The Labor Market Consequences of Disability: Types, Severity, Persistence, and Onset.

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Abstract

This paper analyzes the vast variation in labor market outcomes across disabilities by representing disability as a bundle of characteristics. Rich with information on the characteristics of a disabling condition, I use the Participation and Activity Limitation Survey to compare the relative importance of each characteristic and their interactions on employment, wages, hours worked, and annual employment income. The set of disability characteristics includes the type of activity limitation, number of limitations, timing of onset, severity, and duration. I find substantial cross-sectional variation in labor supply, wages, and annual earnings across the activity limitations. Severity is most predictive of labor supply, while persistence, given by the duration of disability, is predictive of all outcomes. Cognitive types of disabilities have more impact on wages than physical. Lastly, I find the timing of onset has important implications for wages and annual income. My results are consistent with disabilities that onset by age eighteen inflicting additional wage penalties through reduced skill accumulation.

Keywords: *Disability, Labor, Human Capital, Wages, Employment*

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1 Introduction

Individuals affected by disability are less attached to the labor force, have lower earnings, and experience greater income risk.[1] Disability rates have been rising over the past few decades in much of the developed world.[2] Understanding the variation in labor market outcomes across disabilities is policy-relevant, as the increasing prevalence of disability places an increasing burden on public programs (Autor and Duggan, 2006). This paper aims to better understand the variation in labor market outcomes across disabilities by disaggregating disability into a bundle of characteristics.

A disability can result from a variety of medical conditions that may vastly differ in physiology and functional impairment. Representing disability as a bundle of underlying characteristics gives a tractable way to summarize and study a wide range of disabling conditions.[3] In this paper, I distinguish disabling conditions using measures of severity, the duration since its onset, hereby called persistence, the type of functional limitation, the number of functional limitations, and the timing of onset. With this representation of disability, I compare the relative importance of these characteristics, and their interactions, in a unified framework. This analysis is a first-order step for building an intuition of which disability characteristics drive the variation in its effect on labor market behavior.

My first contribution is jointly analyzing which disability characteristics are most predictive and impactful on hourly wages, employment, hours worked, and annual earnings. I use the 2001 and 2006 Participation and Activity Limitation Survey (PALS), a Canadian cross-sectional dataset with rich measures of the characteristics of disability, in conjunction with labor market outcomes and incomes. Many datasets for economic research on disability are often designed for non-disabled individuals. Consequently, these data often suffer from small disability sample sizes, especially when conditioning on characteristics. Data with reasonably sized samples of people with disabilities and detail on the characteristics of disability often lack detailed information on labor market outcomes or income.[4] PALS overcomes these data issues making it well suited to analyze the labor market consequences of this disaggregated set of disability characteristics. Moreover, a

[1] For summaries and recent evidence see Burkhauser et al. (1993), Bound and Burkhauser (1999), Haveman and Wolfe (2000), and Meyer and Mok (2019).

[2] In Canada, adults aged 25-64 with a disability have 20% less employment relative to non-disabled adults, and the employed earn between 10-30% less annually than workers without a disability. The percentage of Canadians ages 15 and over with a disability rose from 12.4% in 2001 to 22.3% in 2017, and this trend is likely to continue with an aging population. This change is also related to the evolution of the definition of disability and changes in reporting behavior. For more details on the economic position of Canadians with disabilities see Morris et al. (2018), and Cossette and Duclos (2002).

[3] This idea is similar to representing differentiated products as bundles of characteristics as is often done in industrial organization models of demand, such as Berry et al. (1995), or representing human capital as a bundle of skills, such as Yamaguchi (2012).

[4] A notable exception is the Health and Retirement Study, which has substantial information on the characteristics of health conditions and labor market outcomes. However, these data focus on individuals over the age of 50.

unified framework alleviates concerns with drawing comparisons across studies or datasets, which can add bias due to differences in the measurement of disability or sampling.

Much of the empirical literature measures disability as a single binary indicator of status.[5] This approach averages out the impact across all conditions, conflating variation in its effect. More granular representations capture variation by distinguishing disability based on some notion of the magnitude or frequency of its impact, either categorically or as a continuous index.[6] Moreover, it is often preferable to separate disabilities based on similarity in functional or activity limitations, such as physical or cognitive.[7] Additionally, the implication of when a disability occurs matters when considering the individual's life cycle. For instance, a permanent disability at birth impacts the individual throughout their life, whereas a disability that occurs during retirement does not affect labor market behavior.[8] A better understanding of the importance of the characteristics and their correlation structure complements empirical research with limited data on the characteristics by shedding light on what aspects of disability are driving results. To the best of my knowledge, this paper is the first to study a full set of characteristics in a unified framework.

My analysis reveals substantial heterogeneity in the effects of disability across the characteristics, which would be lost without disaggregating disability into this bundle of characteristics. Severity is most important for the intensive and extensive margins of labor supply. Cognitive types and disabilities that onset early in life result in greater penalties to wages and employment income. This ladder result is consistent with a higher market value for cognitive skills and with disability at young ages disrupting human capital production at crucial periods of skill development. Persistence has significant implications for all outcomes, motivating the importance of research on the dynamic effect of disability.

My second contribution explores the dimension of timing. PALS has a relatively large sample of individuals whose disability onset occurred by age 18, defined early-onset.[9] Working individuals with an early-onset disability earn approximately 14.6% less in hourly wages and 22% less in annual employment income relative

[5]For examples see Burkhauser et al. (1993), Acemoglu and Angrist (2001), Baldwin and Johnson (2006), Campolieti and Riddell (2012), and Ameri et al. (2018).

[6]For instance, Stern (1989) builds an index using questions on self-reported health and limitation, Low and Pistaferri (2015) distinguish mild and severe disabilities, Charles (2003) partitions those with disabilities based on the chronicity of the disability, Meyer and Mok (2019) partition those with a disability by both chronicity and severity.

[7]For instance, Lundborg et al. (2014) has medical reports on specific diseases or physiological conditions, and Mori (2016) summarizes conditions as being either physical or cognitive.

[8]Examples of studies about the timing of onset include Charles (2003), Hollenbeck and Kimmel (2008), and Lamichhane and Sawada (2013).

[9]To my knowledge, Hollenbeck and Kimmel (2008) and Lamichhane and Sawada (2013) are the only studies that include individuals with both early and late-onset disabilities. Lamichhane collects unique data from Nepal to estimate the determinants of wages. He includes dummy variables for age ranges of onset. He finds the earlier the onset, the less detrimental a disability is to wages. Hollenbeck and Kimmel use US data and separately estimate Mincer-style wage regressions for those without disabilities, those whose disability onset before 25, and those whose disability onset after. They find the coefficient on schooling is largest for the late onset individuals. Unfortunately, both studies face severe data limitations in their disabled samples and are not able to explore this dimension further.

to late-onset. A disability occurring before the completion of formal education can affect a person's skill development and influence their human capital during this critical period of investment.[10] This ladder effect is reflected in differentials between observationally similar individuals who differ in the timing of onset.

I partition my disabled sample into early and late-onset individuals and compare the determinants of each group's wages, hours, and annual employment incomes. I find that cognitive disabilities are more detrimental to wages when early-onset. Cognitive types have a more significant impact on hours worked for late-onset. Outcomes for individuals with early-onset disabilities improve over time, whereas the negative effects of a disability tend to get worse for late-onset, suggesting that early-onset individuals are better able to adapt to or accommodate their disabilities.

The remainder of the paper is structured as follows. Section 2 motivates the set of disability characteristics. Section 3 describes the dataset and disability measures used for this analysis. Section 4 explores the difference across and within groups of disabilities as defined by the characteristics and analyses their joint impact on employment, weekly hours, hourly wages, and employment income. Section 5 partitions my sample into early and late onset and compares the different effects of the other characteristics across these two groups. Section 6 concludes.

2 The Characteristics of a Disability and Why they Matter

Disability impairs functions and limits the set of productive tasks someone can perform, which directly links to human capital. In a standard human capital framework, an individual's wages are set according to their marginal product, relating human capital to the returns to work. Hence, disability is directly linked to wages, labor supply, and total employment income through its connection to human capital.[11] This intuition is convenient to motivate the relevance of the set of characteristics specified in this analysis

The severity of a disability represents the magnitude of its impact on human capital. The onset of a more severe disability causes a greater decline in the stock of human capital and subsequent productivity. The persistence of a disability describes the duration of time a disability has been present. On its own, the more persistent a disability, the longer it affects productivity (i.e., the stock of human capital), which has dynamic implications for the accumulation of human capital.[12]

[10] This idea is expressed in Hollenbeck and Kimmel (2008), Currie (2009), Lamichhane and Sawada (2013), and Mori (2016).

[11] For instance, Grossman (2017) considers models where health capital affects the amount of productive time, Hanushek and Woessmann (2008) discusses a model of HC inputs that depend on health among other important determinants, and Mori (2016) models productivity as a result of complimentary stocks of multidimensional health capital and human capital.

[12] The sign on the effect of persistence can go either way depending on if the disability becomes more or less limiting or if one can adapt to it. Related studies have found conflicting signs of the effect of persistence depending on its interactions with the other characteristics of disability. For example, see Charles (2003), Lamichhane and Sawada (2013), Mori (2016),

The type of disability describes the functional impairment and kinds of activities that are limited. In the context of multi-dimensional human capital, types of disabilities differ in the dimensions of human capital that are impacted. For instance, the onset of a physical disability, such as paralyzation below the waist, negatively affects the stock and accumulation of physical capital used to complete manual tasks at work.[13] Literature on the economic effects of different "types" of health conditions or disabilities finds substantial heterogeneity in their impact on outcomes. These studies often find that disabilities with a degree of cognitive impairment are more detrimental to economic welfare than physical or sensory disabilities.[14]

Finally, timing refers to the age at which the disability onset occurs. Younger people have more years to work and benefit from their human capital and have an incentive to spend more time investing in it (Ben-Porath, 1967). This insight suggests an important distinction between a disability that occurs during times of high human capital investment, i.e., formal schooling, and during times of high earnings when education investments are completed. Individuals affected by late-onset disabilities have less scope to retrain and adapt to them. In comparison, the disruption to education returns and choices can affect one throughout their life. Studies that consider timing typically restrict their sample to include only individuals whose onset occurred before or after labor market entry.

3 Data: The Participation and Activity Limitation Survey

I use PALS to study the characteristics of disability. PALS is a Canadian repeated cross-sectional survey of individuals flagged for disability in the 2001 or 2006 long-form Censuses. It was designed to provide detailed information on the characteristics of disability and the experiences and barriers an individual with a disability faces in daily life. An advantage of PALS is the inclusion of modules on education, the labor market, and incomes.

3.1 Measuring and Defining Disability

PALS adopts its definition of disability from the International Classification of Functioning (IFC) of the World Health Organization. The IFC defines disability as a concept that relates body functions and structures to activities and limitations to these activities, social participation in all aspects of life, and other

and Meyer and Mok (2019). Considering persistence interacted with the other disability characteristics may disentangle the conflicting signs. For instance, a persistent non-severe disability may be easier to adapt to, having more of a positive effect than a persistent severe disability.

[13]However, physical limitations can positively affect investment in, and accumulation of, the now relatively more productive cognitive human capital Mori (2016).

[14]For instance, Case et al. (2005), Lundborg et al. (2014), and Mori (2016).

environmental factors that influence these relationships. PALS emphasizes the characteristics of disability as they relate directly to the activity limitations they induce. The questions on health and limitations are self-reported in PALS.

To identify an individual as disabled, PALS uses a 2-stage screening process. The first stage consists of identifying those responding positively to disability screening from the long-form census.[15] This is ultimately how PALS targets its desired population of interest. The second stage involves additional screening questions included in PALS. If individuals are (1) flagged for disability in the census and (2) respond positively to the disability filter questions in PALS or respond positively to the detailed questions on activity limitations in PALS, then they are flagged as disabled.[16]

Using self-reported functional limitations to measure disability is not without its share of criticism, as are all other methods of defining disability.[17] Opponents of using self-reported disability are often concerned with self-reports being endogenous to an individual's economic circumstances, resulting in over-reporting.[18] However, it has been found that self-reported disability is close to exogenous, may actually under-represent the disabled population, and may even under-estimate the true impact of disability on relevant labor market outcomes (Stern, 1989; Bound and Burkhauser, 1999; Burkhauser et al., 2002). Using specific health questions, such as the activity limitation screening questions in PALS, rather than directly asking about disability status, can further reduce the concerns associated with self-reports being endogenous (Bound and Burkhauser, 1999). The combination of this evidence is sufficient to validate the use of self-reported disability, as defined by specific questions on functional limitations.

3.2 Measuring the Characteristics of Disability

PALS flags individuals with different types of disabilities based on their responses to a series of questions about limitations to specific activities of daily living. If the respondent reports positively, they are flagged for the respective functional limitation. PALS distinguishes ten categories of disaggregated functional limitations: Hearing, Seeing, Communication, Mobility, Agility, Pain, Learning, Memory, Developmental,

[15] Census questions are; "Does this person have any difficulty hearing, seeing, communicating, walking, climbing stairs, bending, learning or doing any similar activities?" and "Does a physical condition or mental condition or health problem reduce the amount or the kind of activity this person can do? at home? at work or school? in other activities, for example, transportation or leisure?" Responses can be "No", "Yes often", or "Yes sometimes". The individual is flagged if responding positively to any of these questions.

[16] Aggregate disability screening questions are same as the census. A specific activity limitation question could be "How much difficulty do you have hearing what is said in a telephone conversation with at least 3 other people?" The individual is flagged if responding "some difficulty," "a lot of difficulty," or "I cannot hear." The sample of disabled individuals in PALS is, therefore, necessarily a subset of the sample identified as disabled in the Canadian Long Form Census.

[17] For instance, using insurance receipts to define the disabled has been found to underrepresent the population of individuals who are limited enough in the labor market to be classified as "disabled" (Bound, 1989).

[18] For instance, someone may be incentivized to report being disabled to justify low productivity.

and Psychological. I discard hearing and seeing for my analysis and group the remaining disabilities into either physical or cognitive.[19] Physical disabilities include mobility, agility, and pain limitations. Cognitive disabilities include learning, memory, communication, developmental, and psychological limitations. Many disabling conditions cause functional impairments in multiple areas. I define a concurrent group, which consists of individuals flagged for both physical and cognitive limitations, giving me three mutually exclusive groups.

Severity is measured in levels that are derived from the responses to the questions about specific activity limitations.[20] The severity levels are mild, moderate, severe, or very severe. To improve tractability and improve predictive power, I create an indicator equalling one if the reported level is severe or very severe, and zero otherwise.[21]

The measure of persistence is derived from a retrospective question asking at what age the activity limitation began. I construct a continuous variable for the number of years limited, which equals an individual's current age minus the age at which their disability started. Inference on this characteristic tells how conditions may have changed between onset and measurement (e.g., if becoming more or less impactful on outcomes). I also create a binary measure of persistence, which equals one if an individual has been disabled for ten or more years. The cutoff of ten years is based on Meyer and Mok (2019), who find the longitudinal change in income and employment following disability onset to be nonlinear and to flatten out by approximately ten years after onset.

Lastly, the timing of onset is derived from the same retrospective question used to measure persistence. The response to this question is used to construct an indicator variable for early-onset. If the age of limitation is reported to occur before age 19, I flag the individual as early-onset.

3.3 My Sample

I consider a sample of white individuals aged 25-55 who are not retired. PALS excludes those living on First Nation reserves, in institutional collectives, and on military bases or vessels. After these restrictions, my sample has 6720 individuals with a disability and a 63,720 observation comparison sample of individuals

[19] Hearing and seeing limitations are sometimes grouped into a "sensory" category. However, I opted to remove this group due to limited sample sizes. The remaining functional limitations are grouped based on a simple correlation analysis.

[20] Points are assigned to the responses to questions about specific functional limitations. For example, "completely unable" is assigned 3 points, "a lot of difficulty" is assigned 2 points, "some difficulty" is assigned 1 point, and "no difficulty" is assigned zero points. A severity score is built from the points from all questions on the functional limitations associated with a specific type of disability. The levels of severity are derived using this score.

[21] Separating disability into more and less severe is common in related research, such as in Low and Pistaferri (2015)

who are not disabled.[22]

3.4 Sample Descriptive Statistics

Table 1: Descriptive Statistics by Disability Characteristic.

	Non-Disabled	Disabled	Types			Timing		Persistence		Severity	
			Physical	Cognitive	Concurrent	Late-Onset	Early-Onset	<10 Years	>10 Years	Non-Severe	Severe
Age	40.2	43.4	44.3	38.5	42.6	44.9	38.7	43.2	43.6	43	44.1
	(8.2)	(8.1)	(7.8)	(8.8)	(8.2)	(7.3)	(8.8)	(8.1)	(8.2)	(8.3)	(7.7)
Female	50.8	51.9	50.9	34	56.2	51.8	52.1	52.8	51.3	50.4	54.5
Married	58.3	54.4	61.1	37.5	45.6	60.3	35.6	58.5	51.6	58.2	47.7
High School Dropout	15.7	24.8	20.8	32.3	30.3	22.9	30.7	22.8	26.1	19.7	33.5
High School	24.6	24.1	24.2	20.5	24.5	24.4	23.2	23.2	24.7	25.1	22.5
Post-Secondary	59.7	51.1	55	47.1	45.2	52.7	46	54	49.2	55.2	44.1
Fraction Employed	91.3	72.5	82.7	75.2	55.3	73.4	69.7	78.3	68.7	84.1	52.6
Weekly Hours	41	38.3	39.6	36.5	35.5	38.7	37.1	39	37.7	39.2	35.8
	(12.8)	(15.1)	(14.6)	(14.4)	(16)	(14.8)	(16)	(13.9)	(15.9)	(14.3)	(16.8)
Hourly Wage	21.6	20.6	21.2	17.9	19.7	21.3	18.2	21.1	20.3	20.3	21.6
	(15.3)	(15.7)	(14.9)	(16)	(17.3)	(15.2)	(17)	(15.3)	(15.9)	(14.2)	(19)
Annual Employment Income	40895.3	33606.7	36555	26510.3	27651.6	35392.2	27608.6	35538.3	32149.4	34895.6	30058.1
	(31265)	(24557.2)	(24809.4)	(23446)	(22722.4)	(24634.3)	(23326.2)	(25289.7)	(23890)	(24552.4)	(24228.4)
Number of Observations[1]	63720	6720	3670	350	2740	5080	1680	2630	4130	3850	2910

Note: Table reports the mean of each variable and standard deviations in parentheses where applicable. These summary statistics have been weighted and rounded as required by the RDC. Statistics are weighted to represent the population of all Canadians who fit into my sample criterion. Weekly Hours, Hourly Wage, and Annual Employment Income are for the employed. These numbers reflect weighed counts relative to the total sample count. Actual counts can not be released under RDC's vetting restrictions. However, the actual number of observations for each group is similar in size.

[22] These counts are rounded to a base 10 as required in the RDC vetting guidelines. PALS was accessed via the Statistics Canada Research and Data Centre (RDC) at Western University. The RDC requires all descriptive statistics are rounded and weighted when public-ally reported. For instance, annual employment income, which is used to construct hourly wages, was rounded to multiples of ten. Any output that includes confidential data from the RDC must adhere to these restrictions and be vetted before being approved for public release.

I first compare summary statistics for those with and without a disability and then analyze the variation within these summary statistics across the characteristics. Table 1 reports the set of demographic variables and labor market outcomes in rows. Demographics include age, sex, marital status, and education.[23] The labor market variables of interest include employment, weekly hours, hourly wages, and annual employment income.[24] The columns report the subgroup conditioned on, and the cells report the mean of the respective demographic or labor market variable for that subgroup.

Individuals with a disability have substantial gaps in their educational attainment relative to non-disabled. They are 9.1 percentage points more likely to drop out of high school and 8.6 percentage points less likely to complete post-secondary education. Only 8.7% of the non-disabled are not employed, 18.8 percentage points less than individuals with a disability. Conditional on employment, the average person with a disability works 2.7 fewer weekly hours, earns $1 less per hour, and brings home $7288 less in annual employment income.

Conditional on disability, columns 3 to 5 contrast the descriptives across types of functional limitations. Physical disabilities have the smallest gaps in education and labor market outcomes relative to the non-disabled. People with some cognitive impairment are 14.6-16.6 percentage points more likely to drop out of high school and 12.6 to 14.5 percentage points less likely to earn a post-secondary degree relative to non-disabled, depending on physical impairment. Conditional on employment, cognitive disabilities experience the greatest gaps in wages ($3.7/hour) and annual earnings ($14,485/year) relative to non-disabled. Individuals affected by concurrent disabilities, which are characterized by limitations in multiple areas, are the least likely to work. This result is consistent with this group having a smaller set of productive tasks to engage in due to limitations in multiple dimensions.

Columns 6 and 7 partitions the disability sample as either late-onset or early-onset, respectively. Relative to the non-disabled, the early-onset group is 15 percentage points more likely to drop out of high school and 13.7 percentage points less likely to earn a post-secondary degree. This is consistent with early-onset disabilities impacting the development and returns to productive skills during compulsory schooling and limiting

[23]Education is measured by the highest completed certificate. I have three categories, where post-secondary includes any completed certificate higher than a high school degree.

[24]Individuals are considered employed if receiving any positive employment income in the respective census year.

the returns to post-secondary.[25] Consequently, early-onset individuals have much greater discrepancies in hourly wages and annual employment income relative to late-onset, $3.4/hour and $13,287/year less than non-disabled, respectively.

Last, columns 8 and 9 partition disabilities into those present for more or less than ten years, respectively, to highlight differences by persistence. The final columns distinguish severe from non-severe disabilities. Labor market outcomes tend to be worse for persistent disabilities, consistent with the negative effects on human capital accumulating over time. Unsurprisingly, more severe disabilities are associated with lower educational attainment, employment, and fewer earnings.

The descriptives in Table 1 highlight large differences in average outcomes across the margins defined

Table 2: Conditional Distributions of Characteristics.

	Types			Timing		Persistence		Severity	
	Physical	Cognitve	Concurrent	Late-Onset	Early-Onset	<10 Years	>10 Years	Non-Severe	Severe
Physical	100	0	0	66.1	37.2	69.9	52.1	65	42
Cognitive	0	100	0	2.7	12.8	2.7	6.6	5.7	3.2
Concurrent	0	0	100	31.2	50.1	27.3	41.3	29.3	54.9
Early-Onset	15.2	59.8	33.4	0	100	0.8	39.3	23.2	26.3
Severe	17.9	15.7	38.7	24.4	27.8	24.5	25.7	0	100
>10 Years Disabled	52.9	78.9	69.5	48	98.8	0	100	59.7	61.3

Note: Table reports the mean of each variable and standard deviations in parentheses where applicable. These summary statistics have been weighted and rounded according to the requirements of the RDC. Statistics are weighted to represent the population of all Canadians who fit into my sample criterion.

by the characteristics. However, there almost certainly exists a correlation structure among the bundle of characteristics. For instance, the self-reported severity of a disability may be related to the presence of multiple limitations or to persistent conditions. To better understand the relationship between characteristics, Table 2 conditions a characteristic in each column and displays the marginal distribution of each other characteristics in rows. Within the disaggregated types of disabilities, physical and concurrent limitations tend to onset late, at 84.8% and 66.6%, respectively. In contrast, 59.8% of cognitive disabilities are early-onset. Concurrent disabilities are most often severe, at 38.7%, which may be due to severity being attributed to having multiple limitations. Almost 80% of people with cognitive limitations have been disabled for more than ten years. Late-onset disabilities are over 60% physical, and half of the early-onset disabilities are concurrent. Severity is distributed similarly across persistence and early-onset. Severe disabilities tend to

[25]Education of late onset is interesting as it informs what education levels may put individuals at greater risk to incur a disability in adulthood.

be concurrent, whereas non-severe disabilities tend to be physical. Nearly all early-onset disabilities are persistent, and almost all non-persistent disabilities are late-onset, which is expected given the construction of these variables.

4 Disentangling the Relationship between Disability Characteristics and Labor Market Outcomes

This section estimates models for employment, the log of hourly wages, weekly hours worked, and the log of annual employment income as functions of the disability characteristics and controls. I regress these dependent variables on the rich set of characteristics and a full set of interactions between the characteristics. For each dependent variable, I first estimate a specification with the types of activity limitations aggregated into a single indicator for disability. I then contrast the findings with estimates from a specification distinguishing the types of functional limitations. The estimation sample includes people with and without disabilities. Hence, the coefficients on the disability characteristics are interpreted relative to the non-disabled omitted group.

The models take the following form,

$$\begin{aligned} Ln(Y_i) =&\beta_1 + \sum_{k=1}^{K} D_i^k \Big(\beta_2^k + \beta_3^k P_i + \beta_4^k S_i + \beta_5^k E_i \\ &+ \beta_6^k P_i S_i + \beta_7^k S_i E_i + \beta_8^k P_i E_i + \beta_9^k P_i S_i E_i \Big) + \boldsymbol{\beta_{10}} \boldsymbol{X}_i + c\lambda_i + e_i, \end{aligned}$$

where Y_i corresponds to the dependent variable of interest. K=1 for specifications aggregating types and K=3 otherwise.[26] P_i, S_i, E_i are binary measures of persistence, severity, and early-onset, respectively. Hence, β_2 captures the average effect of having a disability, or a specific type of limitation, relative to non-disabled. β_3, β_4, and β_5 capture the average additional effect of the disability being persistent, severe, or early-onset, respectively. The coefficients on the interactions capture any additional effect that might arise from having two or three characteristics simultaneously.[27]

In all specifications, $\boldsymbol{X_i}$ controls for cohort and sex. In some specifications, $\boldsymbol{X_i}$ also controls for education, labor market experience, and selection into employment.[28] The term λ_i represents the inverse of

[26] $k \in \{1, 2, 3\}$ maps to {physical, cognitive, and concurrent}

[27] For example, the effect of a early severe disability is $\beta_2 + \beta_4 + \beta_5 + \beta_7$.

[28] For education, I include a dummy variable for high school dropout and a dummy variable for any post-secondary completion. Hence, the omitted group is high school. Labor market experience equals age minus years of school minus six. Controlling for selection addresses censorship bias resulting from us not observing the wages and earnings of individuals that do not work.

Table 3: Marginal Effects and Probability of Employment for Characteristics from Probit Model of Employment

Dependent Variable:	Marginal Effects	Pr(Employed)
Physical	-0.0002	0.8379
	(0.0007)	
Severe	-0.0027***	0.6601
	(0.0010)	
Early	0.0002	0.8798
	(0.0003)	
Both Early and Severe	-0.0014**	0.6384
	(0.0007)	
Cognitive	-0.0018	0.7765
	(0.0012)	
Severe	-0.0070***	0.2358
	(0.0021)	
Early	-0.0003	0.7915
	(0.0005)	
Both Early and Severe	-0.0003	0.7389
	(0.0008)	
Concurrent	-0.0022**	0.7647
	(0.0009)	
Severe	-0.0041***	0.5180
	(0.0008)	
Early	-0.0004	0.7191
	(0.0005)	
Both Early and Severe	-0.0017***	0.5229
	(0.0004)	

Note: Standard errors in parentheses. Asterisks denote statistical significance where * is for P<0.1, ** for P<0.05, and *** for P<0.01. See the appendix for estimates of control variables. These variables interact with a continuous measure of the number of years limited. Marginal effects are predictions for single males without children living in the 90s at age 40. Pr(Employed) is calculated at the mean of all other variables, including the number of years limited.

the mill's ratio, derived from a probit estimation on employment, which is the standard Heckman correction procedure (Heckman, 1979). The first stage of the probit recovers the predicted probability of employment conditional on the disability characteristics, various controls, and exclusion restrictions. The first stage controls for cohort, sex, and type of disability interacted with early, severity, and the number of years limited. The exclusion restrictions are marital status, the number of children, the presence of children under six years old, dummy variables for receipt of outside sources of income from government assistance or other

disability transfers, and the cost of transportation.[29]

The first row of Table 3 reports the estimated marginal effect, and the second row reports the implied probability of employment from the disability characteristics from the first stage model for employment.[30] The key takeaway from Table 3 is the importance of severity for the extensive margin of labor supply. Individuals have a lower likelihood of employment for each additional year they have a severe disability of any type. Severe cognitive disabilities result in twice the reduction in the probability of being employed. Each additional year with a severe disability results in a 0.7% lower likelihood of being employed on average. Only concurrent disabilities result in a significantly lower likelihood of employment when not severe, -0.22% lower probability for each year limited. For all activity limitations, the harmful implications of severe disabilities are exacerbated when they are early-onset and physically impairing.[31]

Table 4 reports estimates of the disability characteristics from models for wages, hours, and annual employment income. The first four columns concern the log of hourly wage, where the first two columns aggregate types of limitations and columns two and four include the additional controls in $\boldsymbol{X_i}$.[32] The analysis for hourly wages is reflective of a disabilities effect on productivity, assuming wages are a noisy measure of an individual's underlying productivity. Disability, regardless of severity, persistence, or timing of onset, results in approximately 8% lower hourly wages relative to individuals without a disability.[33] The gap in hourly wages is greatly increased when the disability is early-onset, approximately 55%, and is amplified further when also severe, persistent, or both. These findings are consistent with early-onset disabilities disrupting human capital production during young ages, which are crucial periods of skill development.[34]

Columns 3 and 4 contrast the estimated coefficients for the characteristics across types of limitations, which would otherwise be averaged out when aggregating. Cognitive disabilities show substantial wage gaps when persistent or early, at 20% and 50%, respectively. These penalties are amplified when the cognitive disabilities onset is early and severe, which results in 80-85% lower wages than non-disabled individuals. This result is consistent with a higher value and pricing of cognitive skills in the labor market (Yamaguchi, 2012; Mori, 2016). Physical disabilities show significantly lower wages, approximately 8%, but no added

[29]The outside sources of income include disability insurance from the Canadian Pension Plan Disability, from private disability insurance, workers compensations, and provincial social assistance transfers. These programs generally have limitations on employment for beneficiaries, which can result in the termination of benefits. To exploit differences in programs between 2001 and 2006, I interact this variable with a dummy for the survey year. The exclusion argument is that receipt of transfer benefits predicts whether someone will be employed or not, but not wages assuming wages reflect productivity.

[30]The full set of estimated coefficients from the first stage are in **Appendix 2**.

[31]The relative importance of severity is robust to an alternate specification that interacts the characteristics with a binary measure of persistence. In this alternate specification, persistence is only significant when also severe.

[32]Estimates for the control variables are found in Appendix 2.

[33]The estimate percentage for coefficient β is obtained by $exp(\beta) - 1$.

[34]There are not substantial differences in the estimates for the specification with and without additional controls.

Table 4: OLS Estimates of Disability Characteristics on the Log of Hourly Wages, Weekly Hours, and Log of Annual Employment Income

Dependent Variable:		Log Hourly Wages				Hours				Log Annual Employment Income			
		1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.
Disability		-0.0846**	-0.0718**			-1.1536*	-0.7916			-0.1653***	-0.1249***		
		(-0.0355)	(-0.035)			(-0.5894)	(-0.6015)			(-0.0419)	(-0.0411)		
	Persistent	-0.0686*	-0.051			-1.8247**	-1.3331*			-0.1874***	-0.1333***		
		(-0.0357)	(-0.0386)			(-0.7497)	(-0.7587)			(-0.0375)	(-0.0377)		
	Severe	0.0377	0.0988			-3.4714***	-2.5723***			-0.2026**	-0.0684		
		(-0.0994)	(-0.1207)			(-0.8204)	(-0.8617)			(-0.1023)	(-0.1232)		
	Both Severe and Persistent	-0.0644	-0.0068			-5.9038***	-3.8728***			-0.4244***	-0.2196***		
		(-0.068)	(-0.0729)			(-1.3867)	(-1.4334)			(-0.0865)	(-0.081)		
	Early	-0.7405*	-0.7195*			7.5446	8.0177			-0.8087**	-0.7638*		
		(-0.3938)	(-0.3984)			(-7.7123)	(-7.7597)			(-0.3968)	(-0.3999)		
	Both Early and Persistent	-0.1611***	-0.1431***			-3.0982***	-2.7181***			-0.2686***	-0.2220***		
		(-0.0445)	(-0.043)			(-0.6994)	(-0.7015)			(-0.0508)	(-0.0491)		
	Both Early and Severe	-0.3909***	-0.4571***			0.0566	-0.0058			-0.4938***	-0.5694***		
		(-0.0103)	(-0.0117)			(-0.1665)	(-0.1964)			(-0.0127)	(-0.0141)		
	Early Severe and Persistent	-0.4661***	-0.3673***			-5.1358**	-3.3522			-0.9077***	-0.6701***		
		(-0.1461)	(-0.139)			(-2.0266)	(-2.159)			(-0.1311)	(-0.1315)		
Physical				-0.0957**	-0.0844**			-0.9987	-0.6857			-0.1607***	-0.1244***
				(-0.0403)	(-0.0394)			(-0.6254)	(-0.6362)			(-0.0467)	(-0.0457)
	Persistent			-0.051	-0.0433			-1.1604	-0.8098			-0.1328***	-0.0971**
				(-0.0396)	(-0.0433)			(-0.8704)	(-0.8718)			(-0.0387)	(-0.0382)
	Severe			0.0972	0.1638			-2.9508***	-2.2007**			-0.0224	0.1129
				(-0.1773)	(-0.2162)			(-1.0352)	(-1.1122)			(-0.1553)	(-0.1951)
	Both Severe and Persistent			0.0801	0.1325			-3.7191*	-2.313			-0.2389**	-0.0784
				(-0.0953)	(-0.1096)			(-2.0711)	(-2.1365)			(-0.0998)	(-0.0995)
	Early			-0.7117	-0.7202			4.7277	5.3099			-0.5052	-0.4812
				(-0.5204)	(-0.5454)			(-4.1377)	(-4.4461)			(-0.5319)	(-0.5288)
	Both Early and Persistent			-0.0478	-0.0517			-2.4659***	-2.3932***			-0.1035*	-0.1033
				(-0.0524)	(-0.0523)			(-0.9185)	(-0.9246)			(-0.062)	(-0.0635)
	Both Early and Severe			-0.3913***	-0.4570***			0.0535	0.0116			-0.4945***	-0.5689***
				(-0.0103)	(-0.0117)			(-0.166)	(-0.1949)			(-0.0126)	(-0.0141)
	Early Severe and Persistent			-0.2381	-0.1933			6.9703	7.9645			-0.2055	-0.0854
				(-0.1503)	(-0.1454)			(-5.8039)	(-5.7942)			(-0.2091)	(-0.197)
Cognitive				0.138	0.1274			-3.2071**	-2.9949**			-0.1321	-0.1235
				(-0.1227)	(-0.1154)			(-1.4435)	(-1.4241)			(-0.1844)	(-0.1844)
	Persistent			-0.3820**	-0.3115*			-10.8185***	-10.0785**			-1.2671***	-1.1313***
				(-0.1853)	(-0.1893)			(-4.0937)	(-4.0444)			(-0.31)	(-0.3165)
	Severe			0.1371	0.0476			-4.2244	-2.5035			0.134	0.1581
				(-0.5574)	(-0.5767)			(-10.6859)	(-9.8449)			(-0.3207)	(-0.4039)
	Both Severe and Persistent			-0.3998**	-0.4671***			1.7068	5.059			-0.8188	-0.6536
				(-0.1567)	(-0.1779)			(-10.2019)	(-10.1028)			(-0.7705)	(-0.7958)
	Early			-0.7960***	-0.5406***			7.2070***	6.8586***			-1.3934***	-1.0903***
				(-0.0273)	(-0.0307)			(-0.4564)	(-0.5144)			(-0.0345)	(-0.0373)
	Both Early and Persistent			-0.5644***	-0.5019***			-3.3466**	-2.7760**			-0.6935***	-0.5790***
				(-0.1461)	(-0.1359)			(-1.3795)	(-1.3923)			(-0.1551)	(-0.1411)
	Both Early and Severe			-	-			-	-			-	-
				-	-			-	-			-	-
	Early Severe and Persistent			-0.3533*	-0.2573			-10.6166***	-9.8275***			-0.8095***	-0.6280***
				(-0.2028)	(-0.1711)			(-3.0608)	(-2.7394)			(-0.2413)	(-0.2226)
Concurrent				-0.0731	-0.0603			-1.6373	-1.1923			-0.2092**	-0.1609*
				(-0.0663)	(-0.0677)			(-2.1856)	(-2.1693)			(-0.1005)	(-0.0928)
	Persistent			-0.0954	-0.0554			-3.4284**	-2.5661*			-0.2501***	-0.1483
				(-0.0838)	(-0.0827)			(-1.3318)	(-1.3472)			(-0.0963)	(-0.1016)
	Severe			-0.0206	0.025			-3.9770***	-3.1184**			-0.3795***	-0.2641***
				(-0.0745)	(-0.0789)			(-1.2823)	(-1.2974)			(-0.0933)	(-0.0969)
	Both Severe and Persistent			-0.1786**	-0.1379			-7.6923***	-5.5470***			-0.5712***	-0.3682***
				(-0.0911)	(-0.0897)			(-1.8725)	(-1.8594)			(-0.1318)	(-0.1244)
	Early			-0.799	-0.7321			13.3918	13.5773			-1.4198***	-1.3522**
				(-0.5726)	(-0.5162)			(-20.614)	(-20.6227)			(-0.521)	(-0.5762)
	Both Early and Persistent			-0.1543**	-0.1242*			-4.3825***	-3.5798**			-0.3662***	-0.2733***
				(-0.0692)	(-0.0672)			(-1.4952)	(-1.4886)			(-0.0814)	(-0.0763)
	Both Early and Severe			-	-			-	-			-	-
				-	-			-	-			-	-
	Early Severe and Persistent			-0.5334***	-0.4361**			-7.2622***	-5.4247**			-1.0835***	-0.8365***
				(-0.1949)	(-0.1866)			(-2.2076)	(-2.3595)			(-0.1624)	(-0.1645)
Additional controls		No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Inverse Mills		No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
R^2		0.026	0.073	0.027	0.074	0.094	0.095	0.095	0.096	0.084	0.131	0.086	0.133

Note: Standard errors are in parentheses below estimates. Asterisks denote statistical significance where * is for P<0.1, ** for P<0.05, and *** for P<0.01. See the appendix for estimates on control variables.

effects from the characteristics. Concurrent disabilities only matter when they are persistent and either early, severe, or both.

Next is the number of hours worked per week, shown in columns 5 to 8. The intensive margin of work is informative of a disabilities impact on the availability of work on the demand side and the ability or preference for work on the supply side. Disability, on its own, results in one hour less per week when

averaged over the types. Severe disabilities, which can increase the marginal cost of working and lower expected productivity per hour, result in three fewer hours per week on average. Early-onset disabilities that are persistent show approximately three fewer hours worked per week. Again, this is consistent with the early-onset disability disrupting skill development through schooling, resulting in a lower return to work. Workers suffering from severe and persistent disabilities are most likely to engage in part-time work, between 7.77 and 12.34 fewer weekly hours worked.

Columns 7 and 8 find people with cognitive disabilities to have the largest differences in weekly hours worked, three fewer per week. This is a similar result to the extensive margin of employment. However, working individuals with early-onset cognitive disabilities actually work more weekly hours than non-disabled individuals. Although, This positive relation is offset when the cognitive disability is early-onset and severe. Physical disabilities reduce the number of hours worked when severe or both early and severe. Concurrent disabilities decrease the number of hours worked only when persistent or severe, and the estimated decline doubles when both severe and persistent (approximately 15 hours less). The magnitude of impact for most characteristics is reduced when correcting for selection into employment.

The final four columns report estimates from models for the log of annual employment income. The effect of disability characteristics on annual employment income is similar to the models for wages but of a greater magnitude. Annual employment income combines the effect of disability on both the price and supply of labor. Again, early-onset disabilities come with substantial penalties, resulting in almost 60% lower annual earnings. The penalties jump to 71-89% when combined with persistence, severity, or both. The final two columns again show cognitive disabilities as very impactful when persistent or early-onset. Physical disabilities significantly reduce annual employment income by 11% and have additional penalties when severe. Concurrent types show significant penalties to annual employment income even when not persistent. Otherwise, the magnitude of its effect is similar to cognitive types.

The main takeaway from the statistical analysis of the disability characteristics on wages, hours, and employment income is the importance of considering them jointly (when possible) to avoid confounding their effects. Aggregating disabilities across the different types of limitations masks substantial heterogeneity in how disability affects these outcomes. In particular, the impact of an early-onset disability on hourly wages and annual employment income is considerable.

5 Early, Late, and the Indirect Effect of a Disability

The previous analysis above suggests the distinction between early and late-onset disability has large and significant implications for wages and employment income. As briefly discussed in the Introduction, this partition based on timing is economically meaningful in the context of human capital. We can think of the impact of a disability following onset as having two effects. The first effect is the direct loss of ability from the condition or drop in the stock of human capital, which I call the direct effect. The onset of a disability may also affect one's productivity indirectly by impacting the development of productive skills, which I call the indirect effect. Education is one of the most important human capital investments, so an early-onset disability may also impact human capital through impacting education decisions, which was found to be lower in Table 1.

Separating the sample with disabilities into early- and late-onset is useful when considering the indirect effect of a disability. The earnings of both groups reflect the direct effect of disability. However, when controlling for years limited, the earnings of the early group also reflect the indirect effect on educational attainment. The difference in wages between early and late-onset disability, which I define as the "early-late gap", measures an upper bound of the indirect effect of a disability. For this final analysis, I discard the non-disabled control group and partition the remaining sample into early and late-onset. I estimate and compare models for hours, wages, and employment income for each group, $g \in \{early, late\}$. The models for each dependent variable take the form,

$$y_i = \beta_0^g + \beta_1^g \boldsymbol{X_i} + \beta_2^g \boldsymbol{T_i} + \beta_3^g S_i + \beta_4^g P_i + e_i. \tag{1}$$

The estimates on the other dimensions of disability capture their average effect. Physical disabilities are the reference category, so $\boldsymbol{T_i}$ includes cognitive and concurrent disabilities. Severity, S_i, is the same measure as above and P is a continuous measure of the number of years limited. $\boldsymbol{X_i}$ controls for cohort, sex, education, and experience.[35] Table 5 shows the results of these regressions for the log of hourly wages, weekly hours, and the log of annual employment income.

I first consider the estimated R-squared for early-onset relative to late-onset for each dependent variable. The model for wages and employment income explains 19.1% in the variation of wages for early-onset individuals and only 4.7% for late-onset individuals. Similarly, the model for annual employment income accounts for 22.6% of the variation for early-onset individuals and only 13.2% for late-onset individuals.

[35] There was no meaningful difference in these results when controlling for selection into employment.

Table 5: Table 5. Comparing estimates between Early and Late. Dependent Variable: Ln(Hourly Wage)

Dependent Variable	Ln(Hourly Wage)		Weekly Hours		Ln(Annual Employment Income)	
	Early	Late	Early	Late	Early	Late
Education						
Post-Secondary	0.329***	0.163***	0.610	2.140**	0.309***	0.231***
	(0.083)	(0.058)	(1.609)	(0.914)	(0.109)	(0.065)
Dropout	-0.157**	0.045	-2.042	2.205	-0.254*	-0.002
	(0.096)	(0.089)	(2.024)	(1.438)	(0.130)	(0.090)
Experience	0.077**	0.012	-0.120	0.091	0.080**	0.030
	(0.035)	(0.017)	(0.42)	(0.280)	(0.038)	(0.022)
Experience^2	-0.002***	-3.3E-4	0.005	-0.003	2.39E-3**	-7.30E-4*
	(0.001)	(3.3E-5)	(0.008)	(0.006)	(0.001)	(4.2E-4)
Type						
Cognitive	-0.345**	-0.028	-3.954**	-5.606***	-0.541***	-0.483**
	(0.113)	(0.116)	(1.987)	(1.975)	(0.128)	(0.188)
Concurrent	-0.144*	-0.084	-4.67**	-1.844*	-0.435***	-0.191***
	(0.087)	(0.061)	(2.151)	(1.014)	(0.100)	(0.070)
Severe	-0.182*	0.118	0.136	-2.479	-0.380***	-0.045
	(0.107)	(0.074)	(2.449)	(0.978)	(0.120)	(0.078)
# of Years Limited	0.008	0.0004	0.038	-0.059	0.015**	-0.004
	(0.005)	(0.004)	(0.099)	(0.064)	(0.007)	(0.004)
Female	-0.085	-0.266***	-7.037***	-8.811***	-0.437***	-0.586***
	(0.082)	(0.047)	(1.340)	(0.799)	(0.096)	(0.051)
Cohort						
60's	-0.115	-0.096	1.396	0.861	-0.145	-0.058
	(0.158)	(0.085)	(2.145)	(1.221)	(0.195)	(0.092)
70's	-0.252	-0.118	4.661	0.297	0.017	-0.162
	(0.235)	(0.138)	(3.831)	(2.398)	(0.259)	(0.160)
80's	-0.277	-0.334	3.948	3.903	-0.007	-0.200
	(0.284)	(0.243)	(5.318)	(3.864)	(0.322)	(0.289)
Intercept	2.114***	2.811***	39.781***	42.877***	9.377***	10.224***
	(0.367)	(0.266)	(6.330)	(4.208)	(0.446)	(0.319)
R^2	0.191	0.047	0.073	0.113	0.226	0.132

Note: Standard errors are in parentheses below estimates. Asterisks denote statistical significance where * is for P<0.1, ** for P<0.05, and *** for P<0.01.

The disability characteristics and other covariates can better explain the variation in wages for those with early-onset disabilities than for late-onset.

The intercepts for the log of hourly wages (columns 1 and 2) indicate the omitted group earns approximately twice as much when their disability onset occurs late compared to early.[36] Cognitive and concurrent disabilities inflict large wage penalties when early-onset but are not significantly different than physical when late-onset. Cognitive and concurrent types are estimated to have a significant negative penalty to wages of 29% and 13%, respectively. The effect of disability on wages gets progressively worse when later onset. It

[36]The omitted group is non-severe physically disabled males with a high school degree and no experience born in the 50s.

is insignificant for early-onset individuals, consistent with this group being better able to accommodate or adapt to their disability over time. The estimates for experience also concur with this finding.

Columns 3 and 4 compare estimates for the weekly number of hours worked. The intercept indicates the omitted group of later-onset individuals work longer in a week than the early-onset group. The average effect of cognitive disabilities is worse when late-onset, and the average effect of concurrent disabilities is worse when early-onset. The severity and the number of years limited are not predictive of the number of weekly hours worked for either group. Post-secondary schooling has a significant positive impact on late-onset individuals. Disabled females incur a larger hours penalty for late, which is similar to the findings in the wage model. Finally, the R^2 of both models suggests that this set of predictors does not account for very much of the variation in the number of hours worked.

Finally, the last two columns are for the log of annual employment income. As expected, the average annual employment income for early-onset individuals is less than that of late-onset individuals for the omitted group. Similar to wages, the effects of cognitive and concurrent disabilities are largest for early-onset individuals, and the penalty for cognitive is larger than the penalty for concurrent. Severity has a negative and significant impact on employment income for early-onset individuals but is not significant for late-onset individuals.[37] The measure of persistence significantly predicts annual employment income for early-onset individuals. This is consistent with the ability to adapt to the disability and/or compensate for it. Post-secondary schooling provides both groups with positive gains to annual employment income and is larger for early-onset individuals. However, the difference in the gain is smaller than that of hourly wages and weekly hours. The effect of cognitive disabilities substantially overcomes the gain from schooling. Early-onset individuals incur a large penalty for high school dropouts. Experience is significant and beneficial for early-onset individuals, which is similar to the findings from wages.

6 Conclusion

This paper explores the joint implications of accounting for a rich bundle of disability characteristics on employment, hours worked, wages, and employment income. My findings suggest there is considerable variation in the impact of the characteristics on these outcomes. Disaggregating disability into types of functional limitations is important to account for the heterogeneity of disabilities. The distinction between early and late-onset disability is significant for wages and employment income. The effects of disability

[37] As annual employment income combines wages and hours, this suggests that although severity impacts the number of weekly hours worked for late-onset individuals, it does not impact this measure of labor market welfare. Severity impacts wages for early-onset individuals, and it also negatively affects this measure of economic welfare in the labor market.

on wages for those with early-onset disabilities are consistent with the disability adversely impacting skills development. Severity is more relevant for the intensive and extensive margins of labor supply. Persistence has important effects on all outcomes, motivating the importance of research on the dynamics of the effects of disability.

A better understanding of the effects of the characteristics and their correlation with each other can help inform empirical researchers with limited data on the details of disability. Awareness of what traits of disability correlate with each other and which drive outcomes can offer a better intuition into studies on the effects of disability. Moreover, this intuition can help inform policymakers to better target individuals bearing the greatest burden of their condition.

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Appendix

A1. Census filter questions and example of specific questions on activity limitation in PALS

Disability Screening Filter in Long form Census: 1. Do you have any difficulty heading, seeing, communicating, walking, climbing stairs, bending, learning or doing any similar activities?

- Yes, sometime
- Yes, often
- No

2a. Does a physical condition or mental condition or health problem reduce the amount or kind of activity you can do at home?

- Yes, sometime
- Yes, often
- No

2b. Does a physical condition or mental condition or health problem reduce the amount or kind of activity you can do at home?

- Yes, sometime
- Yes, often
- No

2c. Does a physical condition or mental condition or health problem reduce the amount or kind of activity you can do in other activities, for example, transportation or leisure?

- Yes, sometime
- Yes, often
- No

Questions for activity limitation associated with hearing disability in PALS:

- With your hearing aid(s), how much difficulty do you have hearing what is said in a conversation with one other person?
- With your hearing aid(s), how much difficulty do you have hearing what is said in a conversation with at least three other people?
- With your hearing aid(s), how much difficulty do you have hearing what is said in a telephone conversation?
- How much difficulty do you have hearing what is said in a telephone conversation with one other person?
- How much difficulty do you have hearing what is said in a telephone conversation with at least three other people?
- How much difficulty do you have hearing what is said in a telephone conversation?
- Which of the following best describes your ability to hear?

If respondents answered "some difficulty", "a lot of difficulty", or "I cannot hear" then they were flagged as having a hearing limitation.

A2. Additional Estimates from Probit and Linear Projection Models

Table 6: Probit Estimates of Disability Characteristics and Controls on Employment

Dependent Variable:	Employment
Age	0.0609***
	(-0.0217)
Age^2	-0.0010***
	(-0.0002)
Married	0.1981***
	(-0.0241)
Number of Kids	-0.0308***
	(-0.011)
Presence of Children under 6	-0.2839***
	(-0.0419)
Sex	-0.5794***
	(-0.0217)
Born in 60s	-0.1509***
	(-0.0434)
Born in 70s	-0.1782**
	(-0.0823)
Born in 80s	-0.1096
	(-0.1398)
Physical	-0.0028
	(-0.0082)
Severe	-0.0295***
	(-0.0106)
Early	0.0024
	(-0.0038)
Both Early and Severe	-0.0150**
	(-0.0069)
Cognitive	-0.0202
	(-0.0128)
Severe	-0.0801***
	(-0.0226)
Early	-0.0083
	(-0.0054)
Both Early and Severe	-0.0037
	(-0.0089)
Concurrent	-0.0244**
	(-0.0098)
Severe	-0.0450***
	(-0.0085)
Early	-0.004
	(-0.0054)
Both Early and Severe	-0.0187***
	(-0.0038)
Survey = 2001, Outside income = 1	-0.1968*
	(-0.1128)
Survey = 2006, Outside income = 0	0.1080***
	(-0.0271)
Survey = 2006, Outside income = 1	-1.5071***
	(-0.0752)
Transport Costs	0.0634**
	(-0.0268)
Intercept	0.9934**
	(-0.4746)
R^2	0.1139

Note: Standard errors are in parentheses below estimates. Asterisks denote statistical significance where * is for P<0.1, ** for P<0.05, and *** for P<0.01.

Table 7: OLS Estimates of control variables on the Log of Hourly Wages, Weekly Hours, and Log of Annual Employment Income

Dependent Variable:	Log Hourly Wages				Hours				Log Annual Employment Income			
		1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.
Sex	-0.1632***	-0.1632***	-0.1668***	-0.1708***	-7.7547***	-7.7559***	-7.0387***	-0.1708***	-0.4288***	-0.4286***	-0.3872***	-0.3941***	
	-0.009	-0.009	-0.013	-0.0131	-0.1459	-0.1458	-0.2047	-0.0131	-0.0105	-0.0104	-0.0156	-0.0154	
Born in 60s	-0.0482***	-0.0481***	-0.0875***	-0.0877***	0.4176**	0.4222**	0.4058	-0.0877***	-0.0517***	-0.0516***	-0.1005***	-0.1015***	
	-0.0106	-0.0105	-0.016	-0.0158	-0.1702	-0.1702	-0.2644	-0.0158	-0.012	-0.0119	-0.0179	-0.0176	
Born in 70s	-0.1585***	-0.1579***	-0.1933***	-0.1937***	0.0347	0.0423	0.2431	-0.1937***	-0.2237***	-0.2228***	-0.2559***	-0.2571***	
	-0.0114	-0.0114	-0.0238	-0.0237	-0.183	-0.1823	-0.4007	-0.0237	-0.0137	-0.0137	-0.0278	-0.0276	
Born in 80s	-0.3310***	-0.3305***	-0.3341***	-0.3345***	-1.8818***	-1.8671***	-1.5663**	-0.3345***	-0.4548***	-0.4533***	-0.4460***	-0.4463***	
	-0.0278	-0.0278	-0.0382	-0.0381	-0.4636	-0.4633	-0.6448	-0.0381	-0.035	-0.035	-0.0459	-0.0458	
Post-Secondary Certificate			0.2529***	0.2525***			0.5049***	0.2525***			0.2873***	0.2865***	
			-0.0107	-0.0107			-0.1855	-0.0107			-0.0126	-0.0126	
High School Dropout			-0.1491***	-0.1485***			0.4400*	-0.1485***			-0.2033***	-0.2020***	
			-0.0151	-0.015			-0.2492	-0.015			-0.0167	-0.0166	
Experience			0.0103***	0.0102***			0.0609	0.0102***			0.0154***	0.0154***	
			-0.003	-0.003			-0.0496	-0.003			-0.0036	-0.0035	
Experience^2			-0.0252***	-0.0252***			-0.0994	-0.0252***			-0.0351***	-0.0355***	
			-0.0068	-0.0068			-0.1064	-0.0068			-0.0078	-0.0078	
Inverse Mills Ratio			-0.1029	-0.0739			-4.9548***	-0.0739			-0.4485***	-0.3979***	
			-0.0685	-0.0682			-0.9813	-0.0682			-0.0845	-0.0828	
Intercept	2.9908***	2.9906***	2.8102***	2.8096***	44.6634***	44.6601***	43.9541***	2.8096***	10.6190***	10.6186***	10.4075***	10.4062***	

Note: Standard errors are in parentheses below estimates. Asterisks denote statistical significance where * is for P<0.1, ** for P<0.05, and *** for P<0.01. Model estimates correspond to estimates in Table 3.