The Longitudinal Effects of Disability Types on Incomes and Employment.

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Abstract

A work-limiting disability can have important impacts on personal income in the years around its onset. Using linked Canadian survey and administrative tax data, I estimate the effect of different disability types in the ten years after onset on the level and composition of the main components of personal income. I distinguish disability types based on reported limitations to daily activities, and group them into physical, cognitive, or concurrent (both). My empirical results show substantial heterogeneity in the effect on personal income by disability type. In the years following onset, people with cognitive disabilities experience larger and more permanent declines in employment and total market income than those with physical disabilities. However, those with only cognitive disabilities receive similar increases in total government transfers, but less transfers from programs most relevant to disability. Instead, this group offsets some of the decline in market income via other transfers, such as programs that target families. Finally, the estimated effect of concurrent disabilities on market income and government transfers appears to be additive as it equals the sum of the effects of physical and cognitive disabilities.

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1 Introduction

The onset of work-limiting disability has sizable and persistent consequences to individual financial independence and causes substantial societal costs of caring for these individuals.[1] Disability limits or can even eliminate one's ability to perform tasks routinely encountered in work and daily life. This is one of the primary risks facing working-aged adults, and much of this population will have experienced some form of a disability spell before retirement.[2]

The level and composition of personal income reveals much about an individual's economic circumstances. Changes in the composition of personal income after onset are telling of the impacts of disability on economic independence.[3] In Canada, working-aged individuals with a disability earn one-third less through employment and receive twice the amount from government transfers compared to their non-disabled counterparts (Wall 2017). The extent to which market income declines relative to the rise in government transfers in the years after the onset of a disability reveals how much public insurance is available for this shock.There is substantial variation in the size and persistence of this effect of disability onset on income and transfer payments. Distinguishing disability based on the types of activities that are ultimately inhibited is a key step towards understanding this variation.

This study examines the heterogeneous effect of disability onset on disaggregated components of personal income, distinguishing disability types based on the limitations to daily activities (LADLs) they cause. For the remainder of this paper, I refer to LADLs and disability interchangeably. A disability is the consequence of one or more physiological conditions, which can differ substantially in their impact on daily life. For instance, a brick layer may be rendered unable to work if limited in bending and flexibility, whereas a computer scientist may be largely unaffected. That is, disabling conditions have the commonality of impairing functionality in some way but vastly differ in the sort of functions that are impaired. Accounting for different types is vital to understand the variation in the effect of disabling conditions on economic outcomes. However, there is a need for a comprehensive analysis that compares onset effects across different types of disability. This paper asks how onset effects across disability types affect earnings behaviour. I distinguish three mutually exclusive disability types based on LADLs that impair cognitive and mental function, phys-

[1]Disability onset in working life reduces labour force attachment, earnings, consumption, and increases reliance on government transfers (Burkhauser et al. 1993, Bound and Burkhauser 1999, Haveman and Wolfe 2000, Prinz et al. 2018).

[2]Disability rates have been rising over the past few decades in Canada, as well as most developed countries. The percentage of Canadians ages 15 and over with a disability rose from 12.4% in 2001 to 22.3% in 2017. This trend is likely to continue with an aging population as disability risk tends to increase with age. This increase may also be partially due to the evolution of the definition of what constitutes disability and changes in an individual's reporting behaviour. For more details on the economic position of Canadians with disabilities, see Morris et al. (2017), and Statistics Canada (2001).

[3]For instance, an individual whose personal income comes from solely welfare transfers has very different economic circumstances than someone with income solely from business investments.

ical ability, or both, labelled concurrent.

Disability is a dynamic condition, and longitudinal measures are essential to understand the breadth and duration of its effects. On the one hand, some disabling conditions are degenerative, becoming progressively worse over time. On the other hand, disabling conditions may be temporary or accommodated, mitigating the adverse effects of the condition over time. In this paper, I measure the average effects of onset in each of the five years prior to and ten years after its onset.[4] Additionally, longitudinal measures of income changes offer better insight into how individuals adjust their earnings behaviour in response to a disability shock. Discriminating between the characteristics of disability that drive changes in income is valuable to disability insurance and welfare policy to better target individuals most effected by a disability.

After onset, the changing level and composition of personal income is informative of a disability's influence on earning behaviour and economic opportunities in the labour market. An individual's personal income equals the sum of income earned through market activities and transfers payments from the government. Good health is generally viewed as complementary to human capital (HC) in terms of labour market productivity.[5] Movements in market income and employment rates are telling of the magnitude and persistence of a disability's impact on HC, the return to labour market participation, and engagement in other market activities. The level of government transfers received reflects an individual's dependence on the social safety net, including programs that are not explicitly for disability. If it is the case that government transfers increase to offset the entire decline in market income following disability onset, then an individual's personal income is perfectly insured to this risk.

I use a two-way fixed-effect model to estimate the effect of disability types on incomes. This approach simultaneously controls for unobserved individual-fixed and time-fixed confounding factors. I use a dynamic design to estimate the per-year change in various measures of personal income around onset. Additionally, I control for time-varying observables to address differences in pre-onset trends between the disabled groups and their never-disabled reference counterparts. Recently, the two-way fixed effect model has come under scrutiny when used for causal inference with variation in the timing of treatment, which is disability onset in my application.I make use of recent innovations to this method to justify the application in this paper. The model specification in this paper is most similar to the framework studied in Sun and Abraham (2020), and I use their alternate estimator to check the robustness of my estimates to treatment effect heterogeneity.

I estimate my model using the Canadian dataset, the Longitudinal and International Study of Adults

[4]This time frame is the same as that studied in Meyer and Mok (2018).

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

(LISA). These data combine a short panel containing rich details on disability and demographics with a yearly panel of administrative tax records. In the tax records, personal income is disaggregated into subcategories of market income, such as employment or self-employment income, and government transfers are disaggregated by federal and provincial transfer policies and tax credits. Disability is derived in this survey using self-reported measures of the extent of LADLs, which I use to distinguish different types of disabilities.

I find substantial heterogeneity across the disability types in affecting the components of personal income. A cognitive disability causes three times the decline in market income relative to a physical disability in the ten years after its onset. The discrepancy is driven by declining employment income earned through wages, salaries, and commissions (WSC). This finding is consistent with a higher pricing of cognitive skills in the labour market, making a cognitive disability more detrimental to labour market returns than a physical disability. Despite this result, the onset of a physical disability results in higher average income from transfer programs that explicitly target individuals with disabilities. The increase in total government transfers does not significantly differ between physical and cognitive. However, those affected by a cognitive disability receive more from other government transfer programs, notably family benefits. The onset of a concurrent disability results in the largest decline in average annual income. The size of this effect is approximately the added the effects of impairment to physical and cognitive activities, with no additional interaction effects of having both.

The first contribution of this paper estimates novel measures of the dynamic changes in the level and composition of personal income around the onset of different types of disability. Access to detailed information on disability in conjunction with rich measures of life-cycle behaviour, labour market outcomes, and demographic characteristics is difficult to come by. Consequently, estimates of the labour market effects of disability have previously come from binary measures of disability status or by distinguishing disability by some measure of its severity.[6] Related studies have acknowledged that disability status represents one or multiple medical or physiological conditions, which vary substantially in their impact on one's daily life. When able, studies typically find heterogeneity in the impact of different types of disabling conditions.[7] To the best of my knowledge, no study has jointly analyzed the relative dynamic effects of onset for different disability types as this paper does. A unified framework facilitates comparisons across types of disability without concerns of external consistency that arise when comparing findings from different studies or

[6]For examples see Stern (1989), Burkhauser et al. (1993), Acemoglu and Angrist (2001), Charles (2003), Baldwin and Johnson (2006), Campolieti and Riddell (2012), Low and Pistaferri (2015), Ameri et al. (2018), Meyer and Mok (2018), Autor et al. (2019), among many others.

[7]For instance, Maestas et al. (2013) find heterogeneity across different medical conditions in rejected SSDI applicants, Lundbourg (2014) has medical reports on specific diseases or physiological conditions, and Mori (2016) summarizes disabling conditions as being either physical or cognitive.

datasets.

Second, I contribute to studies on the dynamics of earnings behaviour and income sources following a health shock. The disaggregated income measures facilitate comparing the rate and extent to which market income is replaced with government transfers across the disability types. Furthermore, I reconcile the comparative results on disaggregated income by analyzing the effect of disability onset on total income before and after taxation. I contribute to the understanding of how individuals use the tax and transfer system to insure against and buffer the effect of an income shock. My research most directly contributes to a series of studies that use dynamic or "event-study" style designs to measure the dynamic effects of health and disability shocks on various outcomes.[8] My main novelty is differentiating disability by types, and analyzing heterogeneous implications for personal income. Additionally, the use of administrative tax data offers detailed measures of incomes and transfers that are less likely to be affected by measurement error and under-reporting of incomes (Meyer, Mok and Sullivan 2009).

The remainder of my paper is structured as follows. Section 2 describes the working model of disability and how it relates to incomes. Section 3 describes the dataset used in my analysis. Section 4 illustrates features of the data, highlighting the demographic composition and differences across the disability types. Section 5 describes the empirical framework and its suitability for this analysis. Section 6 analyzes the results from the empirical model, and Section 7 concludes.

2 A Model of Disability and Implications for Income

This section describes a working framework to motivate the analysis and help interpret the effects of disability. Measuring disability is difficult as it is subjective to an individual's environment and personal characteristics. To give intuition for my paper's interpretation, I describe a simple working model of disability. I then discuss how disability, and health more generally, can be integrated into a canonical Human Capital (HC) framework. Linking disability to income through HC offers an intuitive understanding of its impact. Some types of income are direct functions of HC. Notably, employment earnings are directly determined by productivity. Other types of income are indirectly related to HC, such as government transfers, which are needed to help individuals with barriers to employment that may be driven by a lack of productivity.

[8] My research most closely relate to Meyer and Mok (2018), whose empirical strategy is the main inspiration for mine. Additional event study designs on heath and disability shocks include Stevens (2001), Meyer, Mok and Charles (2008), Singleton (2012), Fadlon and Neilsen (2021), among others.

2.1 A Representation of Disability

I model disability based on self-reported measures of LADLs. This has the advantage of honing in on a critical intermediate step in the mapping from a health condition to an individual's labour market outcomes. It is often unclear if, or how, a given health condition will influence behaviour. However, focusing on the activity limitations caused by a given health condition reveals if it impairs performance in productive tasks at work. To illustrate, when left untreated, diabetes can result in a substantial physical impairment, which may restrict the set of physically demanding tasks a worker is able to perform. However, with proper treatment, diabetes may not limit one's activities or significantly impact their work or productivity. Measuring the extent of physical impairment helps to overcome this ambiguity.

I represent disability status using a latent index framework. The "extent" of individual i's disability is modeled as a continuous latent univariate index, $\hat{d}_i$, that summarizes the extent of limitation in set whose elements represent a specific activity of daily living (ADL) chosen by the analyst. Disability status of individual i, d_i, is a binary variable that equals one for an individual when the extent of their disability breaches some threshold, $\bar{d}_i$. This threshold is indexed by i, as the threshold of disability depends on an individual's unique economic characteristics and environment.[9] That is, disability status is represented as

$$d_i = \begin{cases} 1, \text{ if } \hat{d}_i > \bar{d}_i \\ 0, \text{ otherwise.} \end{cases}$$

I assume that if $\hat{d}_i = 0$, then an individual is completely uninhibited in performing tasks comprising the specified set of ADLs. The larger the value of this index, the more limited an individual is in performing the set of ADLs. For instance, a mild sprained ankle would give a lower value to $\hat{d}_i$ than a broken ankle if the activities include walking or running. If $\hat{d}_i > \bar{d}_i$, the individual is considered disabled.[10]

Even this simple representation of disability illustrates the difficulties associated with its measurement and representation. $\bar{d}_i$ and $\hat{d}_i$ are private information and are endogenous to the environment, lifestyle, and occupation of the individual. A mild ankle sprain may be more disruptive to the livelihood of a professional athlete than a software engineer.

Defining $\hat{d}_i$ based on a chosen set of ADLs helps to address the empirical difficulties associated with the subjectivity of $\hat{d}_i$ and $\bar{d}_i$. I assume the activities are summarized by a vector, v_i, whose elements are

[9] For instance, people differ in the sets of tasks making up work, daily life, and their tolerance for dealing with barriers to performing these tasks.

[10] That is, someone with a mild ankle sprain may not be limiting enough for them to consider themselves disabled, whereas a broken ankle requiring crutches may breach this threshold.

continuous indexes representing the extent of limitation for a specific activity. For instance, an element may represent the extent of limitation in walking on a flat surface for 20 minutes. This vector maps into $\hat{d}_i$ by a chosen function or metric, $F : D^v \to D^d$, where D^j is the domain of "j" for $j \in \{v, d\}$. The threshold, $\bar{d}_i$, can be chosen in terms of v and the mapping from v to $\hat{d}_i$. For example, one may normalize d_i and elements of v_i between 0 and 1. Then F can be: "if the average of the elements of v_i is greater than 0.5, then individual is flagged for disability." This strategy takes a stance on what constitutes a disability. The definition of disability is relative to the chosen activities, the reported limitation of these activities (observed), the mapping F, and the choice of $\bar{d}_i$. In this paper, I take these components directly from the model used in LISA, which is outlined in Section 4.

This framework offers a flexible way to summarize the large variety of disabling conditions and the presence of multiple disabling conditions. For instance, it could be the case that someone may be flagged as disabled if they are severely limited in a given daily activity but uninhibited in all others. Alternatively, someone may be moderately limited in multiple activities, where the combination causes them to be considered disabled (i.e., breach the threshold in the latent index of the extent of disability). In contrast, they may not be flagged if they were only limited in one of these dimensions.[11]

2.2 Types of Disability and Relation to Human Capital

An individual's underlying HC is the primary determinant of their productivity and returns to working in the canonical HC model. In this framework, firms value HC as it is used directly in the production process, and thus, an individual's per-unit wage is set equal to their marginal product (Katz and Murphy 1992, Autor and Acemoglu 2011). The market valuation of one's HC is an important determinant of their labour market decisions. At any point in working life, an individual's value to labour market participation depends on the market pricing of their HC (wage). Thus, an increase in HC incentivizes people to work more to reap the benefits of higher wages and finance additional consumption. Hence, in this framework, changes in employment and income are informative of underlying changes to HC.

A person's stock of HC is influenced by environmental factors, notably their health. Health can be integrated into the HC framework as itself being valued in the production process, such as physical health and manual labour, or though complementarities with the stock and return to HC. I assume at any given time, individuals are heterogeneous in a vector representing HC and a vector representing health capital

[11] This may be accommodated by adding penalties to multiple conditions in the mapping from v to $\hat{d}_i$.

and that these are complementary to productivity.[12] Differences in productivity and subsequent wages may be due to heterogeneity in HC, health capital, and interactions between the two. Assuming that disability is a component of health capital, then the magnitude and persistence of observed changes in incomes and employment are informative of the magnitude and persistence of a disability's impact on health capital and subsequent HC.

The theory on HC has evolved from being measured as uni-variate source of latent heterogeneity, which was captured by direct measures, such as IQ or test scores, or proxied by schooling in Mincer style models, into a more complex structure that breaks HC into a multi-dimensional set of underlying skills.[13] Different elements of the HC vector, representing different types of skills, are priced differently by occupations based on the importance of the use of skills in production.[14] Following Yamagucci (2013), my analysis distinguishes between 2 elements of HC, physical and cognitive capital. Following Mori (2016), I distinguish two dimensions of health capital, defined analogously. I assume that physical (cognitive) health is positively related to physical (cognitive) capital, and hence productivity in physical (cognitive) work tasks.[15]

This framework of health and HC is useful to motivate the economic importance of each type of disability. Certain dimensions of HC will be more sensitive to certain types of disabilities. The onset of a disability will impact the health capital of that type, which then affects the related HC of that type. Physical disabilities will have a greater impact on physical capital or manual skills, whereas cognitive disabilities will impact cognitive capital or mental skills. For instance, physical disability may be disastrous for the productivity of a bricklayer but may not impact the productivity of a computer scientist at all. In addition, the market pricing of physical skills relative to cognitive will contribute to the level impact of the types of disability on income. As occupations differ in the use or valuation of each type of capital, a physical disability would have different implications for an individual's earnings potential than a cognitive one.[16] Additionally, having a concurrent disability results in an impact on both dimensions of the individual's health capital. Concurrent tells a story of absolute deprivation of skills rather than relative deprivation of a skill.

The previous discussion establishes a useful framework to interpret the empirical analysis conducted in

[12]The complementarity of health capital and HC is consistent with related literature on productivity and health, such as Hanushek and Woessmann (2008), Low and Pistaferri (2015), Mori (2016), Grossman (2017), Autor et. al (2019).

[13]For a review on the evolution of HC theory, see Flabbi and Gatti (2018).

[14]This intuition is present in Heckman and Sedlacek (1985), Poletaev and Robinson (2008), Autor and Handel (2009), Sanders and Taber (2012), among others.

[15]Note that it may the case that physical health impacts cognitive capital and cognitive health affects physical capital. My analysis is on aggregate measures of income, so I identify the effect of a type of disability on income, which captures both channels.

[16]Research on the effects of different types of health conditions or disabilities typically finds heterogeneity in their impact on productivity, earnings, among other outcomes. These studies often find disabilities with a degree of cognitive impairment are more detrimental to economic welfare than physical or sensory disabilities. For example, see Case et al. (2005), Lundborg (2014), and Mori (2016).

this paper. However, it is important to acknowledge that disability affects many other aspects of life. For instance, observed behavioural changes might result from additional costs associated with disability, labour market risks, preference changes, discrimination.[17] The results will reflect these additional consequences of disability. However, this paper will focus the discussion around HC and productivity.

3 The Longitudinal and International Study of Adults

To document the dynamic effects of disability types, I use the Longitudinal and International Study of Adults (LISA). LISA is a panel survey of over 11,000 Canadian households aged 15 and older. LISA consists of four biennial survey waves, starting in 2012, that cover a broad range of topics, including health, education, labour, social participation, and incomes. These data are supplemented with administrative records. Most notably are T1 family files, which contain rich dis-aggregated measures of personal income from individual income tax filings. The linked survey data and panel of T1FF tax data are especially well-suited to study compositional changes in earnings over time.

The panel of incomes comes from the T1FF records. These data include demographic characteristics relevant to tax filings, such as age, marital status, province of residence, and the number of children. These data span from 1982 to 2017 and are linked to each respondent in the main survey waves of LISA. I use all of the years in the T1FF for longitudinal yearly measures of an individual's personal income. For this analysis, I focus on measures of market income, government transfers, and before-tax and after-tax personal income. I emphasize the role of market income from wages, salaries, and commissions (WSC), as they are most directly related to HC. I focus on government transfers that are most relevant for individuals affected by disability. These include disability-specific tax credits and income replacement programs from worker's compensation, employment insurance, federal disability insurance, and provincial social assistance programs. A notable advantage of these tax records is they are less likely to suffer from the measurement and coverage issues often associated with survey data.[18] For a more detailed breakdown of the income concepts covered in these data, please refer to section 9.2 in the Appendix.

[17] Kitao (2014) studies disability-specific labour market risks. Low and Pistaferri (2015) incorporate for utility cost of disability in their framework. Baldwin and Johnson (2006) survey research on disability discrimination.

[18] Meyer, Mok and Sullivan (2009) find survey reports on public transfers often suffer from respondents under-reporting, which can lead to overestimation of total income declines following the onset of disability.

3.1 Measuring disability

2014, 2016, and 2018 waves of LISA include measures of activity limitations and other characteristics of health conditions used to derive disability status.[19] The set of LADLs included in LISA are derived from a short version of "the disability screening questions" (DSQ) developed by Statistics Canada for use in general population surveys (Grondin 2016). These distinguish five main areas of activity limitation: Seeing, Hearing, Physical, Cognitive, and Mental Health. Physical combines limitation to mobility, flexibility, dexterity, and pain. Cognitive includes learning, developmental and memory limitations. Mental-Health includes Anxiety, PTSD, depression, and other conditions. Please refer to section 9.1 in the Appendix for examples of question-wording.

Table 1: Official definition of disability using short version of DSQ

	How often are your daily activities limited by...?				
How much difficulty do you have...?	Never	Rarely	Sometimes	Often	Always
No Difficulty	No Disability	No Disability	Disability	Disability	Disability
Some Difficulty	No Disability	No Disability	Disability	Disability	Disability
A lot of Difficulty	No Disability	No Disability	Disability	Disability	Disability
Cannot do	No Disability	No Disability	Disability	Disability	Disability

Source: Table comes directly from Grondin, C. (2016). A new survey measure of disability: The Disability Screening Questions (DSQ). Statistics Canada. The first column represents possible answers to questions relating to the level of difficulty. The titles of columns 2-6 represent the possible answers to questions relating to the frequency of limitation.

The activity limitations are self-reported, and the age of disability onset is retrospective. For each type of activity limitation, respondents were asked a flow of categorical questions about the magnitude of difficulty and frequency of limitation for each limitation type.[20] The mapping from these questions to disability status is displayed in *Table 1*.[21] Individuals flagged for any type of disability are flagged as disabled.

Using self-reported functional limitations to measure disability is not without its share of criticism, as are all other methods of defining disability.[22] Opponents of using self-reported disability are often concerned with the endogeneity of reporting and over-reporting. However, it has been found that self-reported disability is close to exogenous, may actually under-represent the extent disabled population, and may even underestimate the true impact of disability on relevant labour market outcomes (Stern 1989, Bound and Burkhauser 1999,

[19]The 2012 wave comprises only a small set of questions about the disability. Notably, the 2012 wave excludes the variable that determines the age of disability onset.

[20]Some cognitive conditions, such as developmental disability or learning conditions, were derived based on diagnosis from medical professionals instead of the level of difficulty. Refer to Appendix 9.1 for details.

[21]For example, if someone responds "some difficulty" and "often" to limitation in physical activities, they are flagged for a physical disability.

[22]For instance, using disability insurance beneficiaries to flag people with disabilities has been found to under-represent the population of individuals who are limited enough in the labour market to be classified as "disabled" (Bound 1989).

Burkhauser et al 2002). Using specific health questions, such as the activity limitation screening questions in LISA, 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 provides sufficient evidence to validate the use of self-reported disability, as defined by specific questions on functional limitations.

3.2 Sample Selection

I observe detailed information on disability types and onset in the 2014, 2016, and 2018 survey waves.[23] I group cognitive and mental conditions into a single category relating to activity limitations affecting cognition and mental processing. Lastly, I choose to omit individuals who are blind or deaf and only focus on the cognitive and physical categories.[24]

The age of disability onset is derived from a self-reported retrospective question,"at what age did you first start having difficulty or activity limitation?" I interpret all disabilities as being persistent between the survey and reported onset. Due to the retrospective nature of this question and panel structure of the survey waves, there are instances where an observation reported different ages of onset. To address this issue, I used the earliest reported age of onset.[25]

I restrict my sample to individuals with at least four income observations in the age range of 22-61. I replace missing demographic information using adjacent survey waves and drop observation missing key demographics.[26] I drop observations whose measured onset is lower than 23 or greater than 56 to focus on disability shocks in working life and to abstract from retirement incentives. Additionally, I drop individuals whose disability onset occurred before 1984, and I trim year observations for more than ten years after disability onset. I exclude observation living in the Canadian Territories. The final sample includes working-aged individuals in the Canadian provinces who become disabled and who never become disabled, who serve as the control group.

[23]I retain the 2012 wave to extract relevant demographics, and the survey weights are representative of the Canadian population in 2012.

[24]I explored these conditions in some analyses, but the results are mostly insignificant due to a small sample size.

[25]I am unable to determine which condition occurred first for the concurrent group.

[26]Notably, education level and date of completion are filled in when able,keeping in mind that observations can complete their education during the span of the survey.

4 Summary/ Descriptive statistics

This section of the paper describes some of the features of the populations with and without disabilities, and across the different types of disabilities. There are important differences between these groups, which will be important to address in the empirical exercises. In the current version of the paper, much of the descriptive information is confidential. I have chosen to only vet the minimum amount of information to minimize residual disclosure risk that may prevent my ability to vet results in future drafts of this paper.

Table 2 displays some descriptive statistics from the Statistics Canada report by Wall (2017). The sample for these estimates is from the 2014 wave of LISA and focuses on individuals between the ages of 25 and 64 whose onset occurred at any time, which is slightly different from my sample of interest. Additionally, this study includes sensory disabilities along with the physical group.[27] Additionally, the relative distribution of disability types is very similar to my sample of interest. This table illustrates that, first, there are large differences in labour market outcomes between those with disabilities and those without disabilities. Second, there are large differences in labour market outcome across the types of disabilities. In a cross-section, cognitive and mental disabilities are less likely to be employed, earn less through employment, and are more attached to government transfers.

[27] The population with sensory disabilities, which are seeing and hearing limitations, is very small.

Table 2: Statistics for population aged 25-64 who report having a disability

	Not Disabled	**Disabled**			
		Total	*Physical-Sensory*	*Cognitive-Mental*	*Concurrent*
Proportion of Population	79.7	20.3	12.1	2.6	5.7
Employment rate	84	58	66	63	38
Income Types					
Employment Income	52,200	29,300	35,700	26,800	16,600
Government Transfers	2,500	5,600	4,400	6,000	7,800
After Tax Income	48,300	32,600	37,100	29,800	24,400

Source: Statistics come directly from Wall (2017), "Low Income among Persons with a Disability in Canada." The sample are individuals from the 2014 wave of LISA, aged 25-64 who report having a disability.

Table 3 outlines additional summary statistics for the control group and the ever-disabled group from my sample as described above. First, I discuss the average age and timing of onset. Individuals with a physical disability tend to be older on average than non-disabled, and cognitive tend to be younger in the survey waves. The concurrent group is slightly older than the non-disabled, but the difference is small. In terms of age of onset, physical disabilities tend to occur at older ages than cognitive. Concurrent disability's average age of onset is in between physical and cognitive. However, I can not tease out which condition occurred first and treat this group as having both types of disabilities occur simultaneously.

Next, I discuss the difference in family composition, which are directly relevant for many transfer programs and taxes. Individuals with a disability are more often female than male, and this is true for all types. Cognitive and Concurrent types more likely to be female than physical. People with disabilities are less likely to be married or in a common-law relationship. However, this is driven by differences from cognitive and concurrent, as physicals proportion of married or common law is similar to non-disabled. Some of this may be driven by other characteristics, such as cognitive being younger on average. Surprisingly, individuals with a cognitive disability tend to have more children on average than physical and concurrent. The average number of children is smaller for people with disabilities relative to their able-bodied counterparts on average.

Table 3: Demographic Summary Statistics

	Not Disabled	**Disabled**			
		Total	*Physical*	*Cognitive*	*Concurrent*
Cross-Sectional Averages					
Number of Observations	11900	2,800			
Female	0.488	0.578			
Number of children	0.84	0.68			
	(1.1)	(1.0)			
Age of onset		42			
		(9.3)			
Highest Education					
Dropout	0.064	0.117			
High School	0.181	0.209			
Post-secondary	0.750	0.667			
Entire Panel Averages					
Age	39	39			
	(10.7)	(10.2)			
Married or Common Law	0.68	0.62			

Note: Standard deviations are in parentheses. The variables Age and Marries are averages over the sample years in which the observation was aged 22-61, as per sample selection. Statistics for the disability types are currently omitted to prevent residual disclosure risk that may prevent future vetting of statistics.

Lastly, education differences may affect the risk of disability due to being associated with more or less risky occupations. For instance, a surgeon may be at higher risk of a cognitive disability related to stress, and a labourer may be at higher risk of a physical disability due to strain on their body. The education categories show that people with disabilities have lower average post-secondary attainment and higher rates of dropout. Physical disability tends to be associated less post-secondary attainment and higher rates of dropout, whereas cognitive disability is associated with more post-secondary attainment and lower dropout relative to non-disabled individuals. The concurrent group's education is the lowest of the three types at all levels.

These summary statistics illustrate substantial differences in demographic characteristics across the types of disabilities. These demographics are directly related to the levels and components of personal income.

In the next section, I outline the empirical framework used, which controls for these differences, in order to better pin down the effect of the types of disability on behaviour, outcomes, and subsequent incomes.

5 Empirical framework

This paper measures the change in economic outcomes from disability onset using the following two-way fixed effect design,

$$y_{it} = \alpha_i + \gamma_t + X_{it}\beta + \sum_g \sum_k \delta_k^g A_{kit}^g + \epsilon_{it}, \tag{1}$$

where y_{it} is the income type of interest for individual i at time t. The variables A_{kit}^g are indicator variables equalling one for mutually exclusive disability type $g \in \{Physical,\ Cognitive,\ Concurrent\}$, in year $t \in \{1982,\ ...,\ 2017\}$, and $k \in \{-5, ..., 10\}$ years relative to onset. The coefficients of interest are δ_k^g, which are interpreted as the average level effect relative to the average trend in y_{it} more than five years prior to its onset, which is the reference time period in this setting. I also estimate models that group the disability types to illustrate the average effect of all types. The estimation sample includes individuals never affected by disability to help improve the precision on estimates of age, education, and the other control variables.

The two-way fixed effect design includes an individual fixed effect, α_i, and a time fixed effect, γ_t, that controls for time-fixed individual and year specific confounders simultaneously. Additionally, (1) includes a rich set of time-varying controls X_{it} to better isolate the effect of disability onset on the outcome of interest.[28] Notably, I control for trends in education to address pre-disability differences in skills. I include measures of family characteristics, which are determinants of government transfers and tax rates. Lastly, ϵ_{it} is a potentially serially correlated error term.

5.1 Suitability of the two-way fixed effects design

The two-way fixed effect model has been a workhorse method to recover causal estimates of treatment from a binary policy, mainly due to its analogs to difference-in-difference (DD) and event study identification strategies. I apply an "event study" design, as my interest lies in the dynamics of disability in the years

[28] In all specifications, X_{it} includes province dummy variables, where Ontario is omitted, and year dummies, with 2016 and 2017 omitted, number of kids under 18, marital status, and dummies for education certificates. I include a 2nd order polynomial in age and interact this with education, marital status, number of kids. Additionally, I interact education, marital status, sex, and number of kids with a 2nd order polynomial in time since 1982.

surrounding onset, and the timing of my treatment of interest, disability onset, is staggered.[29] Recent innovations in the theory underlying these types of estimations have cast doubts on the validity of the recovered treatment effects (Borusyak and Jaravel 2017, Goodman-Bacon 2018, Callaway and Sant'Anna 2020, de Chaisemartin and d'Haultfoeuille 2020, Sun and Abraham 2020a, Imai and Kim 2020). Mechanically, this approach will recover a linear combination of average differences in trends of outcomes between different cohorts and relative time periods.[30] Achieving causal interpretation of the estimated parameters requires satisfying a set of identifying assumptions, which can be difficult to satisfy in many empirical settings.

Interpreting disability onset as a treatment effect raises some empirical challenges. Causal interpretation of estimates requires some form of parallel trends assumption for the control group to serve as a valid counterfactual to not being treated, assumptions restricting anticipation of treatment, and restrictions on the heterogeneity in the treatment effect itself.[31] The disability types aggregate a variety of physiological conditions that differ in the scale and dynamics of their effects on individuals, which may violate the identification requirements. However, I address these issues using the insights from the aforementioned literature regarding causal inference with the staggered two-way fixed effect design.

I include a large sample of individuals who never become disabled to serve as the control group.[32] This group can serve as a counterfactual outcome to disability onset only if satisfying a parallel trends assumption. I include time-varying controls to address any confounding in parallel trends. Hence, my identification relies on assumed parallel trends between treatment and control groups, conditional on covariates.[33] My design includes leading indicators, as I am interested in the dynamic path of the effects of disability surrounding onset. Hence, I am assuming that there are no anticipatory treatment effects further than five years before onset.[34] However, the empirical results show that, in most cases, this assumption can be reduced to two or fewer years before reported onset.

The estimates from the two-way fixed effect design when the timing of treatment is staggered have been shown to recover a weighted average of treatment effects from different subgroups, time periods, or both.[35]

[29]Staggered treatment timing means that individuals may receive treatment at different periods.

[30]See proposition 1 in Sun and Abraham 2020.

[31]See Sun and Abraham (2020a) or Callaway and Sant'Anna (2020) for variations of these identifying assumptions in dynamic settings.

[32]A large control sample helps address collinearity issues in dynamic event study designs, as opposed to using a pre-treatment period as the control group (Borusyak and Jaravel 2017).

[33]Adding covariates requires the additional assumption that trends are linear in the covariates. I include polynomials as many of my controls to accommodate non-linearities in trends.

[34]It is worth noting that significant effects in the year before onset may be capturing gradual increases in the extent of limitation before the individual becomes labelled disabled, permanent anticipation, or may reflect measurement error in the reported timing of disability onset. I am unable to distinguish between these.

[35]See Goodman-Bacon (2018) or de Chaisemartin and d'Haultfoeuille (2020) for this result in the static setting. See Sun and Abraham (2020a) for this result in a dynamic setting.

This result is especially worrisome when treatment effects are heterogeneous across groups or time, as the weights can be negative and bias the estimated treatment effects.[36] I employ a flexibly dynamic design, most similar to that studied in Sun and Abraham (2020a), which allows for treatment effects to vary over time. However, the dynamic path of treatment must be the same across cohorts that become disabled at different times. That is, I assume treatment effect homogeneity in the path of effects for cohorts treated at different calendar years. Sun and Abraham decompose the estimated treatment effect for a given relative period in the dynamic specification, δ_k^g in my notation, as a weighted sum of treatment effects for different cohorts in that period, and other relative periods. They also show how, even under the parallel trends assumption, effects from other relative periods can contaminate estimates for a given relative period when the path of treatment is heterogeneous across cohorts.

Heterogeneity in treatment paths across cohorts may be particularly relevant for disability onset. The timing of onset may have occurred between 1984 and 2014. Any changes in labour market structure, such as the composition of jobs and valuation of skills, may induce heterogeneity in the effect of a type of disability on market income, notably employment earnings. For instance, the movement away from manual task jobs to service sector jobs, which may value cognitive skills greater, may change the effect of the onset of a cognitive disability, as there are relatively fewer manual jobs to substitute towards. Additionally, changes in the parameters governing social insurance policy over this time frame can also introduce cohort-specific treatment effect heterogeneity.

I check the robustness of my estimates using the procedure of Sun and Abraham (2020a), who develop a method to estimate the set of weights on the effects from all relative periods that may be contaminating a given δ_k^g. These weights are derived from an auxiliary regression that depends only on the distribution of cohorts and the relative to treatment time indicators included in the main regression.[37] I find that conditional on covariates, the weights attached to the treatment effects from other relative periods in each group is fairly close to zero for all disability types.[38] This implies each of the estimated effects of disability onset is a weighted average of the cohorts within that relative period, and are not overly contaminated by the effects from other periods. This gives more confidence in the use of leading variables to test parallel trends.[39]

[36] The occurs when newly treated units are compared to previously treated units (Goodman-Bacon 2018).

[37] I estimate the weights using the STATA command *eventstudyweights*, which was developed and made publicly available by Sun 2020b.

[38] To the best of my knowledge, there is no systematic framework to interpret a permissible size of the weights. The estimated weights from other relative periods in a given δ_k^g are of the order 1×10^{-2} at most.

[39] In unreleased work, I use the estimation strategy of Sun and Abraham. I find very similar results to those reported below, however, the scale of the effect is slightly larger for physical, and the effect of cognitive is reduced in the later periods relative to onset.

6 Results

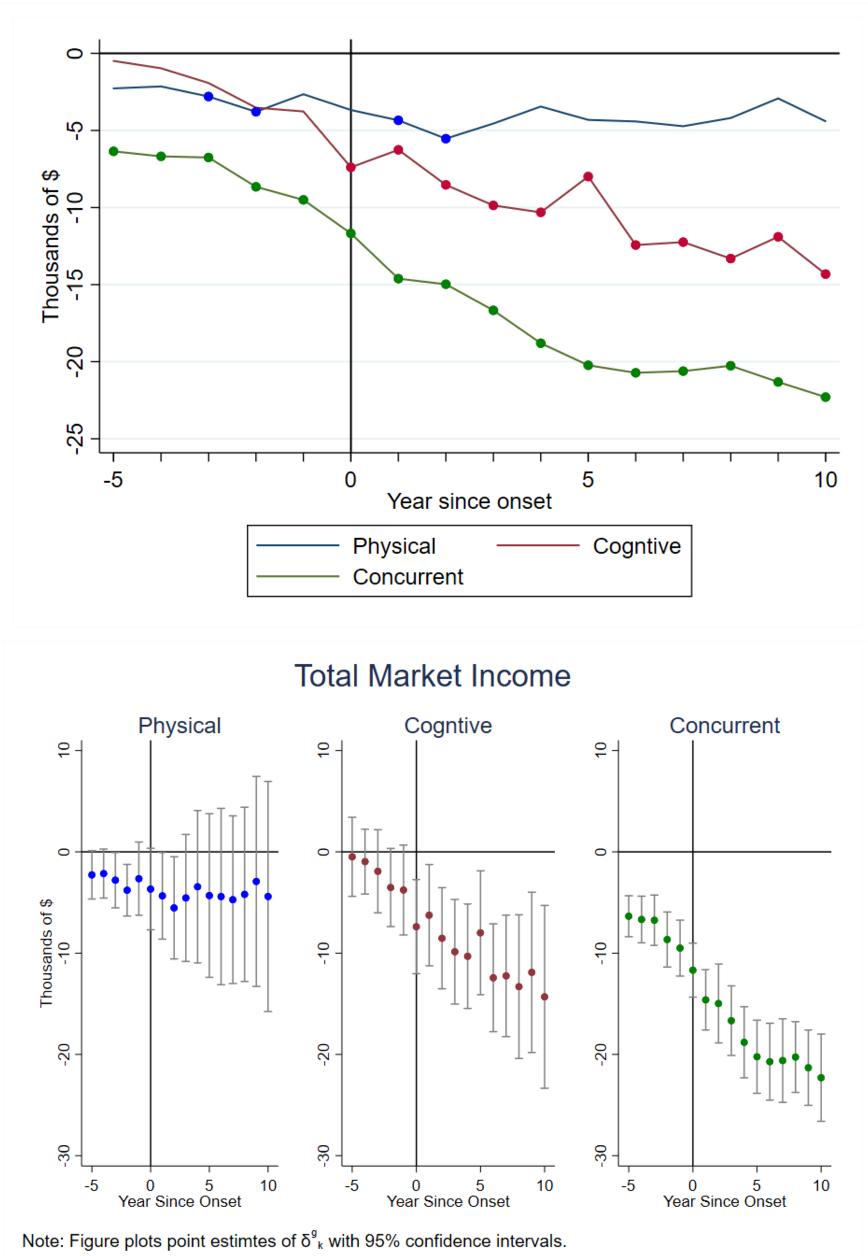
This section analyses the dynamic effects of disability onset for disaggregated measures of personal income. I proceed with the results in 3 subsections. I first estimate the effect of disability on total market incomes and then narrow in on employment income earned from wages, salaries, and commissions. Income from employment is most closely related to an individual's HC, the central determinant of labour market productivity. Next, I study the changes in government transfers to understand the extent of income replacement available to counter the changes in market income. Finally, I compare the first two sets of results with changes in total personal income before and after taxation. Personal income before taxes combines market income and government transfers, which measures the insurance for a disability shock. The total personal income after taxation is informative of how much of earnings from all sources is actually taken home. Point estimates for these results can be found in Appendix section 9.3.

6.1 Total Market and Employment Incomes

An individual's market income combines all of their financial returns from participation in market activities. Market income is a useful measure of one's earning capacity or economic independence. Market income is the sum of earnings made through paid employment, self-employment, returns to savings and personal investments, and other business activities.[40]

[40]Income from other market activities includes corporate dividends, limited partnership income, private pensions, and retirement savings plans. Child support or alimony would be considered market income, but I do not include this in my measure. For more details, see section 9.2 in the Appendix.

Figure 1: The Effect of Disability Onset on Total Market Income.



Note: Figure displays the estimated level changes from a two way fixed effects model for mutually exclusive types of disability. Blue line represents physical, red line represents cognitive, and green represents concurrent. In the top figure, the dots represent estimates with an estimated $p < 0.05$. The dashed grey line represents a separate estimation with the types of disability aggregated over the 3 mutually exclusive categories. The bottom figure shows the 95% confidence interval for each point estimate.

Figure 1 displays the estimated level effect of disability onset on total market income in $k \in \{-5, ..., 10\}$

years relative to disability onset. The blue, red, and green lines show the change in market income from physical, cognitive, and concurrent, respectively. The onset of aggregate disability is followed by a persistent decline in market income. However, this finding masks substantial heterogeneity across the types.

Disabilities with a component of cognitive impairment are worse on average than those that are exclusively physical. Average market income steadily declines by almost -15,000$ in the ten years after onset for the cognitive group.[41] Whereas, the initial drop in market income, which troughs around -$5,500, recovers slightly after the third year from onset for the physical group.[42] The size of the effect of concurrent disability is approximately equal to the combined effect of physical and cognitive. The rate decline in market income slows down after five years, slightly below -$20,000.[43]

To hone in on the effect of disability onset on HC, *Figure 2* reports the estimated changes in annual income from wages, salaries, and commissions (WSC). The coefficients of disabilities types on this income source are informative of the combined effect on an individual's labour supply, and the market pricing of their labour.[44]

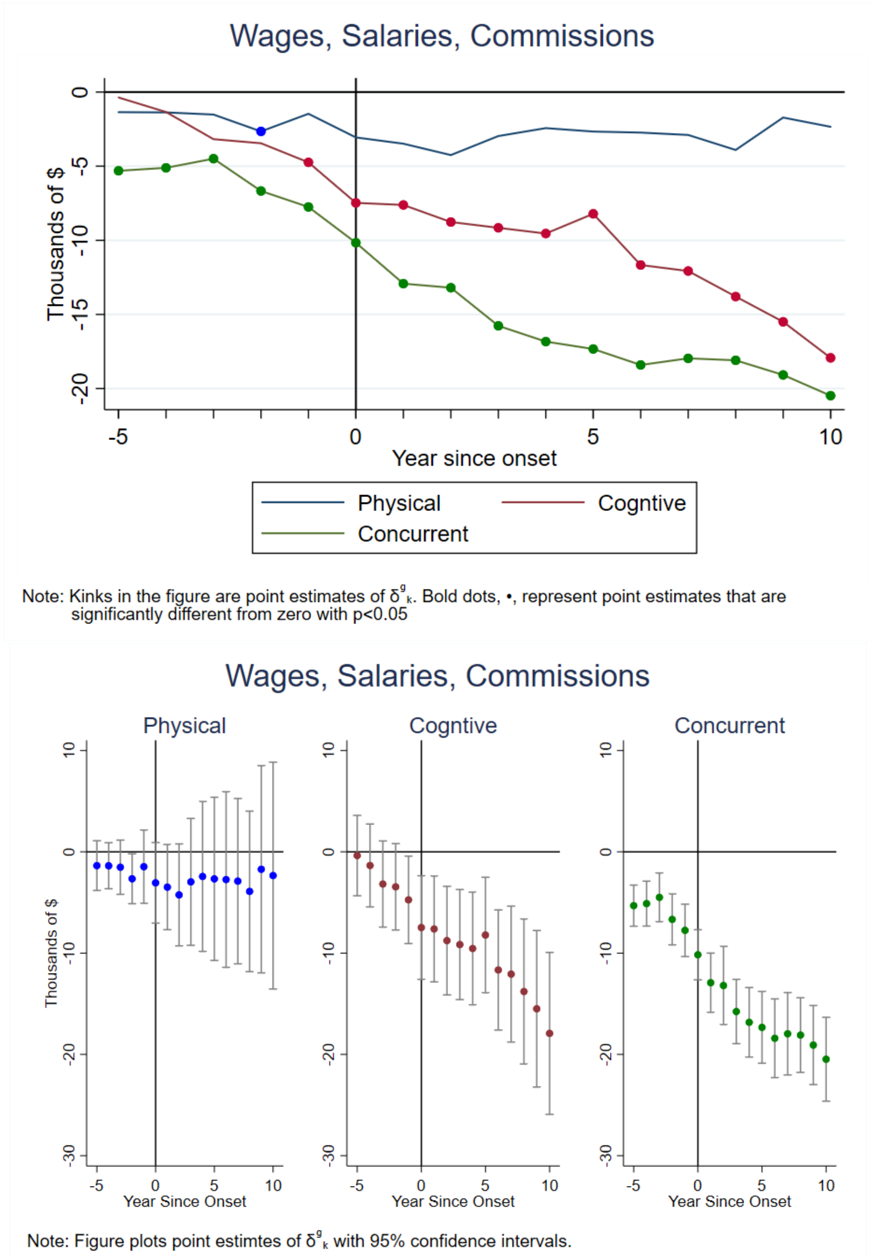
[41] The eyeball check for parallel trends holds in all leading variables for cognitive onset. The leading variables for physical are significant in $k = -2$ and $k = -3$. The pre-trends for the concurrent group are significantly different from zero, raising concerns with causal interpretation for this group.

[42] Many of the lagging point estimates for physical onset are marginally significant. However, the set is jointly significant from zero with p=0.0031.

[43] I fail to reject joint hypothesis that the effect of concurrent equaling the sum of the effect of physical and cognitive.

[44] Additionally this would reflect any lost income from occupation switching.

Figure 2: The Effect of Disability Onset on Income Earned from Wages, Salaries, and Commissions.



Note: Figure displays the estimated level changes from a two way fixed effects model for mutually exclusive types of disability. Blue represents physical, red represents cognitive, and green represents concurrent. In the top figure, the dots represent estimates with an estimated $p < 0.05$. The dashed grey line represents a separate estimation with the types of disability aggregated over the 3 mutually exclusive categories. The bottom figure shows the 95% confidence interval for each point estimate.

Figure 2 shows the results for market income are mostly driven by WSC for all types of disability. The onset of a cognitive disability has a more rapid and persistent effect on WSC relative to physical. Furthermore, after five years, the gap in WSC between physical and cognitive widens substantially.[45] This result is consistent with a higher market pricing of cognitive skills, a greater market penalty to losing these skills, and less substitution from cognitive to physical production. Cognitive skills are likely to be valued higher than physical skills in the marketplace of developed service-based economies like Canada. Upon the onset of a physical activity limitation, it may be the case that individuals substitute to work that uses their cognitive skills more intensely, buffering the impact on their physical disability. In contrast, the onset of a cognitive disability leaves the individuals left with less of the higher valued cognitive capital.

Similar to market income, the effects of physical disabilities tend to be milder and flatten out after 3 or 4 years following onset. The estimates for the lagging effects are jointly significantly different from zero. However, the point estimates are insignificant for lags after year 3.[46]The dynamic effect of concurrent disability onset is approximately equal to the combined estimated effect of both physical and cognitive.[47] These results are informative of a total effect of disability on health capital. The leading effects are all significant for concurrent, suggesting this group's trends are different even after conditioning on covariates.[48]

Comparing *Figure 1* and *Figure 2* finds the level decline in WSC is larger than that of total market income for the cognitive group. This suggests individuals impaired by a cognitive disability substitute income from employment to other market sources. *Figure 9* in Appendix 9.4 shows evidence that cognitive substitutes their earnings source from WSC to self-employment or other employment. Other employment income (OEI) includes income sources not reported as wages, salaries or commissions.[49] I find that two-thirds of the rise in non-WSC employment income is due to self-employment income (SEI), and one-third is due to other income.[50]

[45]These exist some anticipatory effects for in $k = -1$ for cognitive and in $k = -2$ for physical. Otherwise, the leading coefficients are insignificant for these disability types, which is consistent with parallel trends before $k = -2$.

[46]The F-test of $\{\delta_k^{Phys} = 0\}_{k=1,...,10}$ is rejected with p=0.0009.

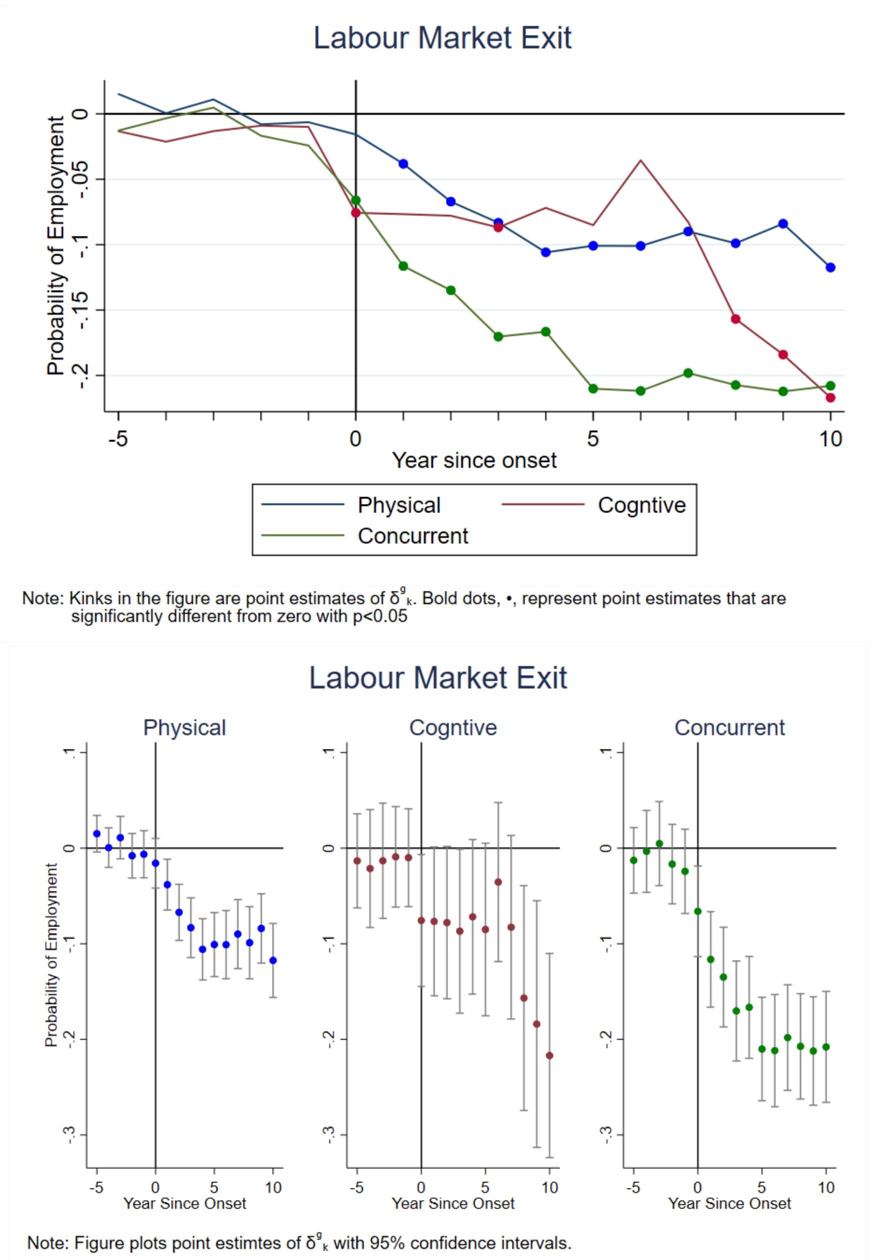
[47]I fail to reject the joint test of $\{\delta_k^{Phys} + \delta_k^{Cog} = \delta_k^{Conc}\}_{k=1,...,10}$ with p = 0.199.

[48]These results are interpreted as trend differences and not causal effects.

[49]These may include tips, graduates, research grants, and most notably Wage-Loss Replacement Plans, which are essentially private arrangements between an employee and employer for disability insurance.

[50]The increase in non-WSC income for cognitive is jointly significant with a p=0.075. However, the point estimates are weakly significant, which may be due to there being a small group receiving income in SEI and OEI for the entire sample population.

Figure 3: Change in the Probability of Employment.



Note: Figures displays the estimated level changes from a linear probability two way fixed effects model for mutually exclusive types of disability. Blue represents physical, red represents cognitive, and green represents concurrent. In the top figure, the dots represent estimates with an estimated $p < 0.05$. *The dashed grey line represents a separate estimation with the types of disability aggregated over the 3 mutually exclusive categories. The bottom figure shows the 95% confidence interval for each point estimate.*

WSC is the main factor explaining the decline in total market income after onset for all groups of disabilities. This may be driven by changes in the market pricing of work, leading to lower returns per hour worked. With a lower return to working, individuals may choose to supply less labour or exit the labor market entirely. Additionally, disability often imposes additional costs and barriers to work that may also contribute to labour market exits, such as workplace discrimination or the need for workplace accommodations. *Figure 3* illustrates the change in the probability of labour market participation in the years around disability onset.

Employment is defined as having observed any positive WSC in a given year.[51] The estimates in *Figure 3* are from a linear probability model for employment.[52] The effect of physical and concurrent onset each show a large initial decline in the probability of employment, then flatten out after five years. The results for cognitive are more volatile but show a substantial decline by ten years after onset.[53] The employment profiles are consistent with the results from WSC. That is, the effects of physical disability flattens and cognitive persistently declines in the ten years after onset.

6.2 Government Transfers and Credits

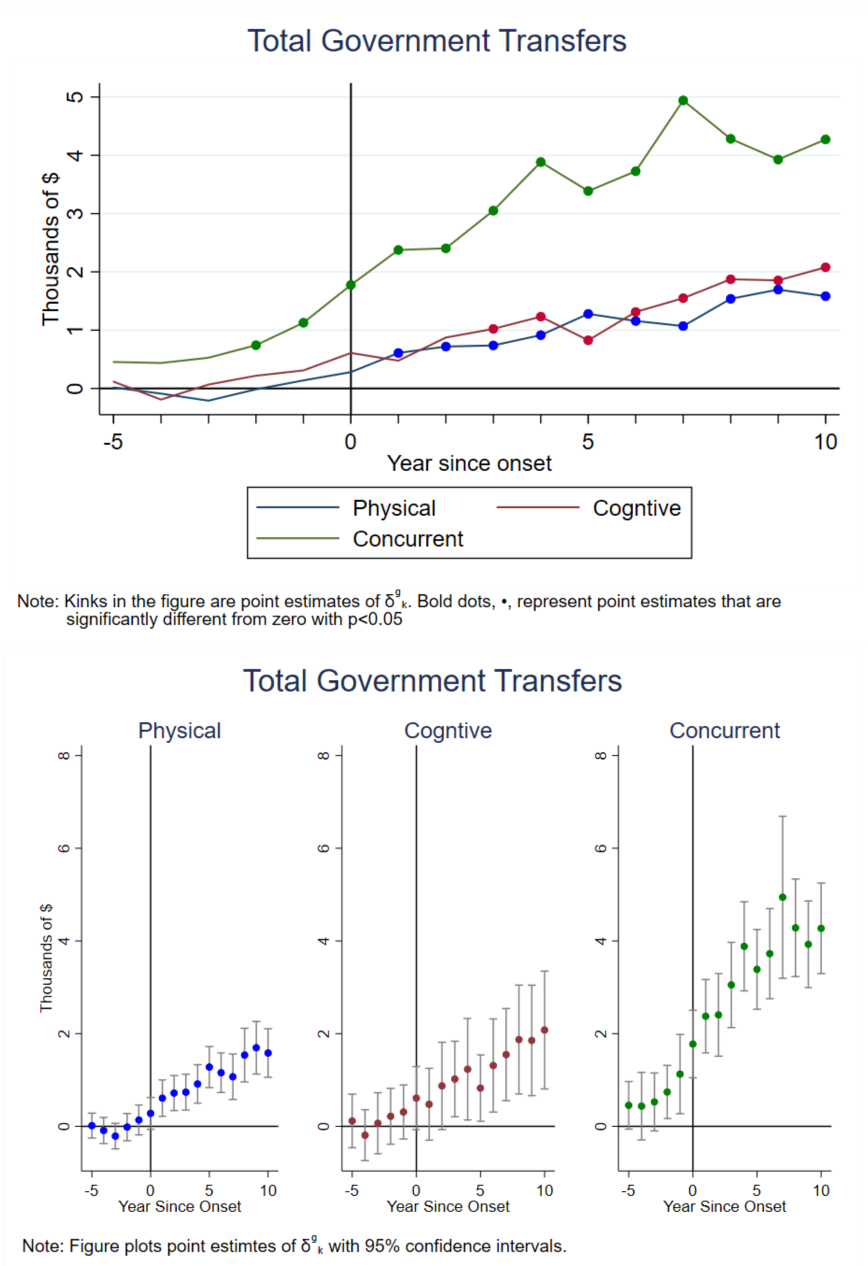
The results in the section on market income find that onset of each type of disability results in loss of market income. This section analyzes the average changes in the level of government transfer programs. Government transfer programs make up the majority of the social safety net in Canada, which offers income assistance and tax credits to individuals with barriers to their economic independence.

[51] The results are robust to defining employment based on lower thresholds of WSC. I check two lower bounds, 3000 and 4000, which are the amount from earning 5$ per hour for 20 hours per week for 6 weeks or 8 weeks, respectively.

[52] The estimates of the leading variables are insignificant and close to zero for all types of disability, suggesting the controls do a good job of addressing any pre-trends for this outcome.

[53] A joint f-test of $\{\delta_k^{phys} = \delta_k^{cog}\}_{k=1,...,10}$ is rejected with a p=0.0049.

Figure 4: Change in Level of Transfers from the Government.



Note: Figure displays the estimated level changes from a two way fixed effects model for mutually exclusive types of disability. Blue represents physical, red represents cognitive, and green represents concurrent. In the top figure, the dots represent estimates with an estimated $p < 0.05$. The dashed grey line represents a separate estimation with the types of disability aggregated over the 3 mutually exclusive categories. The bottom figure shows the 95% confidence interval for each point estimate.

The increase in government transfers around onset reflects relative differences in coverage and eligibility of different types of disabilities within these programs. Total government transfers combine income from programs at both the federal and provincial levels. The main components are income replacement programs, such as Canadian, or Quebec, Pension Plan (CPP), Employment Insurance, family benefits and tax credits, provincial means-tested welfare, tax credits, and programs available for those affected by disability.[54]

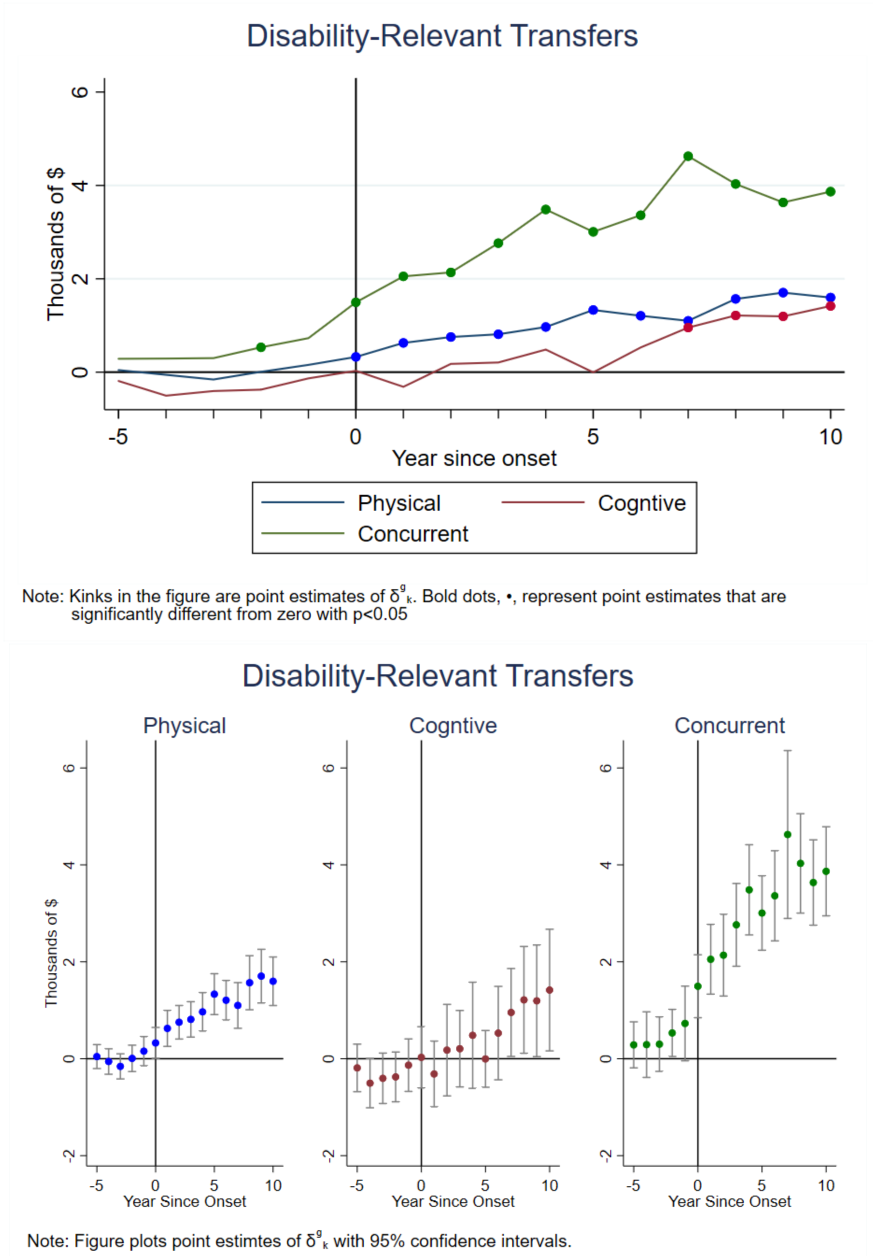
The level change in total government transfers is presented in *Figure 4*. As expected, concurrent disabilities receive the largest increase in total government transfer income, peaking around to 5000$. The increase in transfers in the ten years following disability onset is similar for physical and cognitive, steadily trending up to approximately 2000$.[55] Despite resulting in a substantially larger average decline in market income, those affected by cognitive have a smaller fraction of their income insured by total government transfers.[56]

[54]Government transfers typically include programs for old age security programs. I do not include these programs in my measure as I am focusing on individuals aged 22-61.

[55]I fail to reject a joint f-test of $\{\delta_k^{phys} = \delta_k^{cog}\}_k = 1, ..., 10$ with a p=0.6282

[56]About one-fourth of the decline in market income is replaced for physical. However, approximately one-tenth of the income for cognitive is replaced on average.

Figure 5: Change in Level of disability targeting Transfers from the Government



Note: Figure displays the estimated level changes from a two way fixed effects model for mutually exclusive types of disability. Blue represents physical, red represents cognitive, and green represents concurrent. In the top figure, the dots represent estimates with an estimated $p < 0.05$. *The dashed grey line represents a separate estimation with the types of disability aggregated over the 3 mutually exclusive categories. The bottom figure shows the 95% confidence interval for each point estimate.*

To understand the compositional changes in government transfers, *Figure 5* reports estimates when the outcome variable is government transfer programs that most relevant for people affected by a disability. The first of these programs is the Canadian Pension Plan Disability (CPP-D), which is the main federal disability insurance program in Canada.[57] Another federal program is the Disability Tax Credit, which offers tax deductions and credits for other expenses related to housing, treatment, or the cost of medication. Another relevant federal program is Employment insurance, which provides short-term income replacement. At the provincial level, Workers Compensation (WC) given wage replacement for individuals whose disability is the result of an injury. Finally, provincial Social Assistance (SA) is means-tested welfare programs that give benefits to individuals with substantial barriers to employment. SA programs generally have additional benefits available for individuals with disabilities.[58]

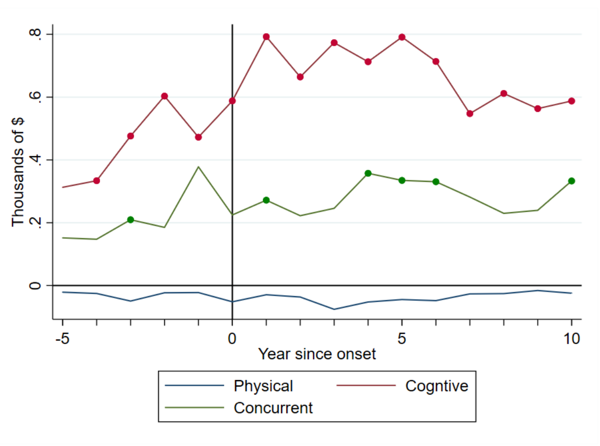
The increase in disability-relevant transfers is the main driver of the increase in total government transfers. However, physical receives more income from this source in all ten years after onset.[59] The cognitive group only experiences a significant increase in the level of transfers more than 5 years after onset. The later increase in disability relevant transfers is due to uptake in CPP-D and provincial SA programs. Cognitive disabilities are almost entirely excluded from WC and the other programs do not offer much assistance to either cognitive of physical on average.

[57]CPP-D is available for individuals who disability renders them incapable of pursuing any gainful employment and who meet a set of other eligibility criterion.

[58]I do not include the Working Income Tax Benefit, which was introduced in 2007. This program is captured in total personal income in the next section.

[59]I reject a joint f-test of $\{\delta_k^{phys} = \delta_k^{cog}\}k1, ..., 10$ with a p=0.0047

Figure 6: Change in Level of family Transfers from the Government



Note: Figure displays the estimated level changes from a two way fixed effects model for mutually exclusive types of disability. The blue line represents physical, the red line represents cognitive, and the green line represents concurrent. The dots represent estimates with an estimated $p < 0.05$. The dashed grey line represents a separate estimation with the types of disability aggregated over the 3 mutually exclusive categories.

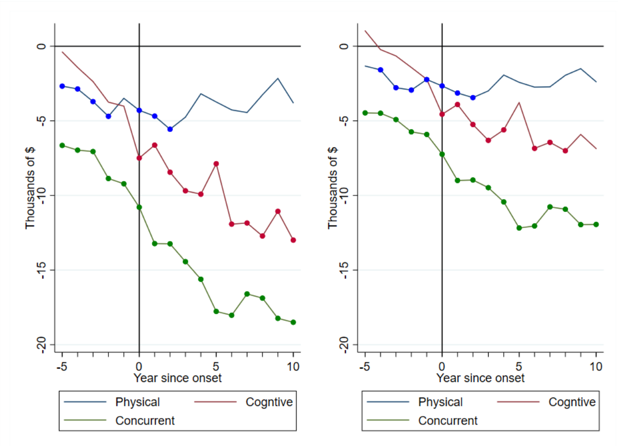
The onset of disability and the resulting decline in market income may knock individuals into becoming eligible for additional tax credits and deductions, such as benefits for low-income families, which are generally progressive.[60] In *Figure 6*, I analyze transfers received from government transfer and tax credit programs targeting families. It may be the case that the change in income from some of these programs is due to the lower earning spouse being required to claim the respective program. To address this, I construct a measure of the total household level of family benefits.[61] As found in *Table 2*, cognitive receives the most family benefits, even before disability onset. Income from family benefits is not relevant for individuals affected by physical disability. In unreleased work, I find this result to be robust for both males and females.

[60]The measure of family benefits does not include the Universal Child Care Benefit, which was introduced in 2007. It may be the case that people decide to now claim unclaimed credits from universal programs after disability onset, but I focus on the progressive programs due to their link to income.

[61]LISA is linked to inter-generational family files, which provides me with T1FF data for each of the members of a LISA respondent's economic household.

6.3 Total Personal Income, Family Income, and Taxes.

Figure 7: The Effect of Disability Onset on Before and After Tax Personal Income



Note: Figure displays the estimated level changes from a two way fixed effects model for mutually exclusive types of disability. The blue line represents physical, the red line represents cognitive, and the green line represents concurrent. The dots represent estimates with an estimated $p < 0.05$. *The dashed grey line represents a separate estimation with the types of disability aggregated over the 3 mutually exclusive categories.*

The effect of disability on an individual's before-tax and after-tax personal income offers a broad illustration of the net effect of disability on market income and government transfers. If there is no change in before-tax personal income, then it may be the case that the onset of a disability has no effect on personal income. More likely, it may be the case that the decline in some components of income are offset by increases in others. *Figure 7 (left)* shows estimated level changes in before-tax personal. Disability onset has a significant net negative impact on one's total income. This suggests that, when aggregating over all types, individual's incomes are not fully insured from health shocks.

The estimates for the different disability types reveal substantial differences in the changes before tax personal income. Cognitive disabilities have a large impact on pre-tax personal income. Those affected by physical disabilities seem to mostly recover from their disability onset, experiencing a convex shape the estimated change in earnings. Concurrent disabilities experience the greatest decline in before-tax income, which is expected under the model of two dimensions of HC being affected. It is worth noting that the point estimates of the leading effects are most significant for physical and concurrent. Hence, these results are not causal and are instead interpreted as trend differences relative to the reference group. Total personal income combines various sources of income and transfers that make it difficult to pin down a suitable control group.

Figure. 2 (right) displays the level changes in total after-tax personal income surrounding disability onset. This figure gives insight into how individuals substitute away from heavily taxed income and become eligible for tax credits and refunds. Additionally, this reflects how the decline in personal income pushes people into lower tax brackets, as the Canadian tax and transfer system is progressive.[62] On aggregate, the impact of disability onset is buffered by the tax and transfer system. The effects of physical disability are recovered ten years after onset. The impact of cognitive disability is still substantially larger than the point estimates of physical and is persistent, although the decline is almost half of the decline in before-tax personal income. Again, the onset of a concurrent disability results in much larger drops in after-tax personal income, but this is buffered as well.[63]

[62]That is, if someone's income from taxable sources falls below certain thresholds, the explicit design of the Canadian tax system itself serves as a buffering mechanism.

[63]These findings are consistent with in *Figure 10* in Appendix 9.4, which shows the results for the dependent variable as net federal and provincial taxes paid.

7 Conclusion

This paper analyzes the dynamic effects of the onset of disability types on measures personal income. My findings suggest there is considerable variation in the impact of the types on these outcomes. Disaggregating disability into types of functional limitations is important to account for the heterogeneity of disabilities.

Cognitive disabilities result in relatively larger declines in market income than physical ones. This is mainly driven by declines in wages, salaries, and commissions, which most closely reflect the effect of disability on human capital and productivity. Concurrent disabilities, which represent an absolute effect on human capital, are are estimated to combine the effects of physical and cognitive. However, these results are interpreted with caution as this group typically has significant leading effects in the market income and total personal income measures. The cognitive group receives fewer disability-relevant government transfers on average relative to physical, despite inuring a larger penalty to their market income. This group sees increases in government transfers from other programs, such as family benefits.

Moving forward, these results will be contrasted with results from the novel estimation strategies that are robust to treatment effect heterogeneity in staggered treatment settings, notably Sun and Abraham (2020a). In addition, there is growing interest in the labour market importance of non-cognitive and socio-emotional skills, which suggests distinguishing disabilities that impair cognitive function from mental health may be important. Unreleased work has found interesting differences for these two more granular types of disabilities and might be a fruitful addition to the results in this paper.

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9 Appendix

9.1 Measuring Disability in LISA

The disability measures in LISA are based on a "social model" of disability that defines it as a multidimensional condition relating to body functions and structures, activities and limitations to these activities, social participation in all aspects of life, and environmental factors that influence the experiences of disabled individuals. LISA emphasizes the characteristics of disability as they relate directly to the activity limitations they induce. The questions on disability are self-reported in LISA.

LISA flags individuals with different types of disabilities based on their response to a series of questions that directly relate to activity limitations in daily life. A specific question could be "How much difficulty do you have walking 20 steps on a flat surface?" The survey distinguishes between the magnitude or difficulty from the activity limitation from the frequency of being affected by the limitation. The difficulty responses are "No difficulty", "some difficulty", "a lot of difficulty", and "can not do." The frequency responses are "never", "rarely", "sometimes", "often", and "always".

Table 4: Questions used to Measure Limitations to Daily Activities

Questions to Derive Physical Disability
How much difficulty do you have walking on a flat surface for 15 minutes without resting?
How much difficulty do you have walking up or down a flight of stairs, about 12 steps without resting?
How much difficulty do you have reaching in any direction, for example, above your head?
How much difficulty do you have using your fingers to grasp small objects like a pencil or scissors?
Do you have pain that is always present?
Questions to Derive Cognitive Disability
Do you think you have a condition that makes it difficult in general for you to learn? This may include learning disabilities such as dyslexia, hyperactivity, attention problems, etc..
Has a teacher, doctor or other health care professional ever said that you had a learning disability?
Has a doctor, psychologist or other health care professional ever said that you had a developmental disability or disorder? This may include Down syndrome, autism, Asperger syndrome, mental impairment due to lack of oxygen at birth, etc..
Do you have any ongoing memory problems or periods of confusion? Please exclude occasional forgetfulness such as not remembering where you put your keys.
Do you have any emotional, psychological or mental health conditions? These may include anxiety, depression, bipolar disorder, substance abuse, anorexia, etc..

Source: Table comes directly from Grondin, C. (2016). A new survey measure of disability: The Disability Screening Questions (DSQ). Statistics Canada.

9.2 T1FF components of income and Variable Construction

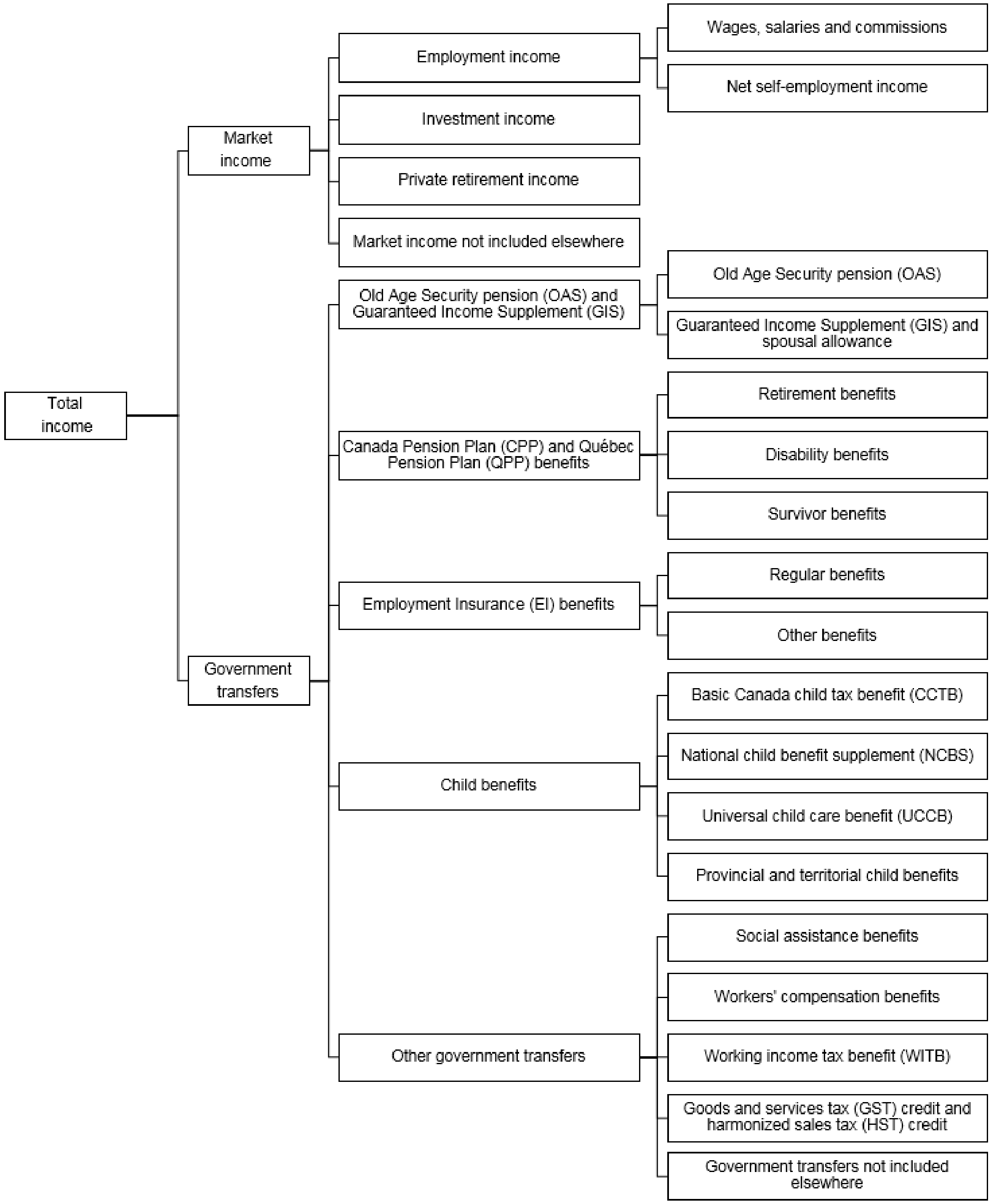
This section offers more detail about the measures of income and breakdown of personal income in the T1FF. Theses data are derived from annual tax filings, which is especially advantageous in mitigating concerns with measurement error that often plagues survey data. Figure 8 shows the breakdown of personal income used for the Canadian Census. There are some slight differences in the more dis-aggregated measures of income. However the overall decomposition is parallel to what I focus on in this paper. For this papers purposes, the income concepts from this figure are the sufficient.

An individual's personal income can be partitioned into market income and income from transfer payments. This distinction is important for separating resources that are earned through market participation, such as the labour market (wages) or investment market (Dividends, savings, etc..). Transfer income is associated with publicly provided resources made available to individuals with low or zero earnings. For instance, Employment Insurance (EI) may be available for people who lose their job, or specific barriers or costs that may limit one's ability to provide for themselves or dependents. For example, disability insurance is available to aid with the costs and barriers to work caused by a disability.

An individual's Market income is mainly comprised of income earned from employment but includes other sources. Employment income can be differentiated into wages, salaries and commissions (T4E), self-employment income (SEI), which includes net business income, farming income, fishing, etc.., and other forms of employment income(OEI), which may include tips, gratuities, or wage loss replacement plans (private disability insurance). Market income also includes interest and investment income, corporate dividends, alimony, limited partnership income, retirement savings plans, and income from private pensions (OTHER).

Government transfer payments combine federal and provincial programs aimed at assisting those with little or no market income. Two of the largest transfer programs are federal EI and Canadian Pension Plan, the latter of which offers supplementary benefits to working-age adults affected by disability (CPP-D). Canada offers a set of transfers and tax credits targeting families at both the federal and provincial levels. Notably, The Canadian Child benefit (CTIB), which replaced the family allowance (FA) program in 1992, and the child tax credit (CTC) lowers taxes for low-income families. Provincial tax credits (PTXI) and goods and service and harmonized sales tax credits are included in government transfers (GHST) Additionally, each province offers family benefits (FABEN). Government transfers also consist of non-taxable income received

Figure 8: Census of Population Components of Incomes.



Source: https://www12.statcan.gc.ca/census-recensement/2016/ref/dict/app-ann/a4_1-eng.cfm.

through provincially administered social assistance (SA), workers compensation programs (WC), and net federal supplements, which consist of transfers targeting the elderly (NFSL).[64]

I do not include old age security (OAS) or other programs targeting retirees because the population of interest are not old enough to be eligible. Also, I do not include the working income tax benefit (WITB), which was introduced in 2007 to reduce taxes for individuals earning low levels of income from work.[65]

9.2.1 Variable Construction

$$\begin{aligned}
MKTINC &= T4E + SEI + OEI + OTHER \\
DISABTRANS &= WC + SA + CPPD + EI + DTC \\
FAMTRANS &= FABEN + FA + CTC + CTBI \\
GOVTRANS &= DISABTRANS + FAMTRANS + GHST + PTXI \\
XTIRC &= MKTINC + GOVTRANS \\
AFTAX &= XTIRC - TAX \\
FTXI &= \sum_i XTIRC_i, \text{ for i in economic family}
\end{aligned}$$

[64]Net federal supplements are grouped in a measure of non-taxable income. But the sample of study is not eligible for these transfers.

[65]For more details on the types of incomes included in this study and these data, refer to https://www150.statcan.gc.ca/n1/en/pub/12-585-x/12-585-x2017000-eng.pdf?st=adGLEEeP.

9.3 Model Results: Tables

Table 5: Changes in Market and Employment income before and after disability onset

Time Since Onset	Total Market Income				Wages, Salaries, and Commissions.				Employment Probability				Self and Other Employment Income			
	Level				Level				Level				Level			
	D	P	C	PC	D	P	C	PC	D	P	C	PC	D	P	C	PC
-5	-3182.06	-2273.703	-491.3834	-6354.284	-2303.44	-1356.966	-366.6299	-5310.482	0.004732	0.015145	-0.01328	-0.01274	-278.6247	-168.4876	265.3173	-666.7381
	(862)	(1216)	(1989)	(1032)	(873)	(1253)	(2024)	(1036)	(0.008)	(0.01)	(0.025)	(0.017)	(216)	(268)	(760)	(321)
-4	-3222.325	-2143.422	-964.9926	-6678.994	-2322.391	-1373.817	-1346.863	-5111.163	-0.00178	0.000512	-0.02129	-0.00339	-173.7446	-41.27885	1423.115	-939.0655
	(893)	(1236)	(1634)	(1176)	(844)	(1158)	(2088)	(1131)	(0.01)	(0.011)	(0.031)	(0.022)	(319)	(415)	(1574)	(368)
-3	-3745.735	-2798.349	-1920.56	-6753.883	-2424.303	-1517.901	-3178.188	-4495.391	0.007516	0.011021	-0.01318	0.004788	-497.9612	-472.3911	1244.961	-1111.156
	(990)	(1391)	(2094)	(1270)	(960)	(1366)	(2170)	(1228)	(0.01)	(0.011)	(0.031)	(0.022)	(259)	(289)	(1388)	(364)
-2	-5052.49	-3789.175	-3522.586	-8656.625	-3766.112	-2655.108	-3453.109	-6672.051	-0.00975	-0.00798	-0.00907	-0.01671	-615.8163	-422.0847	342.0663	-1298.57
	(968)	(1300)	(1968)	(1387)	(926)	(1257)	(2176)	(1283)	(0.01)	(0.012)	(0.027)	(0.021)	(327)	(354)	(1245)	(664)
-1	-4672.648	-2649.667	-3766.895	-9503.198	-3533.106	-1465.964	-4740.363	-7751.598	-0.01111	-0.00637	-0.00998	-0.02421	-646.9484	-694.4732	432.0579	-891.5025
	(1278)	(1846)	(2264)	(1409)	(1255)	(1845)	(2202)	(1319)	(0.011)	(0.013)	(0.026)	(0.022)	(308)	(328)	(1136)	(616)
0	-6299.256	-3673.423	-7392.724	-11680.22	-5474.183	-3062.217	-7476.473	-10164.11	-0.03624	-0.01578	-0.07566	-0.06604	-402.8952	-361.2558	175.8589	-635.9833
	(1402)	(2054)	(2369)	(1358)	(1374)	(2029)	(2610)	(1261)	(0.011)	(0.013)	(0.035)	(0.024)	(345)	(399)	(1357)	(624)
1	-7484.235	-4344.405	-6254.96	-14614.94	-6585.724	-3482.339	-7614.517	-12922.03	-0.06525	-0.03818	-0.07666	-0.1164	-458.9014	-583.0947	862.7471	-602.4492
	(1506)	(2180)	(2551)	(1521)	(1476)	(2146)	(2666)	(1492)	(0.012)	(0.014)	(0.04)	(0.025)	(341)	(363)	(1871)	(535)
2	-8541.118	-5531.393	-8531.414	-14976.76	-7247.765	-4251.004	-8765.995	-13197.59	-0.08832	-0.06712	-0.07786	-0.13488	-612.5972	-522.7861	704.8286	-1138.127
	(1780)	(2575)	(2546)	(1987)	(1766)	(2568)	(2735)	(1970)	(0.013)	(0.015)	(0.041)	(0.027)	(322)	(370)	(1806)	(402)
3	-8629.441	-4552.244	-9863.181	-16667.51	-7338.207	-2966.772	-9156.401	-15767.9	-0.1098	-0.08321	-0.08681	-0.17031	-506.1396	-709.2736	292.5699	-306.112
	(2108)	(3199)	(2636)	(1752)	(2090)	(3196)	(2774)	(1620)	(0.013)	(0.016)	(0.044)	(0.027)	(359)	(358)	(1955)	(632)
4	-8696.678	-3447.031	-10311.77	-18802.5	-7394.086	-2432.745	-9543.273	-16831.53	-0.12051	-0.10587	-0.07186	-0.16654	-623.895	-574.3844	692.8583	-1049.209
	(2485)	(3839)	(2630)	(1792)	(2441)	(3776)	(2837)	(1751)	(0.014)	(0.016)	(0.041)	(0.027)	(358)	(374)	(2110)	(529)
5	-9381.852	-4315.346	-7991.453	-20234.05	-7513.354	-2664.149	-8212.104	-17329.92	-0.1325	-0.10086	-0.0851	-0.21013	-692.06	-615.3022	2029.632	-1604.847
	(2671)	(4122)	(3119)	(1842)	(2651)	(4112)	(2909)	(1808)	(0.014)	(0.017)	(0.046)	(0.028)	(425)	(397)	(3198)	(446)
6	-10187.1	-4415.059	-12432.17	-20721.68	-8380.843	-2734.481	-11665.59	-18406.81	-0.12836	-0.10098	-0.0355	-0.21177	-961.0436	-977.431	-60.10004	-1098.592
	(2819)	(4441)	(2718)	(1939)	(2805)	(4424)	(3027)	(1982)	(0.015)	(0.018)	(0.042)	(0.03)	(361)	(439)	(1395)	(532)
7	-10248.77	-4724.645	-12244.25	-20613.04	-8306.37	-2892.364	-12071.19	-17960.79	-0.12272	-0.08987	-0.08271	-0.19813	-994.7431	-1204.2	1726.379	-1353.939
	(2737)	(4222)	(3060)	(2105)	(2695)	(4164)	(3425)	(2074)	(0.015)	(0.018)	(0.049)	(0.028)	(356)	(412)	(1863)	(441)
8	-9961.456	-4195.009	-13311.6	-20261.95	-9123.094	-3905.688	-13791.4	-18093.22	-0.13852	-0.09892	-0.1568	-0.20734	-627.0217	-943.0768	2911.833	-1070.641
	(2803)	(4388)	(3619)	(1782)	(2617)	(4044)	(3651)	(1880)	(0.016)	(0.019)	(0.06)	(0.028)	(459)	(467)	(3231)	(464)
9	-9481.938	-2920.835	-11897.76	-21316.1	-8401.725	-1719.332	-15496.59	-19078.04	-0.13432	-0.08395	-0.18402	-0.2122	-399.5913	-955.566	5248.386	-1022.578
	(3313)	(5290)	(4037)	(1895)	(3274)	(5221)	(3942)	(1993)	(0.016)	(0.018)	(0.066)	(0.029)	(471)	(497)	(3238)	(437)
10	-10830.25	-4404.675	-14318.66	-22298.96	-9414.772	-2343.258	-17927.28	-20477.76	-0.15503	-0.11744	-0.21695	-0.20791	-686.7739	-1435.925	5387.226	-1155.297
	(3641)	(5795)	(4605)	(2198)	(3581)	(5713)	(4080)	(2113)	(0.016)	(0.02)	(0.055)	(0.03)	(503)	(495)	(3540)	(480)

Note: reported numbers are from estimate coefficients from the time of onset indicator variables in a linear two way fixed effect regression for levels. Standard errors are clustered by person and reported in brackets below the estimates.

Table 6: Changes in Government Transfers before and after disability onset

Time Since Onset	Total Government Transfers				Disability Relevant Transfers				Family Benefits			
	Level				Level				Level			
	D	P	C	PC	D	P	C	PC	D	P	C	PC
-5	136.4161	16.32007	116.1676	453.9391	81.17589	44.27077	-189.1214	286.4103	55.82763	-21.1336	312.8512	151.7902
	(117)	(137)	(295)	(262)	(108)	(126)	(250)	(242)	(41)	(42)	(180)	(96)
-4	30.74198	-88.9818	-191.1035	436.5882	-15.39446	-57.22468	-503.3793	291.168	53.39927	-25.2172	333.8428	147.4471
	(145)	(143)	(280)	(372)	(135)	(134)	(259)	(345)	(39)	(42)	(163)	(85)
-3	16.89167	-210.0042	66.34641	526.6721	-56.95545	-157.0714	-404.1085	300.6169	72.03706	-49.4504	476.0779	209.6002
	(132)	(141)	(336)	(319)	(119)	(132)	(266)	(287)	(42)	(42)	(198)	(96)
-2	210.2895	-15.86492	217.6403	741.3741	111.3195	7.357521	-374.9172	532.0653	93.49736	-23.0674	603.2745	185.2368
	(130)	(150)	(307)	(293)	(115)	(139)	(262)	(248)	(46)	(47)	(197)	(102)
-1	429.6286	137.4753	309.4719	1127.271	285.9973	156.2011	-132.71	728.4515	138.8642	-22.3856	472.4233	377.9764
	(169)	(164)	(297)	(436)	(153)	(154)	(276)	(393)	(73)	(49)	(173)	(211)
0	740.7629	280.377	608.4992	1775.572	636.0976	326.2371	28.71139	1496.041	86.03569	-51.7547	588.0549	224.8309
	(158)	(175)	(347)	(371)	(144)	(163)	(322)	(331)	(50)	(50)	(182)	(117)
1	1109.154	608.0551	476.46	2375.906	953.4304	626.3102	-313.6682	2052.189	134.3925	-29.2821	792.5393	271.7778
	(177)	(200)	(395)	(404)	(163)	(190)	(346)	(367)	(53)	(48)	(278)	(117)
2	1229.943	718.5321	873.0198	2404.295	1112.854	752.6599	177.2954	2136.719	99.35235	-36.5306	664.222	222.3703
	(190)	(193)	(480)	(454)	(178)	(176)	(482)	(430)	(57)	(63)	(233)	(123)
3	1459.709	738.0551	1021.777	3051.066	1346.042	811.5256	207.3193	2763.023	96.06427	-75.6935	773.3472	245.9662
	(194)	(198)	(415)	(469)	(180)	(186)	(403)	(436)	(55)	(53)	(237)	(128)
4	1849.177	914.4997	1231.536	3884.141	1697.638	967.2712	483.7295	3485.131	136.4862	-52.3589	712.6832	357.4079
	(210)	(212)	(559)	(491)	(201)	(202)	(559)	(474)	(60)	(53)	(255)	(143)
5	1861.029	1279.202	825.4753	3387.322	1708.476	1332.075	-3.485876	3006.115	140.5046	-44.5581	791.1808	334.7983
	(198)	(225)	(365)	(439)	(182)	(215)	(299)	(392)	(61)	(57)	(287)	(138)
6	1962.469	1157.101	1312.968	3726.391	1813.753	1207.223	529.0897	3362.037	133.2151	-48.0679	713.5091	330.6361
	(214)	(218)	(512)	(496)	(204)	(208)	(492)	(475)	(65)	(63)	(284)	(144)
7	2332.542	1069.958	1548.84	4942.612	2209.148	1099.64	954.827	4626.009	111.0855	-26.5789	547.4847	281.8626
	(333)	(250)	(507)	(892)	(326)	(241)	(463)	(884)	(67)	(67)	(243)	(155)
8	2417.899	1538.014	1872.776	4283.532	2308.24	1568.318	1214.389	4030.477	101.9234	-25.688	611.6633	229.8523
	(253)	(295)	(599)	(537)	(244)	(284)	(562)	(523)	(64)	(67)	(237)	(142)
9	2391.929	1696.111	1853.923	3927.912	2255.226	1703.831	1194.783	3636.059	107.265	-15.811	563.3972	239.5379
	(237)	(289)	(608)	(477)	(227)	(282)	(588)	(449)	(66)	(63)	(203)	(155)
10	2455.783	1582.46	2078.409	4272.902	2286.293	1598.648	1417.257	3867.151	135.494	-24.3704	587.6806	333.0332
	(235)	(267)	(648)	(498)	(222)	(256)	(640)	(469)	(66)	(69)	(195)	(151)

Note: reported numbers are from estimate coefficients from the time of onset indicator variables in a linear two way fixed effect regression for levels. Standard errors are clustered by person and reported in brackets below the estimates.

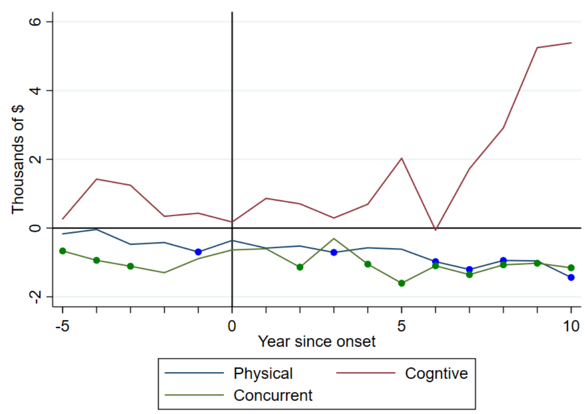
Table 7: Changes in Personal Income before and after disability onset

Time Since Onset	Before-Tax Personal Income Level				After-Tax Personal Income Level				Net Taxes Paid Level			
	D	P	C	PC	D	P	C	PC	D	P	C	PC
-5	-3522.311	-1329.13	-384.7223	-6647.684	-1960.229	-1329.13	1029.42	-4468.325	-1314.185	-960.6159	-1146.057	-2223.853
	(857)	(789)	(1952)	(1065)	(579)	(789)	(1628)	(805)	(332)	(483)	(517)	(339)
-4	-3814.776	-1584.539	-1422.554	-6963.979	-2235.953	-1584.539	-226.8244	-4490.411	-1302.307	-925.7418	-1086.577	-2297.543
	(875)	(804)	(1592)	(1131)	(590)	(804)	(1209)	(878)	(340)	(486)	(513)	(348)
-3	-4449.617	-2778.784	-2367.265	-7056.034	-3122.855	-2778.784	-649.9186	-4913.288	-1243.264	-775.8139	-1555.607	-2230.292
	(975)	(874)	(2088)	(1240)	(640)	(874)	(1674)	(902)	(408)	(600)	(558)	(426)
-2	-5705.444	-2938.436	-3747.85	-8864.272	-3531.662	-2938.436	-1422.573	-5737.803	-1837.637	-1406.283	-1930.117	-2847.365
	(952)	(867)	(1949)	(1344)	(656)	(867)	(1459)	(1048)	(356)	(485)	(633)	(429)
-1	-5135.264	-2230.522	-4015.246	-9214.752	-3253.585	-2230.522	-2214.901	-5910.286	-1673.545	-1073.919	-1407.415	-3121.69
	(1257)	(1121)	(2187)	(1331)	(793)	(1121)	(1612)	(997)	(517)	(775)	(729)	(418)
0	-6436.882	-2661.393	-7495.122	-10788.09	-4146.831	-2661.393	-4557.983	-7237.396	-2005.884	-1246.631	-2613.445	-3487.482
	(1384)	(1239)	(2294)	(1277)	(861)	(1239)	(1769)	(956)	(572)	(860)	(731)	(402)
1	-7323.524	-3135.449	-6626.364	-13225.48	-4901.868	-3135.449	-3906.856	-8996.56	-2296.941	-1476.833	-2370.248	-4083.316
	(1479)	(1299)	(2472)	(1433)	(918)	(1299)	(1903)	(1077)	(611)	(911)	(806)	(438)
2	-8038.497	-3442.724	-8442.709	-13237.45	-5218.047	-3442.724	-5248.167	-8965.434	-2435.425	-1689.756	-2742.69	-4004.826
	(1756)	(1519)	(2464)	(1899)	(1066)	(1519)	(1938)	(1292)	(744)	(1097)	(858)	(724)
3	-8059.19	-2994.391	-9687.824	-14434.71	-5224.043	-2994.391	-6306.772	-9476.125	-2404.014	-1260.495	-2895.915	-4676.495
	(2078)	(1855)	(2533)	(1594)	(1243)	(1855)	(2069)	(1193)	(891)	(1385)	(939)	(479)
4	-7531.183	-1930.528	-9915.224	-15612.78	-4825.123	-1930.528	-5604.489	-10432.76	-2289.85	-776.7309	-3851.84	-4905.933
	(2463)	(2230)	(2567)	(1658)	(1459)	(2230)	(2135)	(1211)	(1058)	(1663)	(782)	(538)
5	-8290.09	-2419.152	-7871.964	-17772.36	-5452.509	-2419.152	-3771.866	-12178.29	-2412.459	-822.5608	-3650.668	-5316.698
	(2640)	(2314)	(2960)	(1710)	(1529)	(2314)	(2523)	(1275)	(1156)	(1823)	(807)	(506)
6	-9216.274	-2742.284	-11921.92	-18025.54	-5993.577	-2742.284	-6844.979	-12045.3	-2793.049	-1028.259	-4591.587	-5700.384
	(2786)	(2521)	(2526)	(1788)	(1623)	(2521)	(2174)	(1310)	(1213)	(1948)	(757)	(566)
7	-8782.913	-2722.286	-11844.8	-16597.71	-5487.539	-2722.286	-6440.117	-10765.62	-2857.45	-1211.146	-4926.522	-5547.788
	(2703)	(2485)	(2850)	(2060)	(1638)	(2485)	(2173)	(1564)	(1113)	(1743)	(910)	(599)
8	-8308.746	-1948.015	-12717.4	-16877.88	-5166.57	-1948.015	-7005.367	-10922.18	-2699.583	-817.8705	-5193.449	-5639.104
	(2752)	(2469)	(3307)	(1651)	(1603)	(2469)	(2749)	(1211)	(1200)	(1912)	(867)	(527)
9	-7996.788	-1504.455	-11064.53	-18233.04	-5168.298	-1504.455	-5911.814	-11955.12	-2349.726	-112.9153	-4594.438	-5941.995
	(3277)	(3036)	(3806)	(1721)	(1918)	(3036)	(3086)	(1230)	(1458)	(2366)	(1101)	(582)
10	-9156.972	-2383.394	-12993.54	-18498.29	-5721.91	-2383.394	-6860.972	-11939.52	-2965.768	-906.3166	-5563.759	-6198.751
	(3604)	(3299)	(4174)	(2147)	(2109)	(3299)	(3602)	(1614)	(1551)	(2509)	(1088)	(635)

Note: reported numbers are from estimate coefficients from the time of onset indicator variables in a linear two way fixed effect regression for levels. Standard errors are clustered by person and reported in brackets below the estimates.

9.4 Additional Results

Figure 9: The Effect of Disability Onset on Employment Income Earned from Sources Other Than Wages, Salaries, and Commissions.



Figures.5.

Figure 10: The Effect of Disability on Net Provincial and Federal Taxes Paid.

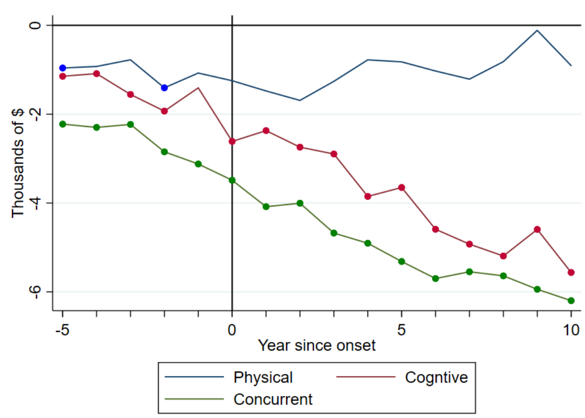


Figure displays the estimated level changes from a two way fixed effects model for mutually exclusive types of disability. The blue line represents physical, the red line represents cognitive, and the green line represents concurrent. The dots represent estimates with an estimated $p < 0.05$. The dashed grey line represents a separate estimation with the types of disability aggregated over the 3 mutually exclusive categories.

Figure 11: The Effect of Disability Onset on Family Before and After Tax Personal Income

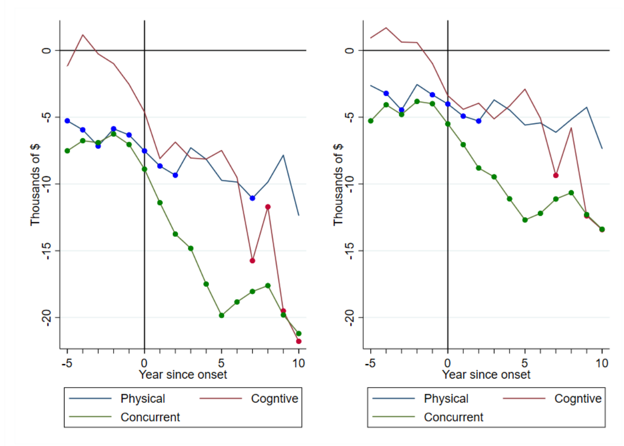


Figure displays the estimated level changes from a two way fixed effects model for mutually exclusive types of disability. The blue line represents physical, the red line represents cognitive, and the green line represents concurrent. The dots represent estimates with an estimated $p < 0.05$. The dashed grey line represents a separate estimation with the types of disability aggregated over the 3 mutually exclusive categories.

The change in taxes paid may reflect the transferring of tax credits or refunds from one spouse to another for families and married households.[66] *Figure 13* shows the changes in Family total income Before and After Taxes. This shows that income on net declines for the household. Family total income after taxes offers insight into the decline of total household resources following disability onset. This includes income pre-tax income sources from all members of a household and hence captures the change in net benefits rather than having benefit merely shift to the lower earning spouse.

[66]For instance, the Child Tax Credit is claimed by the spouse who earns less. Hence, if income declines after onset, the change in tax credits may reflect this.