: Controls for Model Regressions

	(1) Pooled LPM	(2) First Difference	(3) Split First Difference
Unemployment	0.0281	-0.0214	-0.0195
	(0.0236)	(0.0184)	(0.0184)
Blue Collar	-0.0220	-0.0181	-0.0180
	(0.0197)	(0.0176)	(0.0176)
Marital Status	-0.0243	0.0412	0.0418
	(0.0209)	(0.0279)	(0.0276)
ln(Income)	-0.0134	0.00312	0.00310
	(0.00837)	(0.00847)	(0.00847)
Metropolitan Area	0.0129	0.0789	0.0787
	(0.0362)	(0.0483)	(0.0479)
Hist. Work Limit	0.0433		
	(0.0699)		
Hist. Unemployment	0.00579		
	(0.0685)		
Hist. Blue Collar	0.0603**		
	(0.0253)		
Hist. Marital Status	-0.0306		
	(0.0304)		
Hist. ln(Income)	-0.0403**		
	(0.0170)		
Parent Education	-0.0198***		
	(0.00500)		
Parent Age	-0.0198**		
	(0.00942)		
p_age0sq	0.000294*		
	(0.000163)		
Number Siblings	0.0170**		
	(0.00666)		
Hist. Metro Area	-0.0333		
	(0.0389)		
Female	-0.0534***		
	(0.0137)		
Caucasian	0.0196		
	(0.0188)		
N	3887	3979	3979
r2	0.319	0.194	0.196

Standard errors in parentheses
Author's calculations using PSID core and TA supplment
All specifications are unweighted, employ state fixed-effects, and child-clustered robust standard errors
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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