The Dynamic Effects of Disability Types: Incomes, Employment, and Partial Insurance

By Robert Millard*

Abstract

This study analyzes the longitudinal effects of disability onset, differentiating disability types based on the activities they impair. It employs Canadian survey data linked with administrative tax filings to estimate disability type-specific effects on disaggregated incomes in the ten years following onset, contrasting heterogeneity in effects, and identifying partial insurance gaps across types. Generally, mental-cognitive types are more detrimental to market incomes than physical types and are less insured via disability transfer programs, instead relying on other sources of income insurance. A welfare analysis of these results suggests that disability benefits are suboptimal for several types, especially mental health-related disability.

The onset of a work-limiting disability limits a one's ability to execute tasks essential in work and daily life, hampering their financial independence and posing significant societal costs for supporting these individuals.[1] Consequently, disability-related economic inequalities are prevalent in both developed and developing nations (Garcia-Mandico, Prinz and Thewissen, 2022). In Canada, working-aged adults with disabilities were more than twice as likely to be low income (23% vs 9%).[2] Disability is a prominent risk to income stability for working-aged adults, many of whom will experience some form of disability before retirement.[3] However, the effects of work-limiting disability vary considerably across individuals. Understanding the factors driving this variation is crucial to guide the design of insurance policies to optimally allocate scarce resources to those bearing the greatest burden from their disability.

A primary factor driving the varied impacts of disability is the types of tasks and functions that are impeded. Disabilities stem from one or multiple physiological ailments and differ markedly in how they impede daily life

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[1]A vast multidisciplinary literature documents the effects of work-limiting disability on labour force attachment, earnings, consumption, and dependence on government transfers. Articles that summarize the relevant economics literature include Bound and Burkhauser (1999); Haveman and Wolfe (2000); Liebman (2015); Prinz et al. (2018).

[2]Low income is defined as those living in a household earning less than one-half of the median Canadian income, adjusted for household size. These statistics are derived from the 2014 wave of the survey dataset applied in this study. For additional details on low-income Canadians with disabilities, refer to Wall (2017). A comparable size poverty gap persists in the United States, where 25,2% of working-aged adults with disabilities lived in poverty in 2020, compared to a poverty rate of 11.9% for adults without a disability (Houtenville, Shreya and Rafal, 2021).

[3]Disability rates have been rising in Canada and in most developed nations. 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. (2018). In comparison, the Social Security Administration estimates that three in ten individuals aged 20 years old will experience a disability before retirement (Autor, 2015).

and opportunities for productive work. Distinguishing disabling conditions based on the tasks they limit captures a key intermediate step in the mapping from a given health condition to one's economic outcomes. For instance, a bricklayer may be rendered unable to work if limited in bending and flexibility, whereas the work of a computer scientist may be unaffected. This idea is reflected empirically; for example, 17% of Canadians with physical-sensory activity limitations are low-income, compared to 27% with mental-cognitive activity limitations (Wall, 2017). While sharing the commonality of impairing functionality, the economic effects of disabilities vary greatly, depending on how the limited functions interact with the individual's occupational tasks.

In this paper, I analyze heterogeneity in the effects of different types of disability on disaggregated components of personal income. I apply the Interaction-Weighted (IW) estimator, recently proposed by Sun and Abraham (2021) to estimate the effects of work-limiting disability in each of the ten years following its onset, with a separate analysis for mutually exclusive types of disabilities.

Fluctuations in the level and composition of one's income post-disability onset offer valuable insights into their evolving economic situation. First, changes in the components of market income reflect the disability's impact on human capital, labour market participation, and substitution to other earning activities. Second, I compare the effects on market income to changes in a rich set of partial insurance mechanisms available for disability shocks, contrasting the importance of sources of insurance and identifying insurance gaps across disability types. I separately analyze changes in government transfer income, the incomes from household family members, and the impact of the progressive tax system. Analyzing the changes in personal income in the years following onset enables an assessment of the main sources and overall completeness of available insurance.

I conduct my analysis using a Canadian dataset, the Longitudinal and International Study of Adults (LISA), which links a short panel survey containing detailed disability and demographic information with a panel of administrative tax records, known as the T1 family files (T1FF), derived from annual income tax filings. The tax records partition personal income into disaggregated components of market income, such as paid or self-employment income, and government transfers, which include a diverse range of federal and provincial policies and tax credits. These data facilitate direct comparisons of post-onset dynamics in market income with changes in government transfer programs, before and after-tax incomes, and the income of family members in the household.

These Canadian data offer several advantages in examining the impacts of disability shocks, which until recently has predominantly focused on the United States (US). First is the quality of the administrative income tax data. Access to income tax records is mostly restricted in the US, and research about health shocks frequently relies on large panel survey datasets, such as the Panel Study of Income Dynamics (PSID) or the Health and Retirement Study. The administrative tax records provide detailed income and transfer measures that are less susceptible to measurement error and under-reporting, two issues that have been increasingly recognized as problematic in household surveys (Meyer, Mok and Sullivan, 2009, 2015). Second, my analysis facilitates cross-disability type comparisons with an internally consistent measure of disability, addressing the issues with drawing comparisons across samples, datasets, methodologies, and studies. Lastly, Canada grants universal health insurance, unlike the U.S. where health insurance access is intertwined with disability policy. The Canadian setting allows for a cleaner analysis of the incentives from disability policy that are unconfounded by the added value of health insurance (Deshpande and Lockwood, 2022).

A notable limitation of these data is the lack of consumption measures, which provide direct insights into welfare changes following a disability shock. I focus on income dynamics, which may not track consumption when smoothing mechanisms, such as savings, public insurance, or credit markets, are readily accessible. However, given the permanence of income shocks under consideration and that I observe a rich set of smoothing mechanisms, income dynamics are a reasonable proxy for consumption. This study concentrates on permanent disabilities, which, unlike transitory income shocks, are less “smoothable” via personal savings, borrowing, or short-term insurance (Blundell, Pistaferri and Preston, 2008). Permanent disability shocks cause an unanticipated change in one’s permanent income, inducing proportional changes in consumption per the permanent income hypothesis (Friedman, 1957; Attanasio and Pistaferri, 2016). Moreover, income and consumption dynamics tend to align more closely when correcting for non-classical measurement errors present in household surveys, a concern that is mitigated in the administrative tax records (Attanasio and Pistaferri, 2016). Hence, the results in this paper offer insight of the different welfare consequences across disability types.

This analysis contributes to an extensive literature on the dynamic effects of permanent income shocks and the mitigating role of public programs. I document new insights into the mechanisms underlying these shocks and the completeness of partial insurance in smoothing consumption. For instance, Blundell, Pistaferri and Preston (2008), Kaplan and Violante (2010), and Blundell, Pistaferri and Saporta-Eksten (2016) show how transfer programs, family resources, and the tax system play crucial roles in cushioning the impacts of transitory shocks and partially insuring against permanent income shocks. These studies use panel survey data, notably the PSID and Consumer Expenditure Survey. In contrast, this analysis utilizes administrative data from annual income tax filings, offering important advantages as previously discussed. Related studies employing administrative data include Blundell, Graber and Mogstad (2015), who investigate life-cycle income dynamics in Norwegian registry data, including income tax records. They highlight the role of the progressive tax-transfer system in attenuating the severity and persistence of income shocks, particularly for low-income groups. This paper distinguishes itself in the specificity of income shocks under consideration. The interplay between disability types and human capital captures a more nuanced understanding of mechanisms driving the variation in the effects of permanent income shocks. In addition, disability shocks are unique in the available sources of social insurance.

This research fits among numerous studies exploring the longitudinal effects of health and disability shocks on labour supply, incomes, and consumption (Stephens Jr, 2001; Charles, 2003; Singleton, 2012; Lundborg, Nilsson and Vikström, 2015; Polidano and Vu, 2015; Meyer and Mok, 2019; Fadlon and Nielsen, 2021; Collischon, Hiesinger and Pohlan, 2023; Humlum, Munch and Jorgensen, 2023). The utilization of rich, disaggregated personal income measures from administrative records distinguishes this paper from much of the existing literature. However, related studies using administrative data include Lundborg, Nilsson and Vikström (2015), who utilize Swedish administrative registry data to demonstrate how the consequences of health shocks vary by education level. The mechanism of interest is similar, as education correlates with productive skills. Autor et al. (2019) also use Norwegian administrative data to evaluate the insurance-incentive effects of disability insurance on incomes and consumption. While their focus on interactions between sources of partial insurance is similar to this study, they restrict their analysis to disability insurance applicants. Fadlon and Nielsen (2021) use Danish administrative data but narrow their focus on family labour supply responses following health shocks. More recently, Humlum, Munch and Jorgensen (2023) use Danish administrative records to investigate the dynamic effects of workplace injuries on re-education and disability insurance applications, focusing on physical injuries. Collischon, Hiesinger and Pohlan (2023) use German administrative data to examine variation in the effects of disability onset based on the characteristics of work, such as tasks and working hours.

In sum, the contribution of this paper relative to these studies lies in its comprehensive analysis of a full set of partial insurance mechanisms and the broader scope of disability shocks of interest. The extent of disaggregation facilitates the examination of effects on the components of market income, how income from government transfers, family members, and the progressive tax system can alleviate the adverse effects of disability, and how this differs by disability type. Moreover, by distinguishing disabilities based on the tasks they hinder, I explain discrepancies in the magnitude and persistence of effects using a human capital framework and contrast the relative importance of partial insurance channels across types.

The second main contribution of this paper is the analysis of heterogeneity in effects by categorizing disabilities into distinct, mutually exclusive types. Previous research often acknowledges the heterogeneity in the impact of distinct disabling or medical conditions.[4] However, the mechanisms underlying the effects of a specific health condition on behavior and outcomes remain somewhat ambiguous. Focusing on the activity limitations caused by a given health condition clarifies the link between health conditions, productivity, and labour market outcomes.[5] Disability fundamentally alters a worker's human capital profile, creating a mismatch between their skill set and the skill requirements of their work. A disability that limits certain tasks will have varying implications for labour market outcomes depending on the worker's proficiency in these tasks, their use in work, and the market's valuation of these tasks.

To analyze this type-based heterogeneity, I first distinguish disabling conditions that affect physical tasks from those affecting mental-cognitive tasks. This partition aligns with common practice in both disability and human capital research, which often distinguish physical and mental-cognitive skills.[6] To the best of my knowledge, no other study has conducted such a complete longitudinal analysis of both physical and mental-cognitive disability types on both market income components and partial insurance mechanisms within a unified framework.

This broad partition may mask more nuanced heterogeneity within the aggregate physical and mental-cognitive types. I separately estimate the effects of mutually exclusive types of activity limitations within the aggregated disability types. Within aggregate physical, I distinguish disabilities to one's kinetic ability (encompassing limitations to mobility, flexibility, and dexterity) from disabilities that are related exclusively to pain.[7] Within mental-cognitive, I differentiate disabilities affecting cognitive functions (such as learning, memory, or concentration) from those associated exclusively with mental health conditions (like depression, anxiety, or post-traumatic stress disorder). The more granular distinctions along these margins of activity limitation is policy-relevant, as mental health and pain-related disabilities are important contributors to rising applications to disability programs (Autor, 2015). Moreover, this study provides novel estimates on the economic effects of mental health conditions, increasingly recognized as important determinants of economic behaviour and outcomes (Frank and Glied, 2023).

Finally, this paper employs key methodological differences that distinguish it from much existing research on

[4]For instance, Von Wachter, Song and Manchester (2011) find heterogeneity in employment and earnings across types of disabling conditions in their analysis of rejected applicants to disability insurance, Maestas, Mullen and Strand (2013) study heterogeneity across different medical conditions in their analysis of the work incentives of disability insurance, Lundborg, Nilsson and Rooth (2014) finds heterogeneity in the lifetime effects of specific diseases or physiological conditions that occur in adolescence, and Black et al. (2018) study heterogeneity in the relationship between disability insurance and mortality by types of medical conditions.

[5]To illustrate, when left untreated, diabetes can result in a substantial physical impairment, which may restrict the set of physically demanding tasks a worker can perform. However, with proper treatment, diabetes may not limit one's activities or productivity. Data on activity limitations can distinguish these two outcomes, but data on diabetes diagnoses alone can not.

[6]For instance, Yi et al. (2015) define a capability vector whose components are physical health, mental health, and cognitive functioning, Deshpande (2016) study heterogeneity in the effect of removing youth from disability support by physical vs. mental or intellectual disabilities. Wall (2017) groups mental-cognitive and physical in their analysis of poverty and persons with disability in Canada, Mori (2019) distinguishes health capital into either mental or physical and models its complimentary to the accumulation of manual and cognitive productive skills. Humlum, Munch and Jorgensen (2023) focus on physical disabilities related to work accidents and how individuals compensate by investing in their cognitive skills. Finally, Collischon, Hiesinger and Pohlan (2023) discuss type-based heterogeneity in their working paper about the effect of disability onset on labour market performance, partitioning disabilities into physical, sensory, or psychological types. Additionally, studies on multidimensional human capital often differentiate physical and mental-cognitive skills to study the dynamic relationship between earnings and multidimensional skill accumulation (Poletaev and Robinson, 2008; Yamaguchi, 2012; Sanders, Taber et al., 2012; Lindenlaub, 2017; Robinson, 2018; Lise and Postel-Vinay, 2020).

[7]Kinetic ability describes the body's ability to move efficiently, exhibit agility, and perform tasks that require coordination and precision. Kinetic abilities include walking, running, jumping, bending, twisting, reaching, grasping, and manipulating objects.

the longitudinal effects of disability onset. The workhorse approach in these studies is an event study or dynamic difference-in-difference strategy, implemented with a two-way fixed effects estimator (Stephens Jr, 2001; Charles, 2003; Singleton, 2012; Lundborg, Nilsson and Vikström, 2015; Polidano and Vu, 2015; Meyer and Mok, 2019; Fadlon and Nielsen, 2021; Collischon, Hiesinger and Pohlan, 2023). However, a surging literature has shown estimators to be potentially biased when treatment effects are heterogeneous and there is variation in the timing of treatment (Borusyak and Jaravel, 2017; De Chaisemartin and d'Haultfoeuille, 2020; Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021; Imai and Kim, 2021; Sun and Abraham, 2021; Baker, Larcker and Wang, 2022; Rambachan and Roth, 2023). Disability onset generally occurs at different calendar years for different individuals. Moreover, cohort-based heterogeneity in the effects of disability onset is almost certain due to differences in the job composition of the labour market, the market valuation of skills, and the parameters of disability policies in different calendar years. The IW estimator proposed by Sun and Abraham (2021) gives longitudinal estimates of the treatment on the treated that are robust to such biases.

This paper documents several novel findings. I frame my analysis in terms of short-run (five years or less) and long-run (six years or more) effects post-onset. There is substantial heterogeneity in the dynamic effects of the aggregate disability types on the components of personal income. The onset of an aggregate physical disability has modest negative effects on the primary component of market income, wages, salaries, and commissions (WSC), about -$4000 in the short run and persisting around this level over the long run. This effect is predominantly due to labour market exit. The onset of a mental-cognitive disability results in a more pronounced decline in WSC in the short run (-$6000) that worsening to -$16000 in the long run. These effects combine labour market exit and lower earnings for participants. These results suggest a higher market valuation of mental-cognitive skills leading to greater wage penalties for disability-induced skill mismatch in this dimension (Yamaguchi, 2012; Mori, 2019; Lise and Postel-Vinay, 2020; Humlum, Munch and Jorgensen, 2023). Substitution to relatively scarce and lower compensated physically intensive jobs post-onset of a mental-cognitive disability may contribute to negative effects in a service-based economy like Canada. Substitution to productive activities that favor mental-cognitive skills may be more readily available post-onset of a physical disability, mitigating its adverse effects (Humlum, Munch and Jorgensen, 2023).

The decline in market income following onset coincides with an equal size increase rise in total government transfers for the aggregate types, implying a relatively lower proportion of income being insured post-onset a mental-cognitive disability. Compositionally, government transfers following the onset of a physical disability stem entirely from disability-relevant programs. In contrast, those affected by mental-cognitive disabilities only significantly receive disability-relevant transfers in the long run. These individuals receive more resources from government transfer programs targeting families in the short run. Instead, Canada's progressive tax system helps buffer the effects of a mental-cognitive disability, similar to the findings in Blundell, Graber and Mogstad (2015). Total family income experiences a marked decline for both aggregate types but is only significant in the long run for mental-cognitive. Moreover, the onset of an aggregate physical disability decreases the income of other household members, which may be due to increased caregiving responsibilities, as discussed Fadlon and Nielsen (2021). The distinction of the source of income shocks unveils differences in partial insurance that might be otherwise obscured in analyses of generic income shocks.

The second set of results highlights key differences in effects within the aggregate disability types. First, the effect of physical disability on market income and government transfers is driven by kinetic ability disabilities. Moreover, a disability to kinetic ability negatively affects total household income in the years following its onset, as well as the income of family members. Disabilities exclusively related to pain exhibit no significant effects on WSC or government transfers but result in some labour market exit. These results emphasize the importance of distinguishing between physical disability subtypes. Disabilities related exclusively to pain induce noise into estimates of the effects of aggregate physical disabilities.

Exclusively mental health-related disabilities demonstrate a similar post-onset path in effects on market income as cognitive functioning disabilities, albeit with a smaller magnitude. Both types cause immediate declines in wages, salaries, and commissions in the short run (-\$5700 and -\$6900, respectively), which worsen in the long run. Despite their similar effects on market incomes, the sources of partial insurance differ. Cognitive functioning disabilities lead to a considerable increase in transfer payments from disability-relevant programs, coinciding with a sharp long-run decline in labour market participation. In contrast, mental health disabilities do not receive significant income from these programs post-onset. Instead, as market income declines for this group, their marginal tax rate declines, helping to buffer this shock. The magnitude of the post-onset effect on market income for mental health is comparable to kinetic ability, suggesting gaps in available insurance for this group. At the household level, family total income falls in the long run post-onset of a disability to cognitive functioning and mental health.

The results are interpretable with insights from the recent task-based human capital literature. For instance, Guvenen et al. (2020) shows that a mismatch in skills related to math and verbal ability is more harmful relative to a mismatch in social skills. Therefore, a disability to cognitive functioning having greater consequences to math and verbal skills relative to a disability to mental health explains the larger estimated effect on earnings. Likewise, Lise and Postel-Vinay (2020) demonstrates that manual skills have moderate returns and adjust quickly, cognitive skills have much higher returns but are slower to adjust, and interpersonal skills have slightly higher returns than manual but are essentially fixed over one's life. The results are consistent with disabilities to kinetic ability being more closely linked to manual skills, cognitive functioning to cognitive skills, and mental health to interpersonal skills. That said, the link is more complicated by cross-linkages between disability types and skills. For instance, mental health likely has implications for cognitive skills, and cognitive functioning has implications for interpersonal skills. A comprehensive analysis mapping disability types to a full set of skills is left for future research.

The final section of this paper interprets the empirical findings within the optimal benefits framework of Baily (1978) and Chetty (2006). This framework posits that the optimal level of disability benefits is a function of several key parameters: the percentage change in consumption, the coefficient of risk aversion, and the elasticity of time receiving disability benefits with respect to the level of disability benefits. The key idea of this framework is the balancing act between the work-disincentive effects of disability benefits and the welfare gains associated with consumption smoothing. Assuming the change in after-tax income is proportional to the change in consumption after the onset of a disability, which is consistent with the permanent income hypothesis, I use estimates of the elasticity of time receiving benefits from the Meyer and Mok (2019) and compare the implied coefficient of risk aversion that consistent with optimal benefits with values commonly applied in the related literature. I find that current disability benefits are only optimal if individuals have lower risk aversion than is typically seen in the related literature for mental-cognitive disabilities and disabilities to kinetic ability. Those affected by a mental health-related disability deviate the most from optimal benefits.

The remainder of my paper is structured as follows. Section 2 describes a conceptual framework to motivate the importance of distinguishing disability into types. Section 3 details the institutional details of the disability policy in Canada. Section 4 describes the dataset used in my analysis and summarizes its key features, 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 empirical model's results. Section 7 explores the welfare implications of the results in Section 6, and Section 8 concludes.

I Conceptual Framework

In a standard human capital model, an individual's stock of human capital is a crucial determinant of their marginal productivity and subsequent returns to working. The heterogeneous effects of different types of disabilities are readily illustrated with a task-specific human capital framework. In this setting, an individual's human capital vector is defined relative to the skill requirements of occupations. The skill requirements of occupations are typically derived from a larger set of task requirements associated with each occupation.[8] A main advantage of this approach is the ability to formalize an ordinal concept of skills-jobs mismatch. This mismatch is quantified as the distance between a worker's human capital vector and the skill requirement vector of their occupation through some metric function. A greater distance between these vectors indicates a larger mismatch between the worker's skills and the tasks required by an occupation, resulting in larger wage penalties. In the following, I further develop this framework and show how it is extended to incorporate the effects of disabilities.

Formally, an occupation is represented by a k-dimensional skill requirement vector, $x_t \in \mathbb{R}^k$, where each element, $x_t^j \in \mathbb{R}$, represents the complexity of the corresponding tasks involved in producing output in period t. Complexity measures the importance of these tasks in the production process. For example, critical thinking tasks are essential to the productivity of an economics researcher, indicating a high value for the complexity in that dimension of the skill requirement vector. Occupations are thus differentiated by their skill requirements and by the output they produce. A worker's skills are represented by a k-dimensional vector, $s_t \in \mathbb{R}^k$, where each element, $s_t^j \in \mathbb{R}$, represents the proficiency of skill dimension j when engaging in productive work. For instance, an economics researcher with a Ph.D. will have developed their skills in critical thinking, corresponding to a high value in this dimension of their skill vector. Without loss of generality, workers' skills are ordered in terms of their complementary with the respective element in the skill requirement vector. For instance, if x_t^1 represents manual tasks, s_t^1 will summarize physical human capital, such as strength, dexterity, or mobility.

Following Yamaguchi (2012), a worker's hourly wage, w_t, equals their marginal value product, which is defined as

$$w_t = \pi(x_t)q(x_t, s_t)exp(\eta_t).$$

The labour productivity of a worker with skill s_t at occupation with skill requirement x_t can be further parameterized as $\ln q(x_t, s_t) = \theta'(x_t)s_t$. $\theta(x_t)$ is a k-dimensional vector representing the implicit skill prices, which captures the contribution of skill s_t to production in occupation x_t. The market price of a product characterized by skill requirements x_t is $\pi(x_t)$. Lastly, $\eta_t \sim F(\eta)$ represent i.i.d productivity shocks.

In a competitive setting, workers that are heterogeneous in skills will self-sort into occupations based on their comparative advantage.[9] Observed wages maximize the product of the match function (q) and market pricing of the skill requirement of an occupation (π). Further assuming that $\frac{\partial \pi(x_t)}{\partial x_t} > 0$ implies that the market valuation of skills is increasing in task complexity. Moreover, assuming $\frac{\partial^2 q(x,s)}{\partial s_k \partial x_k} > 0$ implies that skills are more intensely used and

[8] A primary source of information on an occupation's task requirements is the O*NET. The dimensionality of task requirements is often higher than that of the skill requirement vector, and dimension reduction methods, such as unrestricted Principal Component Analysis, are often used. For example, Poletaev and Robinson (2008); Yamaguchi (2012); Lindenlaub (2017); Robinson (2018); Guvenen et al. (2020); Lise and Postel-Vinay (2020). Sanders, Taber et al. (2012) summarizes the earlier literature on task-based human capital.

[9] This aligns with Roy's workhorse framework and the life-cycle model of Yamaguchi (2012) (Roy, 1951).

contribute to productivity more, where corresponding tasks are complex.

To incorporate the effects of disabilities, define a disability vector, d_t, as a k-dimensional vector representing the extent of limitation to the respective skills in the human capital vector in period t. The elements of d_t are constrained such that $d_t^j \in [0,1], \forall j \in \{1, ...k\}$. The disability vector captures the degree of impairment in percentage terms, where 1 corresponds to no limitation, and 0 corresponds to total incapacitation in that dimension. Then, redefine wages as

$$\begin{aligned} w_t &= \pi(x_t) q(x_t, h_t) exp(\eta_t). \\ &= \pi(x_t) exp(\theta'(x_t) h_t + \eta_t), \end{aligned}$$

where $h_t = s_t \cdot x_t$.[10] Importantly, wages depend on the dot product of the current stock of skills and the disability vector. This captures the immediate effect of disability onset on productivity, keeping occupation fixed. In the absence of any disability $d_t^j = 1, \ \forall j \in \{1, ..., k\}$ and $q(x_t, h_t) = q(x_t, s_t)$. For any $d_t \neq 1$, optimal pre-onset sorting implies that $q(h_t, x_t) < q(s_t, x_t)$, and the associated wage loss is the size mismatch between "effective skills" and skill requirements scaled by the market valuation of output from this occupation, $\Delta w = (q(s_t, x_t) - q(h_t, x_t))\pi(x_t)$. Or alternatively, the disability-induced mismatch is the weighted sum of the difference between the elements of s_t and $d_t s_t$, where weights are the implicit skill prices, θ, multiplied by the market valuation of these tasks, $\pi(x_t)$.

Certain dimensions of human capital will be more affected by specific types of disabilities. To illustrate, researchers often specify the human capital vector to consist of physical and cognitive skills and occupations to consist of physical and cognitive tasks (Sanders, Taber et al., 2012; Yamaguchi, 2012; Mori, 2019). Additionally, assume that a physical disability only affects the stock of physical skills, and a cognitive disability only affects the stock of cognitive skills. The resulting impact on earnings of a given type of disability will depend on two factors. First, some tasks are more important in certain occupations than others. For instance, the productivity of a labourer will have a higher dependence on physical tasks relative to cognitive tasks, which is captured by θ. Second, the market values the output of certain tasks more than others.[11] For example, if output produced by highly intensive cognitive skills, such as the services of a lawyer, are priced higher by the market, a cognitive disability may result in greater wage scarring for a lawyer compared to an equally severe physical disability.[12] Alternately, the onset of a physical disability may be disastrous for the productivity of a manual labourer and may not meaningfully affect a lawyer's productivity. Hence, the market pricing of physical skills relative to cognitive skills will contribute to the differential impact of disability types on employment income.

A disability shock today can have lasting dynamic effects on earnings through the process of skill accumulation. To illustrate, I follow Yamaguchi (2012) and assume that skills grow from period t to t+1 according to

$$s_{t+1} = Ds_t + a_0 + A_1 x_t + A_2 d_t + \epsilon_{t+1}.$$

[10]This takes a specific stance on the relationship between health and human capital. Health is generally viewed as complementary to human capital, and researchers have taken various approaches to formalizing the relationship between the two. For instance, Hanushek and Woessmann (2008) discusses a model of human capital inputs that depend on health among other inputs to skill production, Grossman (2017) models health capital as affecting the amount of productive time, and Mori (2019) considers multidimensional health capital and human capital as being complimentary in human capital productivity.

[11]The human capital literature on task-specific human capital typically finds a higher market valuation to output produced by cognitive tasks, relative to physical (Poletaev and Robinson, 2008; Sanders, Taber et al., 2012; Yamaguchi, 2012; Lise and Postel-Vinay, 2020)

[12]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 that disabilities with a degree of cognitive impairment are more detrimental to economic welfare than physical or sensory disabilities. For example, see Case, Fertig and Paxson (2005); Lundborg, Nilsson and Rooth (2014) and, Mori (2019).

The matrix D captures the depreciation rate of skills between periods, b_t allows individual characteristics to affect skill accumulation, and ϵ_{t+1} represents idiosyncratic shocks to skills. The matrix A_1 represents a"learning-by-doing" technology of human capital production, where higher task complexity in a particular dimension results in more rapid skill production in that dimension. The off-diagonal elements of the matrix capture complementarities in skill production across tasks. Similarly, the onset of a disability in t results in a permanent shock to skills in t+1, the scale of which is captured by the matrix A_2. The diagonal elements of A_2 represent the direct effects of limitation in a dimension, and off-diagonal elements capture complementary effects. For instance, the onset of a physical disability in t may result in positive complementarities for cognitive skill development, indicating potential compensatory efforts to overcome the physical limitations. Assuming no occupational change, substituting in for previous period skills,

$$s_{t+1} = D^{t-n}s_{t-n} + \sum_{j=0}^{n} D^j A_1 x_{t-j} + \sum_{j=0}^{n} D^j A_2 d_j + \sum_{j=0}^{n} D^j \epsilon_{t-n+1},$$

which shows that in period t, the dynamic effect of a disability which onset in period t-n is $\sum_{j=0}^{n} D^j A_2 d_j$.

Predicting the full extent of the effects of disability onset on incomes and labour market behaviour requires embedding the aforementioned wage and skill transition process within a life cycle labour-leisure framework. Formalizing such a model provides the theoretical basis for predicting labour supply responses to disability-induced wage shocks. For instance, in the neoclassical labour supply model, where leisure is a normal good, substitution effects following wage loss predict decreases in labour supply. In contrast, income effects predict increases in labour supply. However, a disability shock may influence these effects and consequently affect the reoptimized labour supply. A disability may alter the marginal utility of consumption and the marginal cost of work (Cutler et al., 2006; Low and Pistaferri, 2015). Additionally, the relative value of non-participation may increase when disability status gives eligibility to social insurance programs, such as disability insurance. Hence, the income effect may be offset by an increase in the outside option to work. The labour response depends on the extent of wage loss from disability-induced mismatch and the ability to substitute to occupations that better match the post-disability skill vector. Lastly, the aforementioned analysis assumes the absence of market frictions, which may lead to situations where the pre-disability job does not maximize the match function q and create challenges in transitioning to new occupations following disability onset.[13] For instance, observed behavioural changes might result from additional costs associated with disability, labour market risks, and discrimination.[14] Formalizing such a model is outside the scope of this paper and is left for future work.

II Institutional Setting

The policy environment in Canada is comprised of various programs at the provincial and federal levels. These can be partitioned into social security programs for the retired and elderly, economic security programs for families, targeted insurance for specific economic shocks, and welfare programs to fight poverty.[15] Moreover, the Canadian tax system offers economic support for families and individuals with a disability through various tax credits and benefits.

For the population affected by disability, these programs provide income insurance for earnings lost because of their disability, rehabilitation for reintegration into the workforce, and welfare transfers for individuals unable to rein-

[13] The implications of disability onset are most likely to be similar in a setting with market frictions. However, the worker-job match at the time of onset may not be efficient in the sense of optimizing wages for a worker. Guvenen et al. (2020) consider an environment where information frictions about one's ability results in a mismatch. Lise and Postel-Vinay (2020)

[14] Kitao (2014) studies disability-specific labour market risks. Baldwin and Johnson (2006) survey research on disability-related discrimination in the labour market.

[15] My population of interest is working-aged adults, so I will not focus on social security and old-age security programs.

tegrate (Torjman and Makhoul, 2016). Programs differ in their eligibility requirements, the screening of the population covered, the duration of aid provided, and the generosity of aid provided. In this paper, I distinguish transfers most relevant for individuals affected by disability. These "disability-relevant" programs include disability-specific tax credits and income replacement programs from worker's compensation, employment insurance, federal disability insurance, and provincial social assistance programs. This section outlines the features of these disability-relevant programs.

The federal pension program in Canada, the Canadian Pension Plan (CPP), administers disability insurance, which delivers monthly financial transfers to individuals that are deemed eligible for the program. Eligibility requires that recipients be younger than 65, are not currently receiving CPP retirement benefits, have made a predetermined number of contributions to CPP, and are markedly restricted by a physical or mental disability.[16] Importantly, to receive CPP-D, an applicant must prove that their disability is both prolonged and severe. A disability is prolonged if it is expected to be indefinite or likely to result in death.[17] The severity of the disability concerns the applicant's ability to engage in "substantially gainful activity" in the labour market. Substantially gainful is subjectively determined based on an applicant's perceived productivity in the labour market, given the barriers imposed by their disability.[18]

The generosity of disability insurance equals the sum of two components. The first component is equal to 75% of the applicant's potential CPP retirement benefits at the date of application. Potential CPP retirement benefits are equal to 25% of the earnings index that summarizes an applicant's bounded average earnings over their contributory period.[19] The minimum bound to their earnings has been $3,500 per year since 1996, and the maximum, which was $55,900 in 2018, is updated yearly based on a measure of average wages. The second component is a deterministic flat-rate benefit indexed by the CPI each year.[20]

Provincial social assistance programs provide means-tested antipoverty relief for individuals with barriers to sustained employment and who have insufficient or volatile sources of income. Each province separately administers its own social assistance program. As such, these programs vary by province in eligibility criteria and generosity of transfers. However, all provinces have a similar structure to their social assistance programs (Employment and Social Development Canada, 2016). The generosity of aid is based on a means test, which calculates the net difference between an applicant's "assessed needs" and their financial assets. An applicant is deemed eligible if their assessed needs exceed the sum of their income and assets, up to an upper threshold. An applicant's "needs" may include living expenses, family size and composition, and disability status. On the other side of the means test, an applicant's financial assets include liquid assets, such as cash or convertible assets, and fixed assets, such as property. Exempt assets include those used for employment or transport, such as tools or automobiles, and assets related to savings plans used for education purposes, such as registered education savings plans. The combined fixed and liquid assets must not exceed a predetermined threshold, which varies by provincial jurisdiction. Assessed income combines all earnings from market activities, such as paid employment or self-employment, and transfers from other government programs, such as disability insurance.[21] Beneficiaries of social assistance typically receive monthly financial transfers equaling

[16] The contribution requirement is that applicants must have contributed to the CPP in four of the previous six years or three of the previous six years if the applicant has contributed to the CPP for twenty-five years or more. Contributions are mandatory if employed and earning above a specified threshold. The size of contributions to CPP determines the generosity of disability insurance transfers. The contributory period begins at age 18 and ends at age 65 or the year of death and excludes years in which the applicant was receiving CPP-D benefits.

[17] Disability insurance is a program for long-term disabilities and not designed to insure against short-term injuries.

[18] That is, how productive a disabled individual is in a job they could be expected to hold given their qualifications relative to others doing the same work but who do not have a disability. Adjudicators account for an individual's personal characteristics when determining an individual's capacity for substantial gainful activity. Most notably, personal characteristics include age, education, and work experience.

[19] The earnings index is a similar object as the average indexed monthly earnings used by the Social Security Administration in the US.

[20] In 2018, the average disability insurance transfer amount was just under $1000 per month, half of which was the deterministic flat rate component (Employment and Social Development Canada, 2018).

[21] Individuals may receive social assistance while earning from other sources, but this may reduce benefits according to the program's replacement

a basic assistance amount and, in some cases, a special assistance amount. The basic assistance amount covers the costs of living, such as food, shelter, and clothes. A disability may create additional living expenses, and all provinces allocate additional resources available for individuals affected by a disability. Additional details on SA programs can be found in Employment and Social Development Canada (2016).

Worker's compensation provides income replacement paid in respect of an injury, disability, or death to a worker. The main idea of worker's compensation programs is that workers receive insurance for injuries on the job in exchange for forgoing the right to sue the employer. Each province and territory in Canada has its own worker's compensation board/ commission (WCB). WCBs are funded by employers, who pay a certain dollar amount called a "premium." These premiums differ provincially and by industry within that province. Premiums are a fixed amount out of every 100 dollars of payroll. Also, the rate paid depends on each employer's experience rating, which summarizes the number of injuries in that workplace. Premiums go into an accident fund and the resources from the fund may be used to provide wage loss benefits, medical aid, rehabilitation, or to pay for the program's administration. Monies paid to injured workers by WCB are known as benefits. The most common types of benefits are the replacement of lost wages and compensation for permanent disability. Benefits may also be paid out for rehabilitation or for dependent spouses of people who died on the job. Maximum compensated earnings in the provinces range from $52000 to no maximum. The percentage of pre-injury earnings that determine generosity of benefits varies between 75% to 90%.

Disability insurance and social assistance are the primary sources of income assistance for general disability shocks in Canada, and worker's compensation is the main program for workplace injuries. Another source of monetary support is the Disability Tax Credit. The disability tax credit is a non-refundable tax credit that reduces the income tax individuals with disabilities have to pay. Eligibility is similar to disability insurance in that applicants must show they have a severe and prolonged impairment, except the disability tax credit does not depend on employment histories.[22]

A final relevant federal program is employment insurance, which provides short-term income replacement for individuals laid off from their job. Employment insurance is typically allocated to individuals experiencing structural, seasonal, or cyclical employment. However, individuals unable to work for medical reasons can also apply, granted they prove their medical condition and inability to work. Beneficiaries can receive up to 55% of their earnings, to a maximum of 650$ per week, for up to fifteen weeks.

Canada's second main category of government transfer programs are designed to aid families with the costs of raising children. At the federal level, parents may apply for tax-free monthly transfers through the Canada Child Benefit. This is a means-tested program, and the generosity of payments depends on the number of children, their ages, and the total income of the household. In 2021, beneficiaries could receive up to 570$ per month for each child under the age of six and 480$ for each child aged size to seventeen. Moreover, Canadian families may receive supplementary benefits from provincial governments.

III Data: The Longitudinal and International Study of Adults

To estimate the longitudinal effects of disability types, I use the Longitudinal and International Study of Adults (LISA) (Statistics Canada, 2012-2018). 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, the labour market, social participation, and income. These data allow me to identify individuals with disabilities, the

rate. SA may be revoked if sufficient effort is not taken on the beneficiary's part to receive income support from other sources.

[22] Additionally, the federal government introduced the Working Income Tax Benefit in 2007. This program is intended to raise the income of low earners. As people with disabilities are often at the lower end of the earnings distribution, this program targets relatively more disabled.

types of activities limited by the disability, and the timing of onset. Moreover, LISA is supplemented with several administrative datasets. Most relevant are the T1 family files (T1FF), which contain rich disaggregated measures of personal income and transfer payments from individual annual income tax filings. These data are confidential and administered by Statistics Canada's Research and Data Center Network.[23]

The T1FF spans from 1982 to 2017 and is linked to each respondent in the main survey waves of LISA. These data contain details on an individual's demographic characteristics relevant to their tax filings, such as age, marital status, province of residence, and the number of children. A notable advantage of these tax records is that they are less likely to suffer from the measurement and coverage issues often associated with survey data. For instance, Meyer, Mok and Sullivan (2009) show that survey measures of public transfers often suffer from respondents under-reporting, which can lead to overestimation of total income declines following the onset of disability.

For this analysis, the outcomes of interest are the components of market income, government transfers, total before- and after-tax income, and income of family members. Within market income, I focus on paid employment income in the form of wages, salaries, and commissions (WSC), which are by far the largest component of market income and are the most directly related to one's human capital. I use this to define a measure of labour market participation, where I flag someone as a market participant in a given year if they have any positive WSC in that year. Moreover, I analyze changes in the combination of self- and other employment income to explore substitution to other earnings activities. Within government transfers, I distinguish disability-relevant transfers, which are the sum of programs outlined in the institutional background section, from transfers that target families. Total before-tax income combines market income and government transfers, and total after-tax income represents the market income and government transfers individuals take home after taxation. The difference between these two reveals the buffering effects of the tax system. Last, family total income combines total before-tax incomes for all members of one economic household. I also consider a measure of family members' income, which nets out an individual's total before-tax income from the family's total income. For a more detailed breakdown of the income concepts covered in these data, please refer to Section 2 in the Appendix.

A Measuring disability

The 2014, 2016, and 2018 survey waves of LISA include measures of activity limitations and other characteristics of health conditions used to derive disability status.[24] The set of limitations to daily activities included in LISA is derived from the short version of the "Disability Screening Questions," a survey model developed by Statistics Canada for use in general population surveys (Grondin, 2016). This model distinguishes five main areas of activity limitation: Seeing, Hearing, Physical, Cognitive, and Mental Health. Physical combines limitations to mobility, flexibility, dexterity, and pain. Cognitive disabilities combine developmental disabilities, limitations to learning, such as dyslexia or hyperactivity, and limitations to memory and concentration.[25] Mental health conditions encompass many emotional, psychological, and mental health conditions, including anxiety, depression, bipolar disorder, substance abuse, and anorexia.[26]

The first section of my empirical analysis distinguishes heterogeneity by two mutually exclusive aggregated disability types, aggregate physical and mental-cognitive. The distinction between conditions that inhibit physical tasks

[23]Confidentiality of data requires adherence to a set of restrictions on extracting statistics from the data center.

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

[25]It is important to note that developmental disabilities such as Down syndrome, Autism spectrum disorder, Asperger syndrome, or brain damage due to lack of oxygen at birth typically manifest early in life rather than as late-onset disabilities.

[26]More details on the survey questions can be found in Section 1 of the Appendix.

from those impacting cognitive or socioemotional tasks is common in the literature on the heterogeneous effect of disability.[27] Moreover, a simple correlation matrix amongst the disaggregated activity limitations supports these aggregate groupings.[28] Moreover, labour market and demographic descriptive statistics and outcomes are more similar among activity limitations within physical than with cognitive and mental health. Similarly, these statistics are similar amongst the limitations and conditions within cognitive and mental health disabilities. However, this aggregation can mask underlying heterogeneity across the specific activity limitations within these categories.

The second part of my empirical analysis explores heterogeneity within the aggregate disability types. Within physical, I distinguish disabilities to one's kinetic ability, which combines activity limitations related to mobility, flexibility, and dexterity, from disabilities related exclusively to pain.[29] Additionally, I separate mental-cognitive into disabilities related to cognitive functioning (learning, memory, or concentration), from disabilities related exclusively to mental health. Distinction along these margins of activity limitation is policy-relevant, as mental health-related disabilities and pain-related disabilities have driven rising applications to disability programs (Autor, 2015). Moreover, this study provides novel estimates on the effects of mental health conditions, which are becoming increasingly more recognized as significant impediments to economic independence (Frank and Glied, 2023).

The activity limitations are self-reported in LISA. For each type of activity limitation, respondents are asked a flow of categorical questions about the magnitude of difficulty and frequency of limitation for each limitation type.[30] The short version of the DSQ flags disability based solely on the reported frequency of limitation. A respondent is flagged for a type of disability if reporting their condition to limit their activities "sometimes," "often," or "always."[31] 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 persistent between the survey years and the year of reported onset. Due to the retrospective nature of this question and the panel structure of the survey waves, there are instances where an observation reported different ages of onset. To address this, I use the minimum reported age of onset as the truth.

Related studies into variation in the effects of disability often consider heterogeneity by the severity of their impairment.[32] Unfortunately, the severity of a disabling condition at the time of onset is unobserved in these data. Instead, I only observe measures of self-reported severity at the time of the survey. However, as I flag disability based on any positively reported activity limitation, I capture a relatively broad coverage of the disabled population. This approach minimizes the type 2 error of incorrectly flagging someone as not disabled when they have a disability in truth. Although, my disabled population will include individuals with milder conditions that may not be considered disabled in other settings. Consequently, I interpret my results as lower bounds to the average effects of disability onset.

Much research in health economics has focused on the validity of self-reported measures of one's health. One concern relates to the inherent subjectivity of how one assesses their own health. For example, two otherwise identical individuals may differ in the reported severity of their disability. Additionally, critics of self-reported health measures

[27] See footnote 6.

[28] That is, mobility, pain, dexterity, and flexibility limitations are positively correlated with each other and negatively correlated with limitations due to mental health and cognitive functioning. Limitations to mental health and cognitive functioning are positively correlated with each other and negatively correlated with physical limitations.

[29] Kinetic ability describes the body's ability to move efficiently, exhibit agility, and perform tasks that require coordination and precision. Kinetic abilities include walking, running, jumping, bending, twisting, reaching, grasping, and manipulating objects.

[30] Some cognitive conditions, such as developmental disability or learning conditions, are initially flagged based on diagnosis from medical professionals instead of the level of difficulty. Refer to Section 1 in the Appendix for details.

[31] I flag disability based on the frequency of limitation alone, as there are inconsistencies in questions about the magnitude of difficulty across the survey waves.

[32] Some examples of studies estimating the heterogenous labour market effects of disability by some measure of severity include Stern (1989), Acemoglu and Angrist (2001), Charles (2003), Baldwin and Johnson (2006), Low and Pistaferri (2015), Kostøl et al. (2019), and Meyer and Mok (2019).

argue that individuals may exaggerate the existence or severity of their health condition to justify poor economic outcomes or attachment to government programs, a phenomenon referred to as justification bias. The evidence on the endogeneity of self-reported health measures and the extent of measurement error are mixed (Black et al., 2017). Although, it is important to note that recent articles tend to find evidence for state-dependent reporting.[33]

My disability measure is derived from a respondent reporting any positive limitations to a specified activity and abstracts from the degree of impairment. This mitigates concerns related to subjectivity in the scale of impairment from a self-reported activity limitation, as I do not distinguish conditions along the severity margin. Moreover, much of the evidence on justification bias is based on broad questions about one's health or disability, such as "do you have a medical or physiological condition that impairs the type or amount of work you can do." The questions about activity limitations in this survey are linked to specific tasks, such as walking on a flat surface for fifteen minutes, grasping a small object like scissors, or experiencing ongoing memory problems or periods of confusion. Additionally, the presence of some activity limitations is elicited based on whether the respondent has been diagnosed with a specific condition, such as a learning or developmental disorder, by a healthcare professional.[34] Last, mental health is identified using specific examples of diagnoses, such as anxiety, depression, bipolar disorder, or anorexia. These approaches narrow the scope of justification bias to be anchored to the activities in question, base the existence of a limiting condition on the diagnosis of a medical professional, or frame limitations related to mental health with specific examples of diagnoses. I follow much of the related literature and take the responses to questions on limitations to daily activities as given. However, I acknowledge the empirical concerns that are inherent to any self-reported measures of health.

In addition to justification bias, there is the related concern that disability onset itself is endogenous to the labour market outcome of interest. Notably, the onset of mental health disabilities may result from deteriorating economic conditions (De Quidt and Haushofer, 2016). In such scenarios, it is difficult to discern if mental health drives labour market outcomes or vice versa. To address this potential confounding factor, I leverage information about the reasons for disability onset to conduct robustness checks. Specifically, I exclude individuals who attribute the cause of their activity limitation to work-related factors. This selection criterion is aimed at ensuring a more accurate assessment of the impact of mental health on labour market outcomes, free from the bias introduced by work-related disability onset. Table's 2 and 3 in Appendix 3 reports statistics for the reason of onset across the different types of disabilities.

B Sample Selection

I observed detailed information on disability types and onset in the 2014, 2016, and 2018 survey waves. I retain the 2012 wave to extract relevant demographic information and survey weights that are representative of the Canadian population in 2012.[35] I choose to omit individuals who are blind or deaf because of small sample counts and only focus on the mental-cognitive and physical types of disabilities.[36] I restrict my sample to individuals aged 22-61 who have been observed for at least four years. I replace missing demographic information using adjacent survey waves and

[33] 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; Burkhauser et al., 2002). Others have found evidence of justification bias related to labour market states inflating the prevalence of health conditions (Benítez-Silva et al., 2004; Baker, Stabile and Deri, 2004; Black et al., 2017). Moreover, alternate approaches to identify individuals with disabilities, for instance, by using disability insurance beneficiaries to define the population with a disability, have been found to under-represent the population of individuals who are limited enough in the labour market to be classified as "disabled" (Bound, 1989)

[34] This type of question has been used to assess the validity of self-reported health measures in Baker, Stabile and Deri (2004)

[35] This is a necessary choice as survey weights are unavailable for the T1FF records and vetting unweighted results is restricted.

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

drop observations that are missing key demographics.[37] I drop observations whose reported onset is younger than 23 or greater than 56 to focus on disability shocks in working life and abstract from retirement incentives. Additionally, I drop individuals whose disability onset occurred before 1984, and I trim year observations more than ten years after disability onset. I exclude observations living in the Canadian Territories. I include both males and females in my sample to increase the size of the ever-disabled sample, and I include rich controls for sex in the empirical framework.[38] The final sample includes 14717 working-aged individuals living in the Canadian provinces that ever and never become disabled, the latter serving as the control group.

C Summary/ Descriptive statistics

The sample of individuals ever experiencing a disability is selected, as one's unique life experiences and economic situation expose them to differing risks of disability onset. These factors must be accounted for in the empirical analysis to isolate the effect of disability. For example, a highly educated individual, such as a lawyer or surgeon, may have a higher risk of developing a cognitive disability related to work stress. At the same time, a low-skilled labourer may be more susceptible to a physical disability due to strain on their body. Such relationships manifest into a socioeconomic status (SES)-health gradient, the nature of which may differ by disability type.

Table 1: Sample Distribution of Disability and Types

Prevalence of Disability	
No Disability	0.816
Disabled	0.184
Distribution of Types Within Disability	
Aggregate Physical	0.587
Kinetic Ability	0.623
Exclusively Pain	0.377
Mental-Cognitive	0.103
Cognitive Functioning	0.319
Exclusively Mental Health	0.681
Concurrent Physical and Mental-Cognitive	0.311

Note: The sample reflects working age (25-55) Canadians, living in the provinces, whose disability onset occurred in working life. Survey weights have been applied such that the sample reflects the demographic composition of Canadians in 2012.

Table 1 shows the proportion of the population with a disability and the distribution of types within the people with disabilities. 18.4% of the sample reports the onset of any activity limitation during their working life. The majority of these are physical in nature, accounting for 58.7% of cases. Mental-cognitive disabilities make up 10.3% of disabilities, while 31.1% are concurrently physical and mental-cognitive.

There is a strong correlation among the activity limitations underlying physical disabilities. Limitations to mobility,

[37] 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.

[38] The trade-off of including both sex's is that males and females may have different experiences in labour market factors, which I control for in the empirical specifications. That said, the general results hold when conditioning on male or female, although there are some differences in magnitude of effects for some outcomes, which should be mitigated by the rich controls included in the estimating specification.

flexibility, and dexterity are often present simultaneously. Moreover, three-quarters of individuals with a physical disability report some degree of pain-induced limitation. Differentiating the limitations within aggregate physical disabilities into mutually exclusive groups reveals 37.7% of physical disabilities are due exclusively to pain, whereas 62.3% have some impairment to kinetic ability. Limitations due exclusively to mental health comprise approximately two-thirds of mental-cognitive disabilities. Disabilities related to cognitive functioning that onset in working life are less common, accounting for about one-third of mental-cognitive disabilities.

Table 2: Demographic Summary Statistics by Disability Status and Aggregate Disability Type

	No Disability	All Disability	Aggregate Physical	Mental-Cognitive	Concurrent
Age	37.6	38.6	39.8	34.6	37.8
	(8.7)	(7.1)	(7.1)	(6.3)	(6.7)
Age of Onset	-	42.1	43.5	37.6	40.7
	(-)	(9.4)	(9.1)	(9.2)	(9.2)
Female	0.488	0.578	0.563	0.592	0.601
	(0.50)	(0.50)	(0.54)	(0.49)	(0.48)
Dropout	0.064	0.117	0.119	0.041	0.138
	(0.24)	(0.33)	(0.34)	(0.20)	(0.34)
High School	0.181	0.209	0.203	0.172	0.231
	(0.38)	(0.41)	(0.42)	(0.38)	(0.41)
Post Secondary	0.750	0.667	0.674	0.783	0.618
	(0.43)	(0.48)	(0.49)	(0.41)	(0.48)
Married	0.719	0.647	0.722	0.634	0.510
	(0.45)	(0.49)	(0.46)	(0.48)	(0.49)
Number of Children	0.8	0.7	0.7	0.9	0.6
	(1.1)	(1.0)	(1.0)	(1.1)	(0.9)
Pre-Onset Labour Market Statistics					
Labour Market Participation Rate	0.845	0.796	0.808	0.843	0.756
Wages, Salaries, and Commissions	46,770	37,389	37,998	42,022	34,648
Total Government Transfers	2,181	3,038	2,778	2,380	3,806
Disability Relevant Transfers	1,188	1,857	1,683	1,229	2,429
Family Transfers	900	1,044	976	1,053	1,189
Family Total Income	102,909	80,518	82,396	90,931	73,253
After-Tax Income	44,271	36,482	36,860	40,318	34,485

Note: Standard deviations are in parentheses. The sample reflects working age (25-55), living in the Canadians from provinces, whose disability onset occurred in working life. Survey weights have been applied so the sample reflects the demographic composition of Canada in 2012. Pre-onset statistics are predicted from an OLS regression controlling for a 2nd order polynomial in age and evaluated at age forty. All income measures other than transfers are top coded at the 99th percentile.

Table 2 shows how demographic characteristics differ by disability status and across the aggregate disability types. The first two columns compare statistics between individuals with disabilities and the never-disabled control sample. Individuals who ever experience a disability shock have lower average education levels, are more likely female, and have a lower likelihood of marriage. The lower section of Table 2 reports the predicted average labour market outcomes before onset from models controlling for age and age squared and evaluated at age 40. Individuals who ever experience a disability shock exhibit lower employment levels, less employment income from WSC, and receive more government transfers. Once again, these findings are consistent with a disability-related SES-health gradient.

The rightmost three columns in Table 2 compare statistics based on mutually exclusive aggregate disability types.

Table 3: Demographic Summary Statistics By Disability Types Within Aggregate Groupings

	Exclusively Mental Health	Cognitive Functioning	Kinetic Ability	Exclusively Pain
Age	33.8	36.3	40.88	37.9
	(6.1)	(6.4)	(7.15)	(6.51)
Age of Onset	36.9	39.3	44.51	41.89
	(9.1)	(9.3)	(8.74)	(9.47)
Female	0.646	0.477	0.576	0.540
	(0.48)	(0.50)	(0.52)	(0.51)
Dropout	-	-	0.149	0.070
	(-)	(-)	(0.37)	(0.26)
High School	0.213	0.226	0.219	0.178
	(0.41)	(0.42)	(0.43)	(0.39)
Post Secondary	0.787	0.774	0.630	0.746
	(0.41)	(0.42)	(0.50)	(0.45)
Married	0.645	0.611	0.700	0.758
	(0.48)	(0.49)	(0.48)	(0.44)
Number of Children	0.9	0.8	0.59	0.8
	(1.1)	(1)	(0.95)	(1.07)
Pre-Onset Labour Market Statistics				
Labour Market Participation Rate	0.857	0.819	0.811	0.804
Wages, Salaries, and Commissions	43,444	40,933	36,011	41,587
Total Government Transfers	2,192	2,739	3,005	2,391
Disability Relevant Transfers	1,066	1,534	1,884	1,333
Family Transfers	1,029	1,115	984	967
Family Total Income	92,579	89,162	78,634	88,788
After-Tax Income	41,314	39,809	35,855	40340

Note: Standard deviations are in parentheses. The sample reflects working age (25-55), living in the Canadians from provinces, whose disability onset occurred in working life. Survey weights have been applied so the sample reflects the demographic composition of Canada in 2012. Pre-onset statistics are predicted from an OLS regression controlling for a 2nd order polynomial in age and evaluated at age forty. All income measures other than transfers are top coded at the 99th percentile.

The average age of individuals with a physical disability tends to be higher, and the onset of physical disabilities occurs at older ages relative to mental-cognitive disabilities.[39] Mental-cognitive and concurrent disabilities drive lower marriage rates or common law status rates amongst the population with disabilities. However, this difference may be related to other characteristics, such as the age of those with cognitive disabilities. Individuals experiencing mental-cognitive disability tend to have higher education levels than those with aggregate physical disabilities and the never-disabled sample.

Key differences in income and employment prior to onset by aggregate disability types are also highlighted. Individuals experiencing an aggregate physical disability are less likely to be employed and earn less than those who never receive a disability. Conversely, individuals who experience a mental-cognitive shock exhibit similar employment and pre-onset earnings as the never-disabled group. Once again, these patterns are consistent with different exposure risks associated with various occupations and demographics. Individuals experiencing mental-cognitive disabilities tend to work more, have higher earnings prior to onset, and receive fewer disability-related transfers.[40]

[39]The average age of onset for concurrent disabilities falls in between physical and cognitive disabilities. However, I do not observe which condition occurred first or if both types of disabilities occurred simultaneously.

[40]Note the positive amounts of disability-relevant transfers reflect the inclusion of SA programs, which is available for individuals that are not

In Table 3, I contrast differences by the more granular disability types.[41] Within aggregate physical, individuals with exclusively pain-related conditions tend to have higher levels of education and earn more through employment prior to the onset of their disabilities. The opposite is true for disabilities related to kinetic ability. This observation is intriguing because it shows opposite signs for the SES-health gradient among individuals experiencing limitations to their kinetic ability compared to exclusively pain.

Within mental-cognitive, disabilities due exclusively to mental health limitations tend to manifest earlier in working life than cognitive functioning. Disabilities in cognitive functioning tend to be related to work or aging, and mental health conditions are more likely related to work or diseases.[42] Additionally, a higher proportion of females experience mental health disabilities, but there are no noticeable differences in family composition between the two groups. In terms of socioeconomic factors, both mental health and cognitive disabilities have comparable levels of education, employment, and income before the onset of their disability. However, there are notable differences in the attachment to government programs before the reported onset. Individuals limited in cognitive functioning tend to rely more on disability-related transfers provided by the government.

These summary statistics highlight observable differences in demographic characteristics across the types of disabilities. These demographics are directly related to the levels and components of personal income. These demographics will need to be controlled for in the empirical section so as not to confound the effects of disability. In the next section, I outline the empirical framework used, which controls for these observable differences, as well as unobservable differences, in the ever and never-disabled populations to better isolate the effects of the types of disability.

IV Empirical Framework

I estimate the effect of disability types in each of the $k \in \{-5, ..., 10\}$ years relative to onset using the interaction-weighted (IW) estimator proposed by Sun and Abraham (2021). The IW estimator is one among a surging literature of alternatives to dynamic difference-in-difference and event study estimators that are robust to bias occurring in settings with variation in the timing of treatment and with cohort-specific heterogeneity in treatment effects (Borusyak and Jaravel, 2017; De Chaisemartin and d'Haultfoeuille, 2020; Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021; Imai and Kim, 2021; Sun and Abraham, 2021; Baker, Larcker and Wang, 2022; Rambachan and Roth, 2023). My empirical specification explicitly distinguishes heterogeneity in the effect of disability by disaggregated type and by time relative to onset, and the IW estimator is robust to bias that can arise in the presence of treatment effect heterogeneity related to the timing of onset. The IW estimator is a convenient regression-based estimator that has been shown to be as efficient as the alternate proposed estimators for this setting (Baker, Larcker and Wang, 2022). I recover my estimates using the Stata command `eventstudyinteract` (Sun, 2021).

To build intuition, I describe the estimand of interest and the identifying assumptions.[43] Following Sun and Abraham's notation, consider a sample of $i \in \{1, ..., N\}$ individuals observed over $t \in \{0, ..., T\}$ time periods. I observe outcome Y_{it} and treatment status $D^g_{it} \in \{0, 1\}$. In my application $D^g_{it} = 1$ if i has a type g disability in period t, and $D^g_{it} = 0$ otherwise. I assume disabilities are permanent, so treatment is absorbing. The time period of disability onset is given by $E^g_i = min\{t \ : \ D^g_{it} = 1\}$, which characterizes the treatment cohort. I represent the observed outcome of individual i, l periods to the onset of disability type g, if onset occurred in period e as $Y^g_{i,e+l}$, and Y^∞_{it} as individual

disabled.

[41] Demographic characteristics and pre-onset incomes and employment are very similar across mobility, flexibility, and dexterity activity limitations.

[42] Descriptive statistics about reasons for onset can be found in Section 3 of the Appendix

[43] Refer to Sun and Abraham (2021) or Rambachan and Roth (2023) for a more in depth descriptions of this estimator.

i's counterfactual outcome l periods relative to the onset of disability type g if onset never occurred. Now, define the cohort-specific average treatment on the treated l periods relative to disability onset as,

$$CATT^g_{e,l} = E(Y^g_{i,e+l} - Y^{\infty}_{i,e+l} | E^g_i = e).$$

The $CATT^g_{e,l}$'s is the building block of the IW estimator. The treatment effect of interest l periods relative to onset is

$$v^g_l = \sum_e CATT^g_{e,l} \cdot Pr\{E_i = e | E_i \in [-l, T-l]\}.$$

That is, the effect of interest is simply a weighted average of the $CATT^g_{e,l}$'s for that relative period. The weights of interest are the shares of the treatment cohorts in the relative period.

For each disability type, g, and outcome, Y_{it}, the in estimator is implemented in three steps. The first step is to estimate the cohort-specific treatment on the treated, δ^g_l, with the following two-way fixed effect regression,

$$Y_{it} = \alpha_i + \gamma^g_t + X'_{it}\beta + \sum_e \sum_l \delta^g_l A^g_{lit} A^g_{ei} + \epsilon_{it}, \tag{1}$$

where indicator variables for the l periods relative to treatment interacted with cohort indicators estimate a set of $CATT_{e,l}$'s. The A^g_{lit} are indicator variables equaling one in year $t \in \{1982, ..., 2017\}$, $l \in \{-5, ..., 10\}$ years relative to onset. The A^g_{eit} are indicator variables equaling one in year t if i is in treatment cohort e. The specification controls for individual specific fixed effects, α_i, and time period fixed effects, γ_t. Moreover, the vector X_{it} controls for observable differences between the treatment and control populations. Lastly, ϵ_{it} is a potentially serially correlated error term.

In the second step, the weights of the $CATT_{e,l}$'s are calculated as $Pr(E_i = e | E_i \in \{-l, T-l\})$. Last, the IW estimator is recovered by taking a weighted average of $CATT_{e,l}$'s from the first step and the respective weights from the second step.

A Identifying Assumptions

The main idea for identification is that the control sample of never- and not-yet-disabled individuals are a suitable counterfactual for the treatment group if they had not experienced a disability shock. Causal interpretation of estimates is thus achieved conditional on satisfying assumptions to ensure the control group's outcomes serve as a valid counterfactual to never being treated. This involves assuming parallel trends before onset and no anticipation of disability onset.[44]

The estimation sample includes a large control group of individuals that never become disabled. A large control sample is advantageous in addressing collinearity in dynamic event study designs, which can arise when using pre-treatment observations as the control group (Borusyak and Jaravel, 2017). This control group remains the same regardless of disability type of interest. I include a rich set of time-varying controls to account for the differences in populations that never and ever experience a disability onset, shown in Table 2. Following Meyer and Mok (2019), I include a second-order polynomial in age to control for life cycle effects on outcomes. The conceptual framework illustrates how the consequence of disability depends crucially on one's pre-onset skills, so I interact the second-order

[44] See Callaway and Sant'Anna (2021) or Sun and Abraham (2021) for variations of these identifying assumptions in dynamic settings.

polynomial in age with education level to control for differences in pre-disability skill types.[45] Moreover, I interact education levels with a second-order polynomial of time since 1989 to control for trends in the effect of skills over time. I control for marital status, sex, and number of children under the age of eighteen, which are determinants of government transfers and tax rates, interacted with second order polynomial's in age and in time since 1989 to account for trends effects from these variables over the life-cycle and over time. Last, I include province dummy variables to control for average differences by province. The empirical specification includes five periods of pre-onset effect, as in Meyer and Mok (2019) and Collischon, Hiesinger and Pohlan (2023).

Next, I assume there are no anticipatory treatment effects before disability onset. Violations in this assumption can be addressed by adjusting the treatment period such that the start of anticipatory effects becomes the new treatment date. It is worth noting that significant effects in the year before onset may capture gradual increases in the extent of limitation before the individual becomes labeled disabled, the anticipation of disability, or may reflect measurement error in the reported timing of disability onset. Due to the nature of my data, I cannot distinguish between these phenomena.

Last, my empirical specification explicitly models various dimensions of treatment effect heterogeneity. First, the dynamic design separately estimates treatment effects in each period relative to disability onset, accounting for heterogeneity in treatment effects across time. Second, I separate the ever-disabled sample by disaggregated disability types and separately estimate a series of models for each type to distinguish heterogeneity by this type. Finally, the IW estimator is robust to any residual contamination that results from cohort-specific heterogeneity in the effect of 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 given type of disability on one's market income, notably their employment earnings. For instance, the shift from manual task jobs to service sector jobs, which may place a greater value on cognitive skills, will alter the effect of the onset of a cognitive disability, as there is less scope to substitute into the more scarce manual jobs. Additionally, changes in the parameters governing social insurance policy over this time frame can also introduce cohort-specific treatment effect heterogeneity.

V Results

I begin the analysis by comparing the effect of disability types on market income. I then analyze how government transfers respond to partially insure the impact on market income in the years following onset. Lastly, I examine the tax system's role and family members' income as alternate channels for smoothing consumption following the income shock from disability onset. I frame the discussion around the short run, which corresponds to five or fewer years post-onset, and long-run effects, referring to more than five years post-onset.

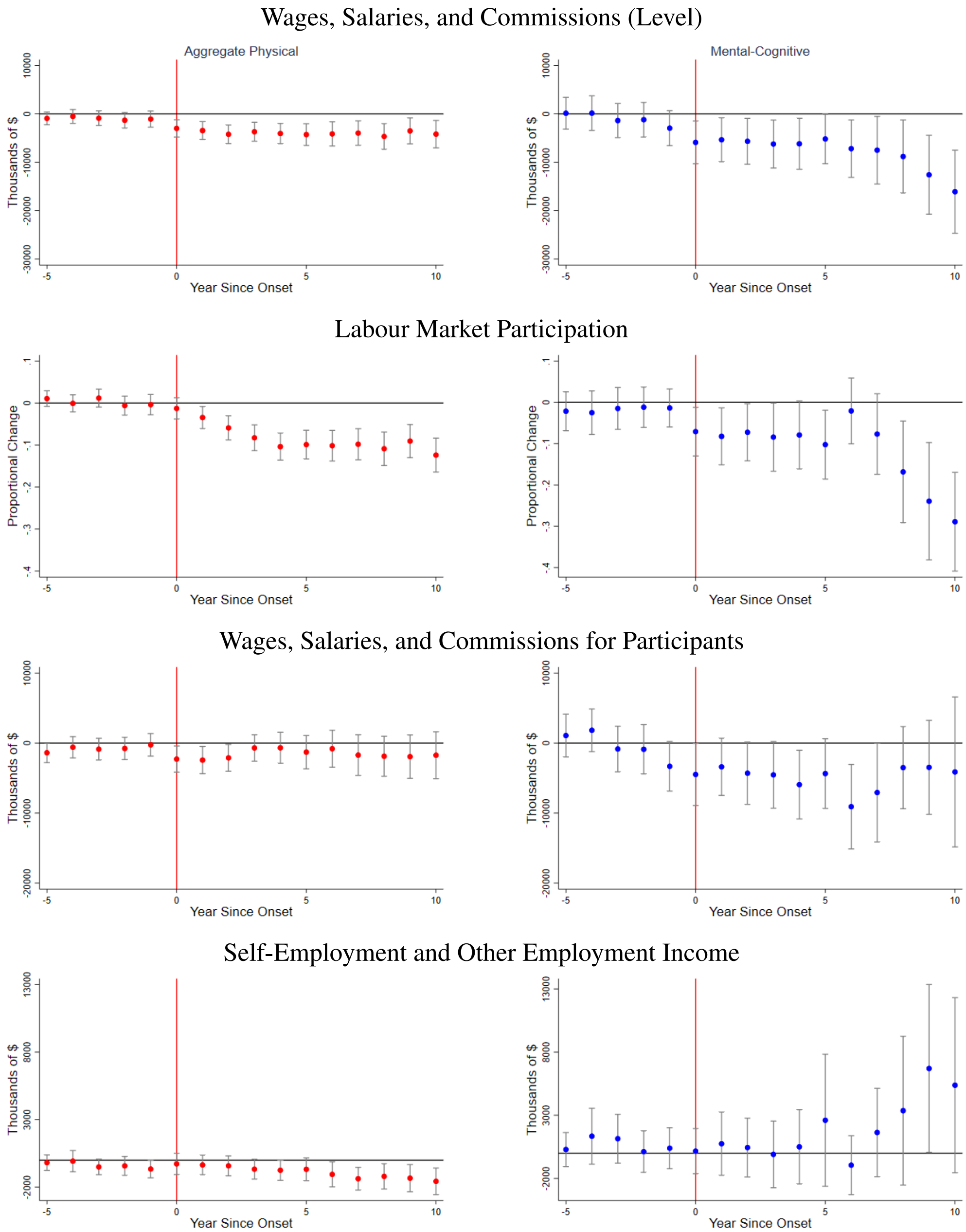
A Market Income

Market income combines all incomes earned through market activities. The largest component is paid employment income in the form of WSC.[46] An individual's employment income is most directly related to their productivity, reflecting the effect of that type of disability on the stock and accumulation of corresponding skills in the human capital vector. Figure 1 plots the point estimates of the average effect of a physical disability (left) and a mental-cognitive

[45] Education categories include high school dropout, college graduate, bachelor's degree, and above a bachelor's degree. I note that pre-onset occupation is an ideal control for pre-disability skills, but this information is not available for the years covered by the T1FF.

[46] I do not separately analyze market income from business and investment activities, which is only relevant for a small proportion of the sample.

Figure 1: Effect of Aggregate Disability Types on Market Income

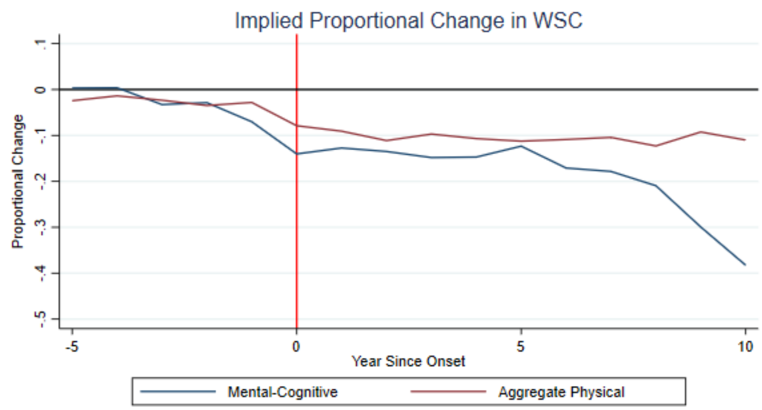


Note: Figures plot point estimates and corresponding 95% confidence intervals from estimating the models specified in Section 5. Data on WSC is top-coded at the 99th percentile. Underlying estimates for graphs are reported in Section 5 of the Appendix.

disability (right) in each of the $l \in \{-5, ..., 10\}$ years relative to it's reported onset. The vertical lines represent the 95% confidence intervals for each point estimate. The dependent variables for each graph are unconditional WSC (top row), labour market participation (second row), WSC conditional on participation (third row), and the combination of self-employment income and other employment income (bottom row).

The results for total WSC reveal clear differences in the longitudinal effects of aggregate physical and mental-cognitive disabilities following onset. The onset of an aggregate physical disability results in modest reductions in WSC, and the longitudinal profile is flat and persistent. The average effect on WSC is -$3940 in the short and long run. A mental-cognitive disability immediately affects WSC of approximately -$5750 in the short run, which worsens in the long run, culminating to less than -$16000 ten years after onset. It is often valuable to analyze income shocks in terms of the percentage of prior earnings to understand the breadth of the shock.[47] I obtain percentage effects with a back-of-the-hand calculation based on the average pre-onset WSC from Table 2.[48] The implied percentage changes for aggregate physical and mental-cognitive are plotted in Figure 2. The longitudinal path of percentage effects is similar for both aggregate types in the short run, with mental-cognitive disabilities resulting in a 3.7% larger average decline of WSC income than aggregate physical. The percentage effect of mental-cognitive substantially grows in magnitude in the long run, dropping by 38% ten years after onset, which is a 27 percentage point larger decline than that of aggregate physical. The onset of a mental-cognitive disability results in a greater loss in the level and proportion of pre-onset income than the onset of an aggregate physical disability, and the difference is substantial in the long run.

Figure 2: Percentage Effect of Aggregate Disability Types on Wages, Salaries and Commissions



Note: Implied percentage effects are derived using ratio of estimates from models for WSC in Figure 1 and the average pre-onset WSC from Table 2.

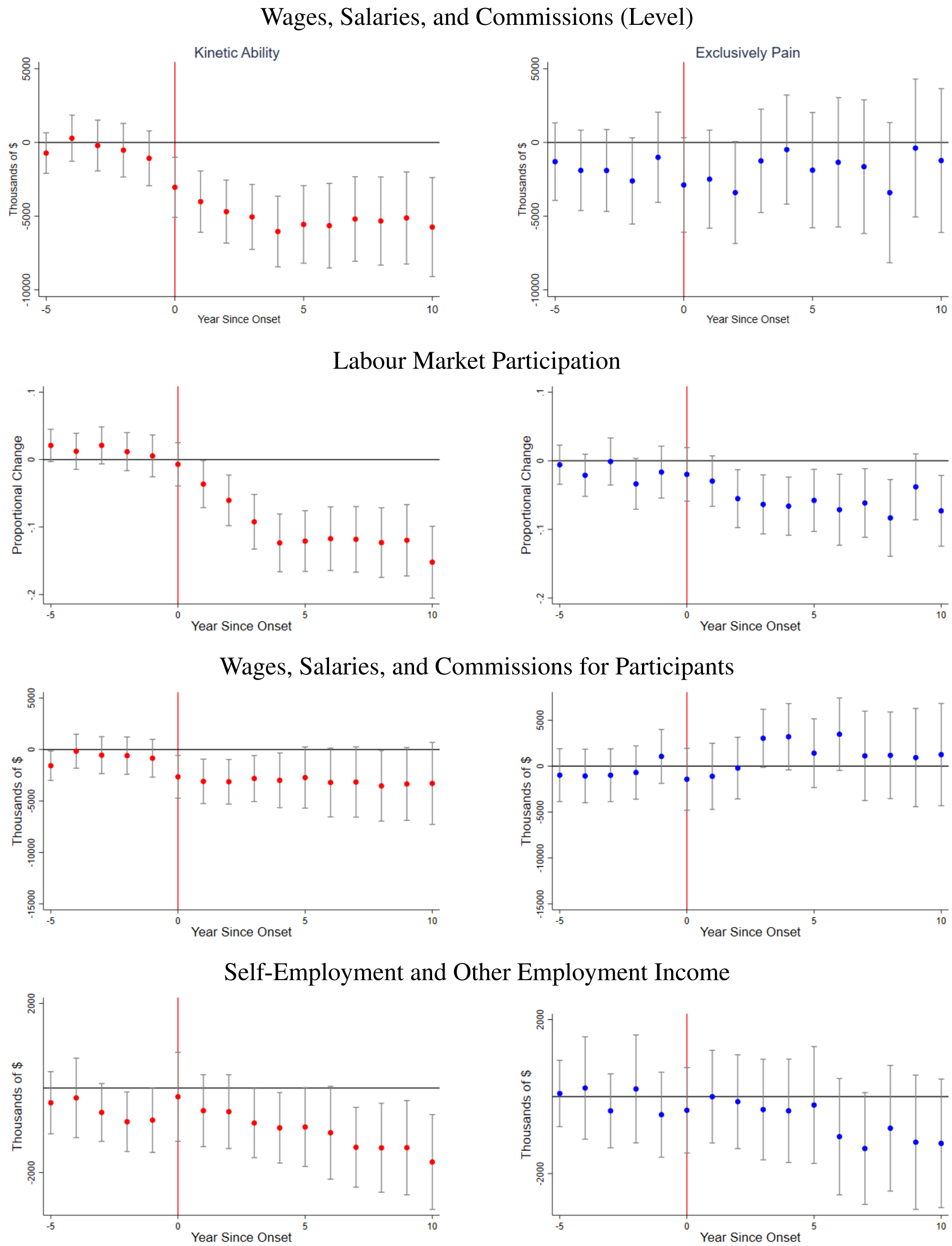
The effects on WSC may result from labour supply responses at the intensive or extensive margin. With a lower return to working, individuals may choose to supply fewer working hours or exit the labour market entirely. As discussed in Section 2, a disability may distort incentives to work by imposing additional costs and barriers to working, such as the need for costly workplace accommodations, or by altering the value of the social insurance environment. The second and third rows of Figure 1 help to discern whether intensive or extensive margin effects drive the results on total WSC. The second row of Figure 1 plots the effects of onset on labour market participation.[49] The third row

[47]For instance, a $10,000 loss of income is substantially more impactful on someone whose income was $30,000 compared to someone whose income was $300,000.

[48]A more direct approach to obtain estimates of the percentage effects is with a log transformation of the dependent variable or with a Poisson regression. However, each approach results in a loss of observations related to outcome values of zero (for log transformation) or little variation in outcomes (for Poisson regression). This issue causes a residual disclosure risk that can prevent extracting results from the Statistics Canada Research and Data Center. Moreover, these lost observations are not constant across various income measures, creating a tradeoff in sample sizes if choosing to omit them entirely. However, the back-of-hand calculations of the percentage effects were compared to the estimated effects from a Poisson regression, and there was no meaningful difference in the estimated longitudinal path of effects for the aggregate types. Due to residual disclosure risk, I opted not to extract the results from the Poisson regressions.

[49]These 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 six weeks or eight weeks, respectively.

Figure 3: Effect of Disability Types within Aggregate Physical on Market Income

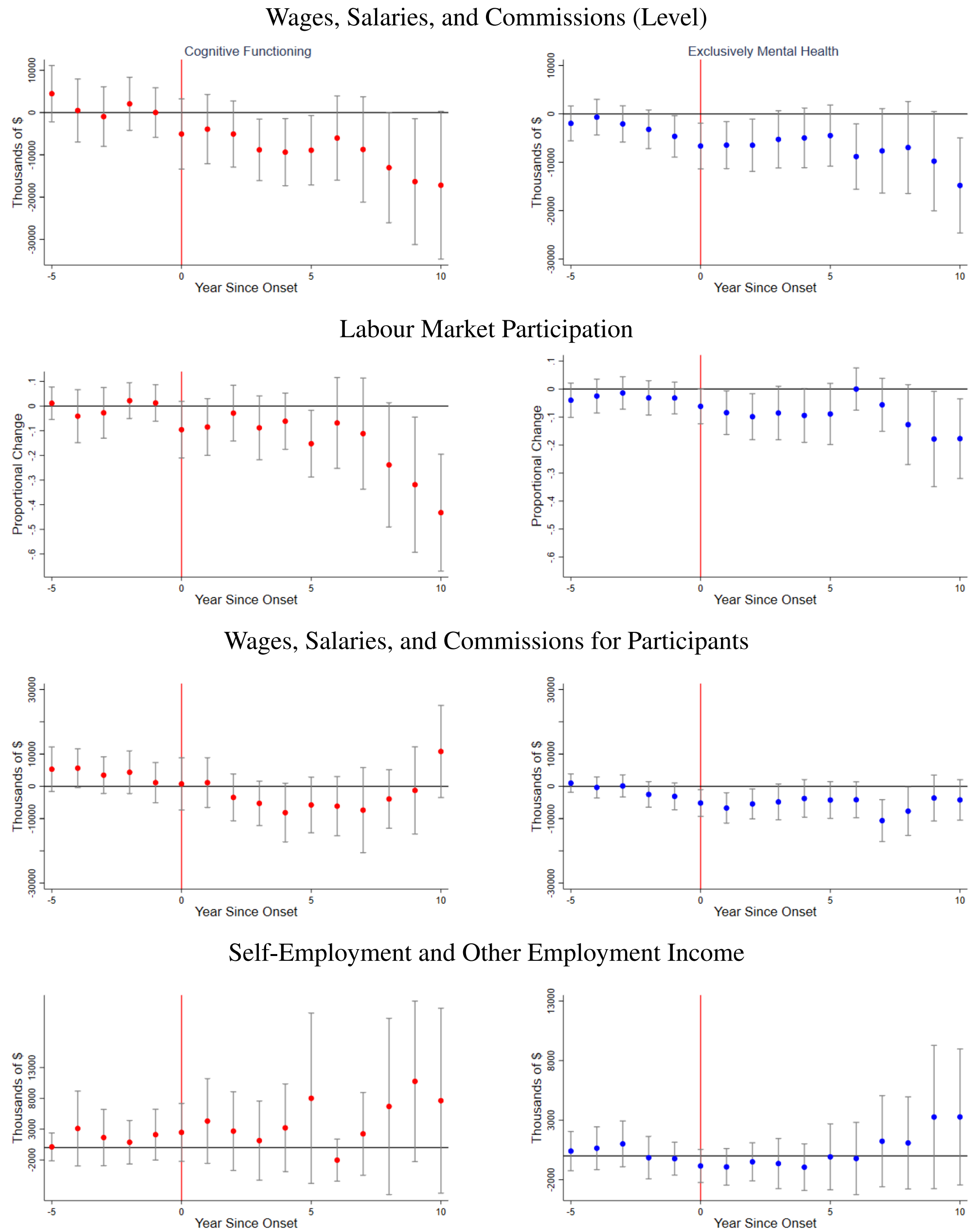


Note: Figures plot point estimates and corresponding 95% confidence intervals from estimating the models specified in Section 5. Data on WSC is top-coded at the 99th percentile. Underlying estimates for graphs are reported in Section 5 of the Appendix.

of Figure 1 plots the estimated effect of onset on WSC conditional on participation, reflecting the combined effect on wages and the intensive margin.[50] The onset of an aggregate physical disability causes gradual labour market exit in the short run, which persists and flattens out at -8.3% of pre-onset levels into the long run on average. The effect of an

[50]Unfortunately, I cannot discern between wages and the work hours supplied within the data.

Figure 4: Effect of Disability Types Within Mental-Cognitive on Market Income



Note: Figures plot point estimates and corresponding 95% confidence intervals from estimating the models specified in Section 5. Data on WSC is top-coded at the 99th percentile. Underlying estimates for graphs are reported in Section 5 of the Appendix.

aggregate physical disability on WSC for participants is modest in the first couple of post-onset years but is otherwise insignificant and of low magnitude. Hence, the effect of physical disabilities is primarily due to labour market exit at the extensive margin. In contrast, a mental-cognitive disability immediately affects labour market participation, which drops -8.2% on average in the short run and rapidly declines by -29% in the tenth year after onset. The effect of mental-cognitive on WSC for participants significantly falls by -$4500 on average in the short and mid-run, but estimates become noisy and insignificant in the long run. Hence, following the onset of a mental-cognitive disability, the decline of unconditional WSC is primarily driven by labour market exit in the long run. However, participants experience significant effects on their earnings as well, especially in the short run.

Finally, the bottom row of Figure 1 plots estimates from models on market income from self-employment and other employment income. After the onset of a mental-cognitive disability, individuals substitute for other forms of market income. Although, this evidence is noisy and taken as merely suggestive, as the only significant estimate is eight years after onset. In contrast, the onset of a physical disability results in a significant decline in all sources of market income, including self-employment and other employment income.

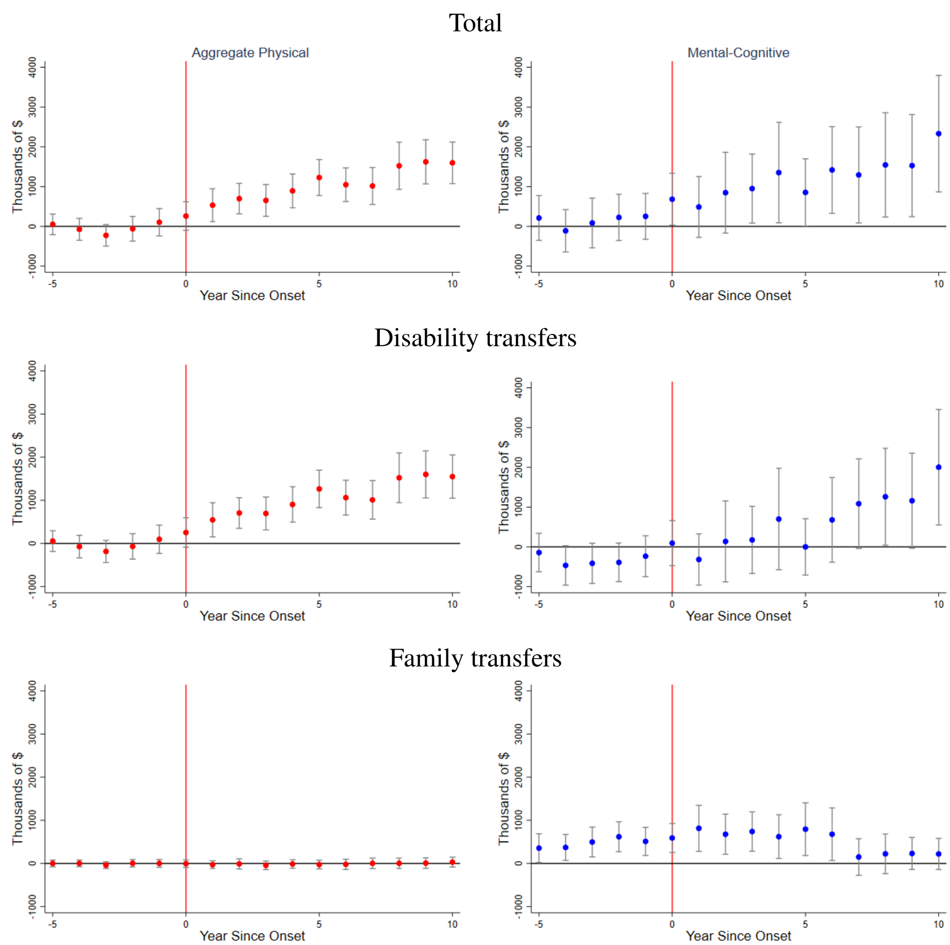
Relating these findings to the conceptual framework, the results for market income are consistent with a higher market valuation for mental-cognitive skills (π) or a higher implicit skill price (θ) of mental-cognitive skills. These findings are consistent with much of the related literature that finds manual skills to have moderate returns and be more easily adjusted (Yamaguchi, 2012; Lise and Postel-Vinay, 2020; Humlum, Munch and Jorgensen, 2023). In contrast, cognitive and interpersonal skills have higher returns and are more difficult to adjust. Hence, the cost of mismatch following a mental-cognitive disability results in a greater impact on market income and does not rebound as well as a physical disability. Cognitive skills are likely valued more than physical skills in a service-based economy like Canada. Moreover, in Canada, individuals may have greater scope for substituting to work with higher complexity in mental-cognitive tasks following the onset of an aggregate physical disability, given the relative abundance of these jobs. In contrast, jobs with greater complexity in physical tasks are more scarce.

Next, I analyze the heterogeneous effects of the onset of the more granular types within aggregate physical and mental-cognitive disabilities. Figure 3 plots the results when partitioning aggregate physical types into disabilities related to kinetic ability (left) and exclusively pain (right). First, the onset of an aggregate psychical disability on market income is mainly due to impairments to one's kinetic ability. The point estimates on unconditional WSC, labour market participation, and WSC for participants follow an analogous longitudinal path and are greater in magnitude. In contrast, the effects from the onset of a disability due exclusively to pain are noisy and mostly insignificant. The exception is labour market participation, which declines by an average of 5.6% in the ten years after onset. The activities that are limited by a disability to kinetic ability have a clearer link to productive tasks. For instance, mobility and flexibility limitations will impede productivity in tasks related to manual labour, and limitations to dexterity will impede the productivity of hands-on work, such as carpentry, landscaping, or even musician. It is less obvious what productive tasks a disability induced exclusively by pain will impact.

Lastly, Figure 4 reports the results for models partitioning aggregate mental-cognitive types into limitations due exclusively to mental health (left) and limitations related to cognitive functioning (right column). The onset of disability related to either of these types has substantial effects on WSC that progressively worsen over time relative to onset. The estimated effect of exclusively mental health is of similar magnitude to that of kinetic ability but becomes progressively worse in the long run, culminating to -\$14,800 in the tenth year after onset. Following the onset of disabilities related to cognitive functioning, WSC declines by -\$6900 on average in the short run and progressively worsens to -\$17,200 in the long run. The longitudinal path in effects on participation is similar for disabilities related exclusively to mental health compared to cognitive functioning. The short-run effects in both are modest, around -10% lower than pre-onset levels, and the effects worsen in the long run. That said, the magnitude decline for cognitive in the long run is substantial (-40%), whereas the point estimates are noisy for mental health. The effect of onset on WSC for participants becomes progressively worse in the short run, although point estimates are all insignificant for cognitive functioning.

It is important to note the marginal significance estimate on WSC in the period prior to onset of a mental health disability. This may be due to measurement error in retrospectively reported age of onset or leading effects if onset results from gradual degeneration of mental health (Jenkins and Rigg, 2004). More problematic is the reverse causality of declining WSC causing the onset of a mental health disability, as discussed in Section 4.1. Fortunately, I observe the reported reason of onset, and conduct robustness to the latter explanation. That is, I drop individuals who report their disability to be work-related and re-estimate models for WSC, WSC of participants, and labour market participation on this selected sample. I find no meaningful, no significant difference in the estimated effects. These results are shown in Figure 2 Section 4 of the Appendix.

Figure 5: Effect of Aggregate Disability Types on Government Transfers

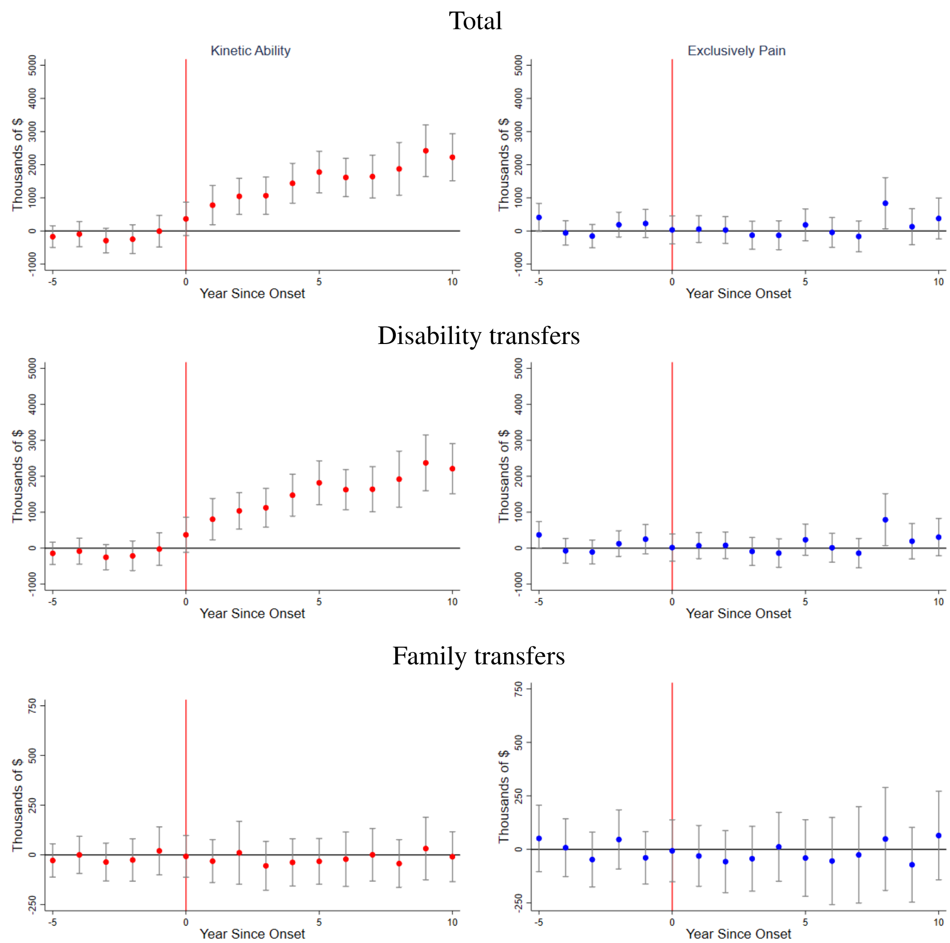


Note: Figures plot point estimates and corresponding 95% confidence intervals from estimating the models specified in Section 5. Underlying estimates for graphs are reported in Section 5 of the Appendix.

B Government Transfers

The results for market income find significant effects on WSC and labour market participation following the onset of each type of disability. This section analyzes how the takeup of government transfer programs responds to the impact on market income. Government transfer programs make up the majority of Canada's social safety net, offering income assistance and tax credits to individuals with barriers to their economic independence. As productivity declines following onset, labour market exit can be driven by the uptake of government programs designed to insure disability shocks. The increase in government transfers around onset reflects relative differences in coverage and eligibility across the types of disabilities. Moreover, comparing the effects on market income with government transfers reveals differences in the extent of partial insurance across disability types.

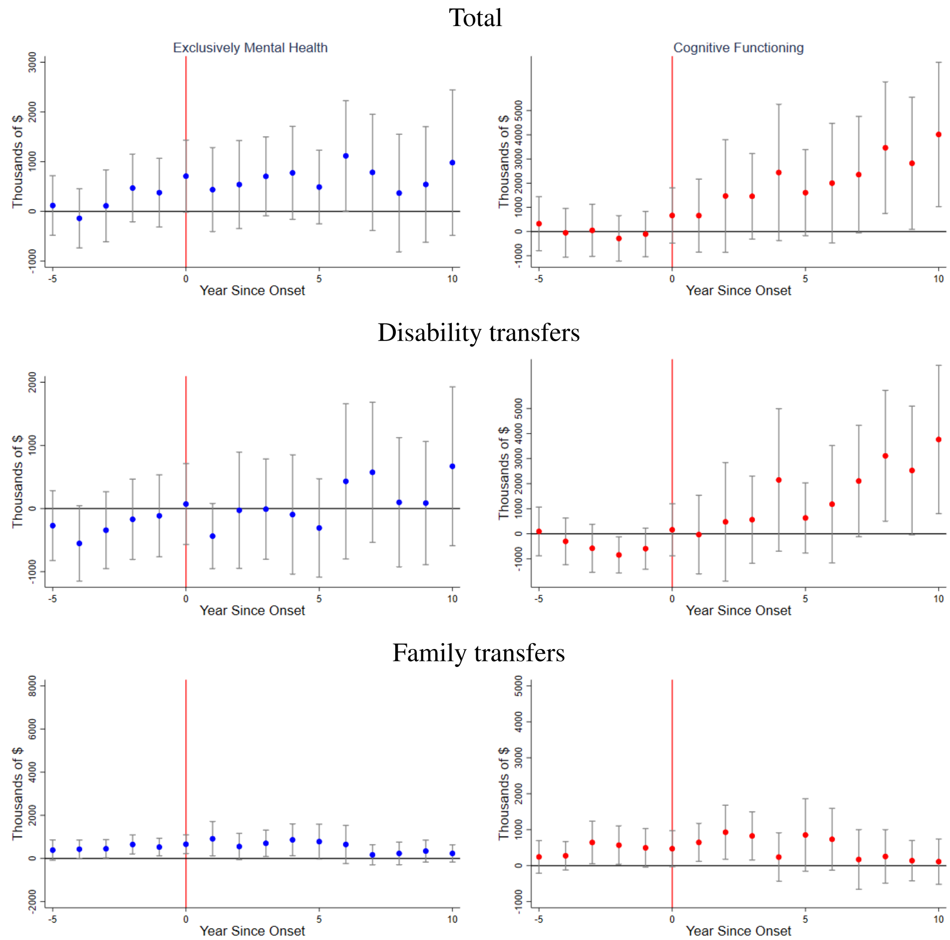
Figure 6: Effect of Disability Types Within Aggregate Physical on Government Transfers



Note: Figures plot point estimates and corresponding 95% confidence intervals from estimating the models specified in Section 5. Underlying estimates for graphs are reported in Section 5 of the Appendix.

Again, I start by comparing the aggregate disability types and then explore heterogeneity within aggregate types. Figure 5 reports results from models where the dependent variable is total government transfers (top row), disability-relevant transfers (2nd row), and family-relevant transfers (3rd row). The effect on total government transfers in the ten years following onset is similar for aggregate physical and mental-cognitive types, culminating to approximately \$1500 ten years following onset. That said, there are composition differences between these two types. The rise in transfers for aggregate physical is driven entirely by disability-relevant transfers. Disability-relevant transfers only significantly increase in the long run following the onset of a mental-cognitive disability. Instead, the mental-cognitive type receives more transfers from family-relevant programs, which tend to be means-tested and increase as total

Figure 7: Effect of Disability Types Within Mental-Cognitive on Government Transfers



Note: Figures plot point estimates and corresponding 95% confidence intervals from estimating the models specified in Section 5. Underlying estimates for graphs are reported in Section 5 of the Appendix.

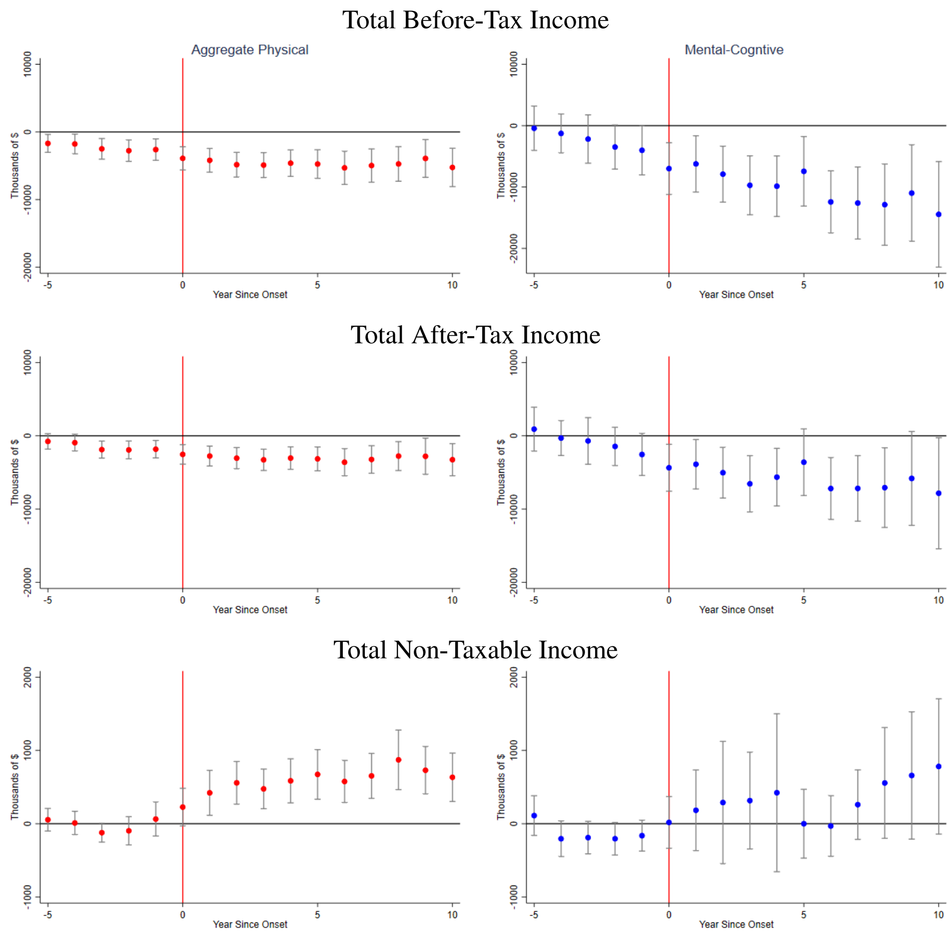
income levels decline. However, estimates of the rise in family transfers are interpreted as descriptive and not causal due to the significance of pre-onset coefficients, which clearly violates parallel trends.

When partitioning aggregate physical disabilities in Figure 6, we see that the rise in government transfers is driven entirely by disabilities related to kinetic ability. This finding is expected given the effects on employment income. The onset of a disability due exclusively to pain does not significantly increase government transfers from either source. Again, this insignificance is consistence with the effects on total WSC, although there was significant labour market exit following the onset of a disability-related exclusively to pain. In addition, these results may be partly related to difficulties verifying pain-related disabilities. Neither type within aggregate physical significantly affects family-relevant transfers.

The results when partitioning mental-cognitive disabilities in Figure 7 reveal differences in the support received across these conditions. The magnitude rise in government transfers in the long run following the onset of a disability to cognitive functioning is substantial, with a point estimate reaching almost 4000$. However, the point estimates are noisy for this group and insignificant in the short run. This is almost certainly due to the small sample size of this group. The source of government transfer comes mostly from disability-relevant programs. There appears to be a substitution away from family-relevant transfers in the short run to disability-relevant transfers in the long run for this type. The onset of a disability-related to mental health does not result in any significant increase in total government transfers. This finding is notable given the magnitude of effects on WSC and labour market participation are comparable to kinetic ability in the short run and progressively worsen in the long run.

There appear to be sizeable gaps in partial insurance from government transfers following the onset of a mental health-related disability and a lower percentage of income insured for disabilities to cognitive functioning. Relative to physical disabilities, mental-cognitive disabilities can be harder to verify, especially for mental health. Moreover, only recently has mental health received acknowledgment for its impacts on the labour market. Consequently, individuals affected by the onset of a mental health disability in working life must resort to alternate mechanisms to smooth their consumption.

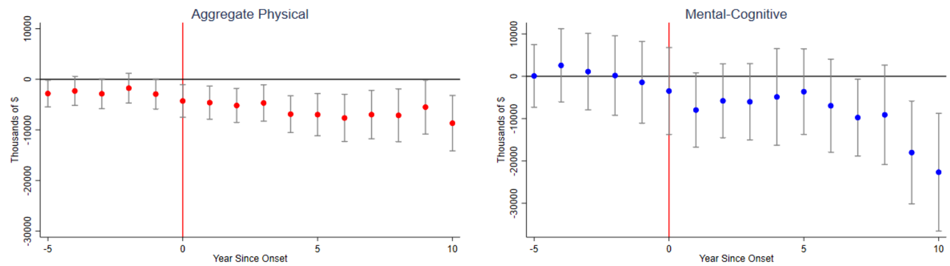
Figure 8: Effect of Aggregate Disability Types on Before-Tax, After-Tax, and Non-Taxable Income



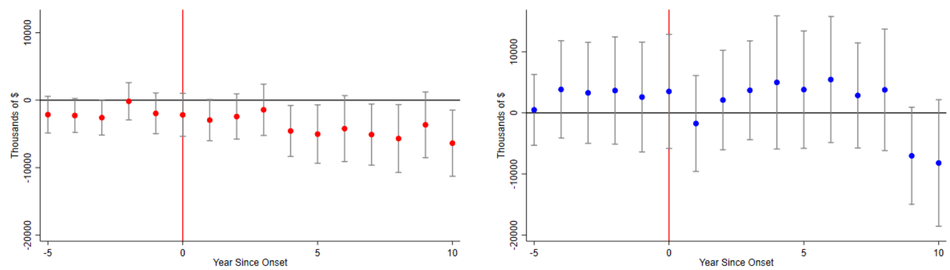
Note: Figures plot point estimates and corresponding 95% confidence intervals from estimating the models specified in Section 5. Data on Total before-tax and after-tax income is top-coded at the 99th percentile for aggregate physical. Underlying estimates for graphs are reported in Section 5 of the Appendix.

Figure 9: Effect of Aggregate Disability Types on Total Family Income and Income of Family Members

Total Family Income



Income of Family Members



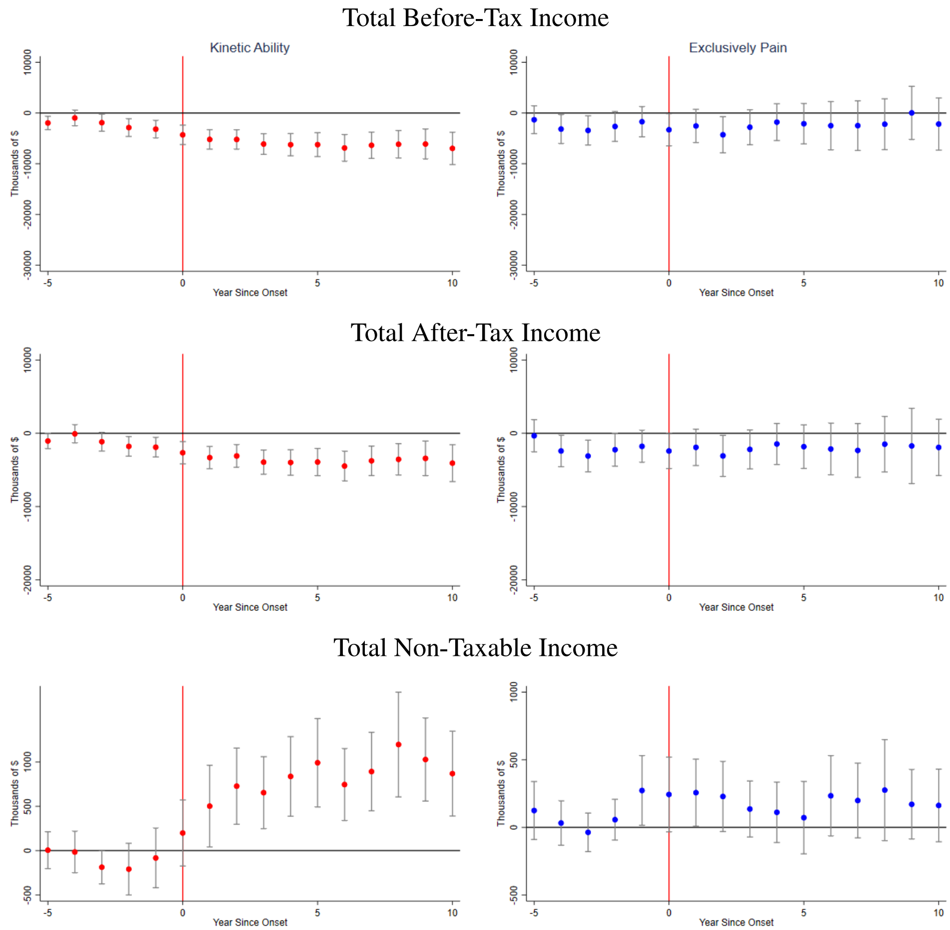
Note: Figures plot point estimates and corresponding 95% confidence intervals from estimating the models specified in Section 5. Data on Family total income is top-coded at the 99th percentile for aggregate physical. Underlying estimates for graphs are reported in Section 5 of the Appendix.

C Alternate Smoothing Mechanisms

The final set of results considers alternate mechanisms that individuals may use to smooth their consumption in response to a disability shock. First, the Canadian income tax system is progressive and exempts various sources of income from taxation, notably many government transfers. The impact of a disability shock on take-home income may be buffered when falling into a tax bracket with a lower marginal tax rate. I analyze the effect of disability onset on total after-tax income to gauge how take-home resources are affected relative to total before-tax income to understand the buffering role of the tax system. In addition, I compare this to the change in total non-taxable income. Lastly, the earnings activities of members of one's household can be an important source of insurance against income shocks. I also estimate the effect of disability onset on the total income of one's family members and the impact on total household income, including the individual.

Notable differences emerge between aggregate physical and mental-cognitive disabilities in the role of the tax system as a smoothing mechanism. Figure 8 reports the results on models for total before-tax income (top), total after-tax income (middle), and total non-taxable income (bottom). Relative to its impact on WSC, the effect of the onset of mental-cognitive appears to be buffered by the tax system. However, due to the large confidence intervals, I can not significantly reject the equality of treatment paths. Despite this, I still conclude that the onset of a mental-cognitive disability results in significantly less take-home income after taxation. The point estimates imply the percentage of the effect of onset on after-tax total income is 63% that of before-tax income in the short run and 55% that of before-tax income in the long run. Additionally, the effect on before or after-tax income does not exhibit a sharp drop in the long run, which was the case for WSC and labour market participation. This suggests that the sharp increase in disability-relevant transfers for this group is partially insuring total after-tax income for this type in the long run. That said, we do

Figure 10: Effect of Disability Types Within Aggregate Physical on Before-Tax, After-Tax, and Non-Taxable Income



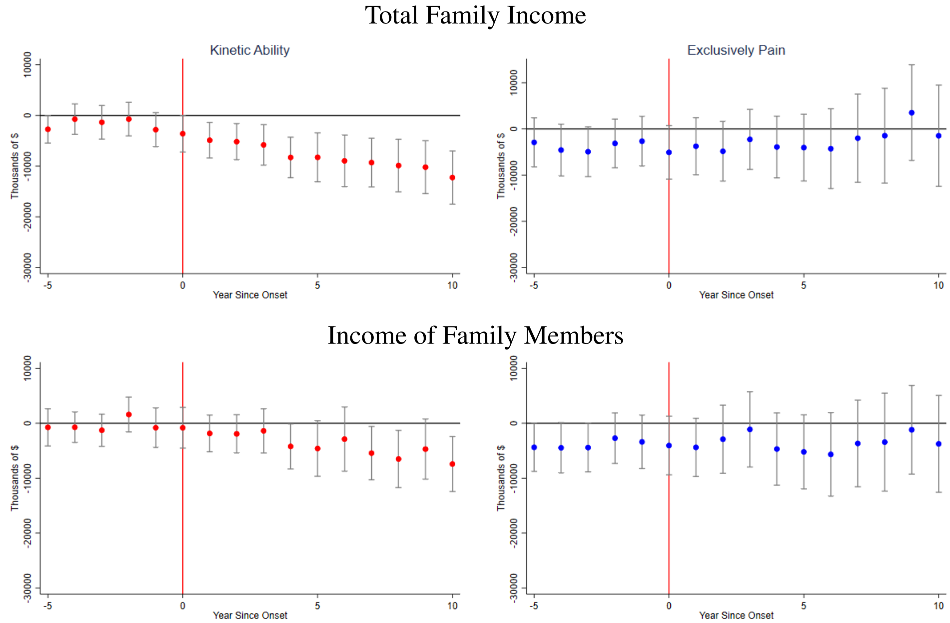
Note: Figures plot point estimates and corresponding 95% confidence intervals from estimating the models specified in Section 5. Data on Total before-tax and after-tax income is top-coded at the 99th percentile. Underlying estimates for graphs are reported in Section 5 of the Appendix.

not recover a significant rise in total non-taxable income following the onset of a mental-cognitive disability. However, this is likely the result of this group substituting family-relevant transfers in the short run to disability-relevant transfers in the long run.

On the other hand, the main source of partial insurance following the onset of an aggregate physical disability comes from non-taxable incomes. The results for total before-tax and after-tax income following the onset of an aggregate physical disability have significant point estimates in pre-onset coefficients, and their dynamic profiles are fairly flat. For this group, the effect of onset on after-tax income is 65% that of before-tax income in both the short and long run.

Figure 9 analyzes how disability shocks disseminate through the household. The effect of onset on total household income is reported in the top row, and the effect on the total household income after netting out income from the survey respondent is reported in the bottom row. First, the onset of an aggregate physical disability immediately impacts total household income, which remains flat and persists into the long run. The onset of a mental-cognitive disability only has significant long-run effects on total family income, but the effect is more than -20,000$ in magnitude. We observe

Figure 11: Effect of Disability Types Within Aggregate Physical on Total Family Income and Income of Family Members



Note: Figures plot point estimates and corresponding 95% confidence intervals from estimating the models specified in Section 5. Data on Family total income is top-coded at the 99th percentile. Underlying estimates for graphs are reported in Section 5 of the Appendix.

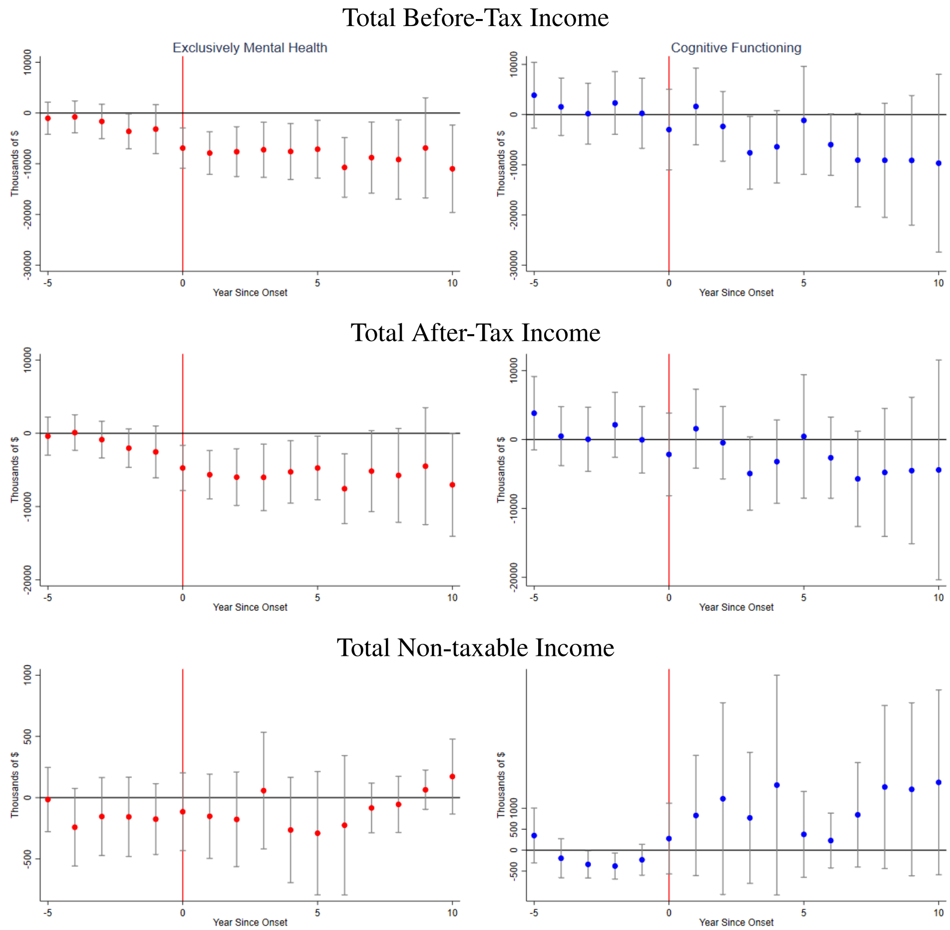
some reduction in the income of other family members following the onset of a physical disability, consistent with a mechanism of family members substituting work for homecare as discussed in Fadlon and Nielsen (2021).

In Figure 10, we see that much of the action within aggregate physical types is driven by kinetic ability. Disabilities related exclusively to pain have low-magnitude effects in point estimates and are mostly insignificant. In contrast, disabilities related to kinetic ability show clear increases in non-taxable income. The effects of the tax system buffer some of the effects of a kinetic ability disability. However, these results show violations in parallel trends and are not interpreted as causal. Hence, income insurance via government transfers seems to be the main channel for physical disabilities that are not exclusively due to pain.

At the household level, Figure 11 reports that disabilities to kinetic ability result in a drop in total family income, progressively worsening in the long run, culminating to -\$12000 ten years after reported onset. Moreover, the income of family members drops in the long run, again consistent family members spending more time at home to care for their family member with a disability. Exclusively pain disabilities do not significantly affect family income and have large standard errors, suggesting much variation in the effects following onset.

The last set of results distinguishes the effects of onset on alternate smoothing mechanisms by disabilities related to mental health and those related to cognitive functioning. In Figure 12, the tax system helps offset the effect of mental health disabilities. There is no significant rise in total non-taxable income following the onset of a mental health condition. These types of disabling conditions receive partial insurance solely from the progressive tax system, which lowers marginal tax rates as their market income decline following onset. Those affected by disabilities related to cognitive functioning smooth their consumption via government transfers, many of which are non-taxable. Whereas those affected by the onset of a mental health disability rely on lower marginal tax rates after their experience income

Figure 12: Effect of Disability Types Within Mental-Cognitive on Before-Tax, After-Tax, and Non-Taxable Income



Note: Figures plot point estimates and corresponding 95% confidence intervals from estimating the models specified in Section 5. Data on Total before-tax and after-tax income is top-coded at the 99th percentile. Underlying estimates for graphs are reported in Section 5 of the Appendix.

declines following onset. This result is partially reflected in the results for non-taxable income, which are insignificant for the mental health group. The point estimates for the group limited in cognitive functioning are large in magnitude, but they are insignificant at 95% confidence.

Finally, both types of disabilities within mental-cognitive cause significant declines in total family income, shown in Figure 13. The path of effects becomes progressively worse in the long run, and point estimates are larger in magnitude for disabilities related to cognitive functioning. However, I find no significant changes in the income of family members following the onset of either type.

VI Welfare Implications and Optimal Benefits

The last section of this paper discusses the implications of these results for individual welfare. To do so, we adopt the optimal insurance framework of Baily (1978), generalized to analyze programs including disability benefits by Chetty (2006). The idea of this framework is that the optimal level of benefits balances the moral hazard relating to the work

Figure 13: Effect of Disability Types Within Mental-Cognitive on Total Family Income and Income of Family Members

Note: Figures plot point estimates and corresponding 95% confidence intervals from estimating the models specified in Section 5. Underlying estimates for graphs are reported in Section 5 of the Appendix.

disincentives inherent to any insurance program with the ability to smooth consumption following an income shock.

The setting is that of a worker who faces risk over two states of the world, good and bad, where the bad state is the receipt of disability benefits in my application. The agent chooses the share of time spent in the bad state, which is endogenous to the level of benefits, b, paid to the agent while in the bad state. Moral hazard results from the disincentive to leave the bad state when b is high. In contrast, increasing b improves the workers welfare by partially smoothing consumption across states. Benefits are financed via a proportional tax on the earnings in the good state. A welfare-maximizing social planner chooses benefit level, and thus the share of time in the bad state, subject to a break-even budget constraint. The optimality condition is derived from the first-order condition of the planner's problem with respect to b and an envelope condition from the optimality of the agent's decision.[51] The Bailey-Chetty optimal benefit condition is,

$$\gamma \frac{\Delta c}{c}(b) = \epsilon_{D,b}$$

.

Here, γ is the coefficient of risk aversion ($\frac{-u''c}{u'}$), $\frac{\Delta c}{c}(b)$ is the drop in mean consumption with benefits evaluated at its optimal level, and $\epsilon_{D,b}$ is the elasticity of time receiving benefits (i.e., not working) with respect of benefit level. The idea is that if the left-hand side of this equation is lower than the right-hand side, then benefits are below their optimal level.

I make several simplifying assumptions in the following analysis. First, I assume the change in consumption is proportional to after-tax income. Hence the percentage change in consumption equals the change in an individual's

[51] See Chetty (2006) for a more detailed description of this setting.

Table 4: Consumption Change After Onset and Coefficient of Relative Risk Aversion Consistent with Optimal Benefits for Select Disability Types

	Cognitive Ability	Mental Health	Exclusively Cognitive	Kinetic Ability*
Pre-Onset Consumption	40318	41314	39809	34285
Average Fall in Consumption	-4288	-5674	-2802	-3655
% Fall in Consumption	-0.11	-0.14	-0.07	-0.11
γ Consistent with Optimal Benefits	1.64	1.27	2.47	1.63

Note: Consumption is assumed be proportional to after-tax income. Hence, percentage fall in consumption is calculated as the percentage fall in after-tax income.

after-tax income. This assumption is reasonable if savings are not a large source of consumption smoothing in the face of a permanent disability shock. Moreover, this assumption ignores the income of family members that may change in response to a disability shock to income consumption. In the disability types analyzed below, I found no significant change in family income following the onset of mental-cognitive disability or disaggregated disability types making up mental-cognitive disability. Following the onset of a disability to kinetic ability, I observe a decline in the income of family members, suggesting that the decline in consumption may be greater than the fall in after-tax income following the onset of a disability to kinetic ability. Second, I assume the marginal utility of consumption is the same before and after the disability onset occurs, an assumption similar to Deshpande and Lockwood (2022) and Meyer and Mok (2019). Under these assumptions, the average decline in after-tax income divided by the total after-tax income in the five years before onset gives a measure of $\frac{\Delta c}{c}$. Third, I assume the elasticity of time receiving benefits with respect to benefit level is 0.174, as in Meyer and Mok (2019).[52] In the table below, I use these assumptions to calculate the implied CRRA that is consistent with optimal benefits. I can then compare this to values of γ in the literature to understand the optimality of disability benefits.

The coefficient of relative risk aversion consistent with optimal benefits in the Bailey-Chetty conditions, shown in Table 4, ranges from 1.27 to 2.47 across disability types. These values of γ are on the lower end of estimates and values found in the related literature. Notably, the implied optimal γ for the mental health group is lowest, implying that this group would have to be relatively less risk-averse in order for benefits to be optimal. In the related literature, values of γ typically range from 1.5 to 4.5 (Chandra and Samwick, 2009; Lockwood, 2018; Deshpande and Lockwood, 2022). In his meta-study of empirical estimates of the intertemporal elasticity of substitution (IES), Havránek (2015) suggests the correct mean estimate of the IES is in the range of 0.3-0.4 in microanalyses, which implies a γ of 2.5-3.3. Hence, within this range, benefits are less than optimal for those with a mental health disability. Moreover, benefits are only optimal if risk aversion is at the lower bound of this range for those affected by a disability to their kinetic ability. Overall, this exercise suggests that benefits are less than optimal for the disability types considered in Table 4.

VII Conclusion

This paper conducts a comprehensive analysis of the dynamic effects of disability on the components of one's personal income. Theoretically motivated by a task-specific human capital framework, the empirical exercise distinguishes disability into mutually exclusive types based on their impaired productive tasks. Disability onset results in a permanent income shock, and the welfare consequences of this shock vary considerably across these types. The empirical results document several novel insights into mechanisms driving the considerable variation in the impact of disability on

[52] See Meyer and Mok (2019) for description of calculating this elasticity

earnings, employment, and sources of partial insurance.

Disabilities that impair physical tasks cause significant declines in market income, primarily due to labour market exit. Nontaxable income steadily rises following onset, providing partial insurance to the decline in market income, primarily from disability-relevant government transfer programs. The onset of mental-cognitive disabilities results in relatively larger declines in market income than physical, driven by a combination of labour market exit and lower earnings for participants. However, the mental-cognitive group receives fewer disability-relevant government transfers relative to those affected by an aggregate physical disability. Instead, this group receives partial insurance via the progressive tax system in Canada. Total family income experiences a marked decline for both aggregate types but is only significant in the long run for mental-cognitive. Moreover, the onset of an aggregate physical disability decreases the income of other household members, which may be due to increased caregiving responsibilities.

Within aggregate types, disability to one's kinetic ability is the driving factor in the effects of aggregate physical types on market income and government transfers. Disabilities exclusively related to pain exhibit no significant effects on wages, salaries, commissions, or government transfers but modestly cause labour market exit. Disabilities that hinder cognitive functions lead to the most substantial decrease in market income. Cognitive functioning disabilities lead to a considerable increase rise in transfer payments from disability-relevant programs, coinciding with the sharp long-run decline in labour market participation. In contrast, mental health disabilities do not receive significant income from these programs post-onset. Instead, as market income declines for this group, their marginal tax rate declines, helping to buffer this shock.

Finally, a welfare analysis of these results suggests that the level of disability benefits is lower than optimal and differs by disability type. Current benefit levels are only optimal if individuals who experience a disability shock are less risk-averse than what much of the related literature suggests. The difference in optimal benefits seems to be greatest for those with a mental health disability.

These results offer novel insight into the connection of disability with the various components of skills examined in related task-based human capital literature. While providing novel estimates of the effect of disability types, this paper does not directly measure heterogeneity in skills and the tasks that make up work at the time of disability onset. An analysis combining skills, job skill requirements, and multidimensional disability types, is left for future work.

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A Model of Disability Based on Limitations to Daily Activities

I model disability based on self-reported measures of limitations to daily activities. This has the advantage of honing in on an 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 can perform. However, with proper treatment, diabetes may not limit one's activities or significantly impact 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 a 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.[53] 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 $\hat{d}_i = 0$, 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 mildly 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.[54]

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 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 the 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 $\bar{d}_i$.

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.[55]

In this paper, I take these components directly from the model used in LISA. LISA derives disability status using self-reported questions on the frequency and magnitude of difficulty associated with performing specific ADLs.[56] These responses to these questions are categorical and are taken as a noisy measure of the elements of v. I flag disability based on frequency responses exclusively, as there are inconsistencies in questions about magnitude of difficulty across survey waves. The grouping is useful to average out any small measurement error in reporting a

[53] 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.

[54] 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.

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

[56] The set of ADL includes mobility, flexibility, memory, dexterity, learning, pain, and mental health.

continuous number and summarizes the elements v while maintaining ordinality.

Sample Survey Questions on Limitations to Daily Activities

Table 5: Questions used to Measure Limitations to Daily Activities

Questions to Derive Aggregate 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 Mental-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.

B 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. An individual's personal income can be partitioned into market income and income from government 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, investments, ..). 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. Disability insurance is available to aid with the costs and barriers to work caused by a disability.

An individual's Market income is comprised of income earned from employment but includes other sources. Employment income can be differentiated into wages, salaries and commissions (WSC), 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 through provincially administered social assistance (SA), workers compensation programs (WC), and net federal supplements, which consist of transfers targeting the elderly (NFSL).[57]

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. For more details on the types of incomes included in this study and these data, refer to `https://www12.statcan.gc.ca/census-recensement/2016/ref/dict/app-ann/a4_1-eng.cfm`.

Variable Construction

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

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

C Additional Descriptive Statistics

Table 6: Reason of Disability Onset: Total Disability and Aggregate Types

	Total Disability	Physical	Cognitive	Concurrent
Existed at Birth	0.049	0.032	0.073	0.072
Disease	0.330	0.321	0.202	0.389
Non Work Related	0.205	0.208	0.109	0.232
Work Related	0.276	0.292	0.193	0.2745
Aging	0.212	0.252	0.126	0.165

Note: The sample reflects working age (25-55) Canadians from provinces who reported to have a disability. Survey weights have been applied so the sample reflects the demographic composition of Canada in 2012.

Table 7: Reason of Disability Onset: Non-Mutually Exclusive Activity Limitations

	Mobility	Flexibility	Dexterity	Pain	Cognitive Functioning	Mental Health
Existed at Birth	0.037	0.033	0.033	0.031	-	0.082
Disease	0.435	0.324	0.475	0.322	0.166	0.205
Non Work Related	0.203	0.232	0.134	0.217	0.177	0.085
Work Related	0.297	0.386	0.303	0.296	0.186	0.205
Aging	0.295	0.260	0.342	0.246	0.233	0.086

Note: The sample reflects working age (25-55) Canadians from provinces who reported to have a disability. Survey weights have been applied so the sample reflects the demographic composition of Canada in 2012.

D Robustness and Sensitivity

This section considers sensitivity of results to alternate selection criterion and coding of variables. In conducting the robustness of estimates to alternate specification, I use a simple two-way fixed effect estimation rather than the IW procedure. It can be shown that this produces nearly identical results as my estimation sample has a very large never-treated control group. The IW estimation is a computationally expensive, which is exacerbated by the low computation power of the computers in the research and data center. Moreover, these robustness exercises involve slicing the estimation sample into smaller subgroups. This creates the risk of the size of some sub populations falling below the count threshold to be approved for extraction from the Statistics Canada Research and Data Center. Given this constraint, in this section I describe the robustness exercises, and note that results from these exercises may be made available upon request.

Years of Post-Onset Observations

In selecting the sample, I drop individuals that have less than 4 post-onset observations. However, my empirical specification is interested in the ten years post-onset, which introduces concerns that censoring in the data may bias estimates of the shorter run effects. To illustrate, estimates of the first few post-onset years reflect effects from disabling conditions that recover in the long run, which may be different from long-term disabling conditions.

To assess this issue, I drop any individuals with fewer than 10 post-onset observation, re-estimate the empirical models, and compare the treatment paths. I find no meaningful changes in the magnitudes of point estimates. Due to the reduced sample sizes, standard errors of point estimates are much larger and I lose significance in many effects.

By Sex

With a finite sample, there exists a trade-off between statistical power and the extent of heterogeneity I can explain. This analysis distinguishes heterogeneity in effects across granular disability types in each of the ten years relative to onset for a rich disaggregated set of income measures, which is a considerable contribution relative to the existing literature. However, reasonable arguments can be made that effects differ within other demographic groups. Notably, the sample in this paper combines males and females to enhance statistical power of estimates, and I include a rich set of controls interacted with sex in the estimating specification outlined in Section 5 of the paper.

To assess the robustness of the empirical results with respect to sex, I separately conduct the empirical analysis by sex, and compare the estimated path in treatment effects. The general results hold when conditioning on male or female. While there exist some differences in the magnitude of effects for some dependent variables, the sign in effects and the path in effects hold for most output. That said, the estimates are considerably less precise due to the smaller sample.

In the interest of transparency, I describe the models with the largest differences in estimates between males and females. The choice criterion is based on whether the point estimate for one sex is outside the 95% confidence interval for the other. This is more restrictive that a simple test of equivalence, which always fails to reject a significant difference due imprecise estimates resulting in a considerable overlap in the distribution of estimates. With this approach, I have more statistical power to highlight sex based differences in estimates.

First, for the aggregate disability types, aggregate physical and mental-cognitive, I follow a similar progression for dependent variables as the results section in the body of the paper. The females third post-onset point estimate of a physical disability on models for WSC of participants was below the confidence interval of the estimate for males. Otherwise, I found no differences in paths between males and females for WSC or WSC of participants. Onset of a physical disability impacted labour market participation more for males than females, but the path in effects was nearly parallel and only a few point estimates were outside the confidence intervals for the respective point estimate of females. Within aggregate physical, onset of a pain limitation results in significant labour market exit for males, but not for females. This is likely due to different composition of jobs for males, notable physically demanding job tasks. Types within mental-cognitive have the smallest sample sizes and the least precise.

Next, onset of an aggregate physical disability results rise by a greater magnitude for males than females, although the path in effects is nearly parallel. This difference is also reflected in results for disability relevant transfer programs. I find no significant change in family transfers following onset of an aggregate physical disability. Following onset of a mental-cognitive disability both treatment paths exhibit concave shape, but of greater magnitude for female, which is consistent with mothers tending to claim these benefits more often. Within aggregate physical, males receive more government transfers in the short run following onset of a disability to kinetic ability, but the rise for females converges to males in the long run. I obtain no significant results on models for government transfer within mental-cognitive.

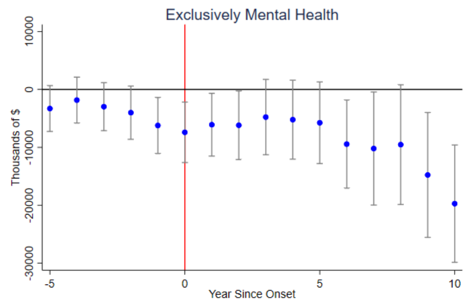
For other smoothing mechanisms, family total income and income of family members declines by more following the onset of an aggregate physical disability for females than males. The effects on total nontaxable income follows from the results of total government transfers. Females experience a sharper decline in total before- and after-tax income post-onset of a mental-cognitive disability in the short run, but effects converge toward males in the long run. Within aggregate physical, income of family members significantly declines following the onset of a disability to kinetic ability for females, but not males. Moreover, the post-onset effects of a disability to kinetic ability results in larger declines of total before and after-tax income for males, but the trend is parallel for females. Again, mutually exclusive disability types within mental-cognitive are mostly insignificant.

Endogeneity of Onset to Labor Market Conditions

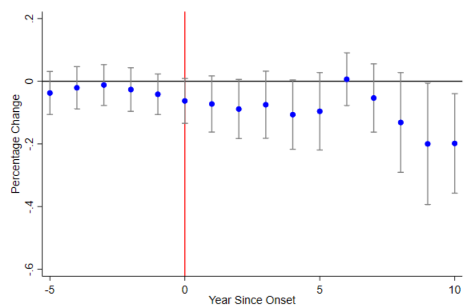
A final robustness check relates to concerns of reverse causality. It may be the case that poor labor market conditions cause onset of work-limiting disabilities. This concern is particularly relevant for mental health disabilities. To assess robustness of this paper results to results to this reverse causality, I exclude all individuals that report their disability onset to be work related and re-estimate all the models. I find no meaningful difference in estimates when excluding these individuals. I extracted the results from this robustness exercise for models considering onset of mental health, which are shown in Figure 14

Figure 14: Effect of Non-work Related Mental Health Disability on Market Income

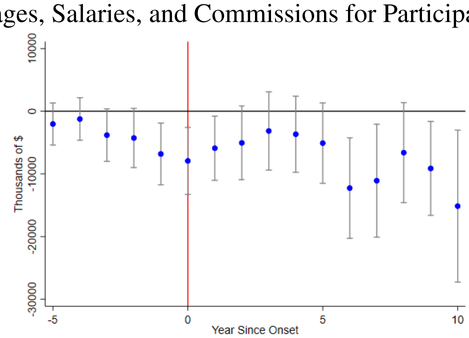
Wages, Salaries, and Commissions (Level)



Labour Market Participation



Wages, Salaries, and Commissions for Participants



Note: Figures plot point estimates from an IW estimation, whose specification is outlined in Section 5. The models for WSC are top-coded at the 99 percentile. These results drop individuals reporting their disability to be work-related, as shown in Section C of this Appendix.

E Model Estimates

The following reports the point estimates and standard errors used to produce the graphs within the body of paper.

Table 8: Estimated Effect of Disability Onset on Market Incomes: Aggregate Physical and Mental-Cognitive

	Aggregate Physical				Mental-Cognitive			
Year Relative to Onset	Labour Market Participation Rate	Wages, Salaries, and Commissions	WSC for Participants	Non-Market Income	Labour Market Participation Rate	Wages, Salaries, and Commissions	WSC for Participants	Non-Market Income
-4	0.011	-923.73	-1385.128	-184.497	-0.022	138.585	1071.846	286.629
	(0.01)	(671.79)	(722.91)	(290.9)	(0.024)	(1676.387)	(1557.093)	(686.866)
-3	-0.001	-522.768	-597.724	-72.228	-0.025	161.642	1823.842	1342.362
	(0.01)	(728.58)	(774.34)	(401.15)	(0.027)	(1821.698)	(1554.492)	(1127.982)
-2	0.012	-885.452	-870.939	-500.234	-0.015	-1376.547	-848.569	1145.907
	(0.01)	(773.37)	(791.81)	(293.41)	(0.026)	(1795.383)	(1662.662)	(987.294)
-1	-0.006	-1321.497	-774.796	-426.346	-0.012	-1201.994	-888.315	121.9
	(0.01)	(823.04)	(812.03)	(356.63)	(0.025)	(1824.706)	(1794.825)	(838.931)
0	-0.004	-1070.075	-254.413	-655.633	-0.014	-2949.359	-3321.337	393.867
	(0.01)	(847.24)	(821.73)	(332.09)	(0.024)	(1842.039)	(1804.479)	(830.291)
1	-0.013	-2995.174	-2286.953	-275.214	-0.071	-5892.798	-4488.747	164.223
	(0.01)	(911.68)	(951.69)	(402.73)	(0.03)	(2254.908)	(2268.2)	(912.803)
2	-0.035	-3447.75	-2433.752	-355.5	-0.082	-5351.647	-3398.434	749.327
	(0.01)	(946.23)	(992.6)	(368.21)	(0.035)	(2314.944)	(2082.628)	(1274.53)
3	-0.059	-4222.687	-2112.182	-421.333	-0.073	-5670.7	-4307.293	446.297
	(0.01)	(977.4)	(977.83)	(376.68)	(0.035)	(2417.189)	(2269.843)	(1187.642)
4	-0.083	-3685.297	-702.396	-667.343	-0.084	-6225.35	-4543.783	-96.712
	(0.02)	(995.29)	(959.98)	(373.88)	(0.042)	(2530.688)	(2424.89)	(1345.774)
5	-0.104	-4059.66	-680.409	-745.597	-0.079	-6181.044	-5937.279	505.373
	(0.02)	(1068.56)	(1131.93)	(382.72)	(0.042)	(2683.891)	(2501.682)	(1501.603)
6	-0.099	-4272.281	-1299.467	-676.097	-0.102	-5182.026	-4358.135	2605.9
	(0.02)	(1147.01)	(1215.21)	(428.63)	(0.043)	(2612.31)	(2537.45)	(2669.489)
7	-0.102	-4134.408	-813.216	-1052.761	-0.021	-7183.298	-9085.652	-948.412
	(0.02)	(1275.54)	(1350.79)	(473.06)	(0.041)	(3027.239)	(3077.976)	(1190.307)
8	-0.098	-3963.577	-1719.126	-1373.152	-0.077	-7496.097	-7066.827	1637.518
	(0.02)	(1284.32)	(1479.64)	(431.48)	(0.05)	(3567.953)	(3604.254)	(1785.308)
9	-0.109	-4668.361	-1883.433	-1199.881	-0.168	-8802.158	-3514.304	3365.661
	(0.02)	(1352.97)	(1458.32)	(476.9)	(0.063)	(3852.54)	(2992.497)	(3004.865)
10	-0.091	-3513.265	-1941.287	-1332.188	-0.239	-12584.01	-3468.583	6705.797
	(0.02)	(1366.28)	(1579.94)	(511.88)	(0.072)	(4161.887)	(3421.509)	(3389.648)
11	-0.124	-4180.601	-1735.851	-1566.553	-0.289	-16080.99	-4126.197	5380.124
	(0.02)	(1444.13)	(1703.99)	(502.48)	(0.061)	(4377.811)	(5462.125)	(3535.865)

Table reports the point estimates from estimation of models specified in Section 5 of the main text, whose dependent variable is reported at the column head. Standard errors are clustered by person and reported in brackets below the estimates. Data on Wages, Salaries, and Commissions is top-coded at the 99th percentile.

Table 9: Estimated Effect of Disability Onset on Market Incomes: Types Within Mental-Cognitive

	Cognitive Functioning				Exclusively Mental Health			
Year Relative to Onset	Labour Market Participation Rate	Wages, Salaries, and Commissions	WSC for Participants	Non-Market Income	Labour Market Participation Rate	Wages, Salaries, and Commissions	WSC for Participants	Non-Market Income
-4	0.012	4457.713	5302.236	117.022	-0.04	-1966.082	988.573	402.179
	(0.034)	(3401.733)	(3522.792)	(1155.672)	(0.031)	(1839.328)	(1452.328)	(841.302)
-3	-0.041	485.433	5627.727	3110.252	-0.025	-672.774	-348.773	642.838
	(0.055)	(3804.94)	(3064.494)	(3102.089)	(0.031)	(1877.945)	(1662.916)	(917.242)
-2	-0.027	-957.226	3458.448	1636.171	-0.014	-2074.141	115.343	1007.342
	(0.052)	(3595.375)	(2900.214)	(2333.426)	(0.03)	(1910.365)	(1741.155)	(981.634)
-1	0.022	2050.133	4342.323	870.548	-0.032	-3192.434	-2518.667	-149.619
	(0.037)	(3206.882)	(3375.339)	(1800.527)	(0.031)	(2037.342)	(2018.286)	(908.625)
0	0.013	2.942	1140.556	2108.667	-0.032	-4643.807	-3118.383	-231.049
	(0.038)	(2991.49)	(3178.701)	(2104.02)	(0.029)	(2185.186)	(2122.481)	(704.581)
1	-0.096	-5073.385	753.557	2473.178	-0.062	-6638.983	-5182.692	-845.102
	(0.059)	(4238.308)	(4131.422)	(2397.294)	(0.032)	(2409.029)	(2117.36)	(709.728)
2	-0.085	-3923.884	1130.774	4314.92	-0.085	-6457.554	-6725.629	-921.875
	(0.059)	(4176.464)	(3932.571)	(3509.128)	(0.04)	(2479.336)	(2402.222)	(783.72)
3	-0.029	-5083.423	-3450.972	2681.85	-0.099	-6479.404	-5456.51	-497.53
	(0.058)	(3988.467)	(3706.799)	(3257.713)	(0.042)	(2757.546)	(2370.751)	(816.028)
4	-0.088	-8820.478	-5280.393	1139.304	-0.086	-5260.933	-4833.266	-643.774
	(0.066)	(3708.242)	(3510.188)	(3278.787)	(0.049)	(3016.917)	(2831.068)	(1073.2)
5	-0.061	-9378.786	-8164.563	3212.804	-0.094	-4965.681	-3765.251	-948.581
	(0.058)	(4050.266)	(4643.59)	(3630.419)	(0.049)	(3146.405)	(2972.329)	(998.033)
6	-0.152	-8912.473	-5777.486	8019.816	-0.089	-4481.618	-4247.026	-80.201
	(0.069)	(4191.419)	(4400.824)	(7056.358)	(0.056)	(3222.25)	(2904.405)	(1411.383)
7	-0.068	-6030.279	-6149.962	-2029.673	0	-8817.988	-4166.298	-218.235
	(0.094)	(5083.251)	(4675.563)	(1745.022)	(0.038)	(3447.006)	(2841.098)	(1547.613)
8	-0.112	-8729.436	-7383.017	2232.931	-0.056	-7640.257	-10632.39	1231.923
	(0.115)	(6355.566)	(6735.697)	(3430.948)	(0.048)	(4449.752)	(3315.58)	(1951.376)
9	-0.239	-13035.27	-3932.927	6681.613	-0.127	-6953.641	-7696.396	1088.849
	(0.129)	(6655.436)	(4630.667)	(7302.566)	(0.073)	(4849.488)	(3844.097)	(1973.053)
10	-0.319	-16339.65	-1272.644	10763.89	-0.178	-9770.67	-3631.802	3264.95
	(0.14)	(7594.526)	(6894.287)	(6652.507)	(0.087)	(5236.537)	(3629.22)	(3068.554)
11	-0.432	-17188.88	10795.57	7626.713	-0.177	-14788.74	-4215.506	3270.299
	(0.121)	(8910.675)	(7284.34)	(7663.188)	(0.073)	(5014.675)	(3201.369)	(2913.761)

Table reports the point estimates from estimation of models specified in Section 5 of the main text, whose dependent variable is reported at the column head. Standard errors are clustered by person and reported in brackets below the estimates. Data on Wages, Salaries, and Commissions is top-coded at the 99th percentile.

Table 10: Estimated Effect of Disability Onset on Market Incomes: Types Within Aggregate Physical

	Kinetic Ability				Exclusively Pain			
Year Relative to Onset	Labour Market Participation Rate	Wages, Salaries, and Commissions	WSC for Participants	Non-Market Income	Labour Market Participation Rate	Wages, Salaries, and Commissions	WSC for Participants	Non-Market Income
-4	0.021	-724.068	-1573.275	-348.507	-0.006	-1304.733	-982.387	80.26
	(0.012)	(701.723)	(730.947)	(375.163)	(0.015)	(1339.973)	(1465.478)	(439.253)
-3	0.012	285.095	-167.107	-233.415	-0.021	-1897.697	-1073.035	223.828
	(0.014)	(798.134)	(844.476)	(479.491)	(0.016)	(1390.707)	(1486.748)	(678.297)
-2	0.021	-212.217	-550.236	-578.36	-0.001	-1904.659	-990.685	-369.852
	(0.014)	(880.469)	(915.112)	(349.066)	(0.017)	(1417.967)	(1465.573)	(489.997)
-1	0.012	-526.63	-599.723	-797.854	-0.034	-2610.244	-696.539	200.198
	(0.014)	(928.026)	(926.626)	(359.003)	(0.019)	(1492.315)	(1482.31)	(715.393)
0	0.005	-1080.258	-848.65	-759.934	-0.017	-1007.025	1055.477	-470.046
	(0.016)	(947.708)	(936.141)	(389.731)	(0.019)	(1561.161)	(1496.009)	(563.492)
1	-0.007	-3044.238	-2656.996	-207.593	-0.02	-2886.425	-1428.426	-354.925
	(0.016)	(1036.987)	(1058.909)	(536.19)	(0.02)	(1636.291)	(1718.818)	(565.912)
2	-0.036	-4016.841	-3096.016	-536.219	-0.03	-2493.331	-1113.444	-1.461
	(0.018)	(1062.482)	(1101.781)	(433.855)	(0.019)	(1696.312)	(1838.481)	(614.19)
3	-0.06	-4693.937	-3132.433	-560.009	-0.055	-3403.003	-214.045	-131.943
	(0.019)	(1089.992)	(1107.099)	(445.424)	(0.022)	(1763.937)	(1711.023)	(621.595)
4	-0.092	-5050.82	-2817.79	-828.535	-0.064	-1251.538	3029.962	-336.259
	(0.021)	(1124.744)	(1138.356)	(417.504)	(0.022)	(1788.238)	(1611.681)	(666.2)
5	-0.123	-6042.952	-2994.104	-942.388	-0.066	-486.777	3199.368	-369.3
	(0.022)	(1222.162)	(1356.41)	(425.488)	(0.022)	(1888.14)	(1842.234)	(684.643)
6	-0.121	-5563.104	-2725.911	-922.365	-0.058	-1880.204	1407.343	-218.587
	(0.023)	(1341.642)	(1516.115)	(475.7)	(0.023)	(1996.834)	(1910.146)	(773.702)
7	-0.117	-5648.411	-3206.643	-1056.906	-0.071	-1350.058	3471.413	-1039.57
	(0.024)	(1464.277)	(1703.918)	(560.544)	(0.026)	(2238.859)	(2011.131)	(770.705)
8	-0.118	-5193.471	-3158.88	-1402.234	-0.061	-1644.831	1118.538	-1347.318
	(0.025)	(1463.272)	(1738.958)	(480.868)	(0.025)	(2312.246)	(2483.751)	(741.144)
9	-0.123	-5333.086	-3534.198	-1413.584	-0.083	-3406.375	1176.052	-822.145
	(0.026)	(1527.164)	(1749.299)	(536.589)	(0.029)	(2425.436)	(2404.532)	(832.466)
10	-0.12	-5126.044	-3350.515	-1411.195	-0.038	-381.805	927.891	-1184.275
	(0.027)	(1594.55)	(1801.865)	(568.311)	(0.024)	(2385.777)	(2725.989)	(889.521)
11	-0.152	-5744.97	-3295.309	-1749.127	-0.073	-1229.523	1251.455	-1214.397
	(0.027)	(1714.146)	(2031.689)	(571.504)	(0.026)	(2489.015)	(2841.963)	(851.598)

Table reports the point estimates from estimation of models specified in Section 5 of the main text, whose dependent variable is reported at the column head. Standard errors are clustered by person and reported in brackets below the estimates. Data on Wages, Salaries, and Commissions is top-coded at the 99th percentile.

Table 11: Estimated Effect of Disability Onset on Government Transfers: Aggregate Physical and Mental-Cognitive

	Aggregate Physical			Mental-Cognitive		
Year Relative to Onset	Total Government Transfers	Disability Relevant Transfers	Family Transfers	Total Government Transfers	Disability Relevant Transfers	Family Transfers
-4	50.238	54.697	0.793	211.068	-143.423	354.659
	(132.68)	(122.9)	(40.13)	(287.678)	(246.667)	(170.806)
-3	-74.766	-73.348	3.074	-112.476	-467.245	371.114
	(140.69)	(133.53)	(39.84)	(271.502)	(252.822)	(153.566)
-2	-225.943	-185.429	-39.225	84.356	-414.336	496.873
	(137.94)	(130.89)	(39.48)	(319.182)	(258.178)	(176.325)
-1	-61.542	-67.697	4.335	224.747	-389.783	619.018
	(158.26)	(150.55)	(43.72)	(296.61)	(247.446)	(177.471)
0	103.138	96.19	1.673	250.879	-236.558	511.382
	(175.32)	(167.26)	(45.76)	(294.491)	(262.586)	(166.646)
1	258.655	254.047	-4.71	682.42	93.693	590.067
	(182.72)	(173.92)	(44.39)	(332.963)	(288.884)	(171.102)
2	530.932	547.697	-28.054	486.851	-318.881	813.783
	(210.64)	(201.81)	(45.32)	(390.271)	(329.068)	(271.692)
3	696.817	705.081	-9.597	846.988	136.218	676.501
	(195.5)	(181.39)	(59.72)	(518.453)	(519.362)	(237.466)
4	651.727	694.788	-43.381	949.564	174.693	739.803
	(203.9)	(193.94)	(50.15)	(443.149)	(430.676)	(232.529)
5	891.636	903.715	-12.072	1351.743	699.338	621.327
	(216.82)	(209.42)	(50.42)	(644.555)	(650.741)	(258.283)
6	1228.078	1262.87	-25.961	852.996	-0.769	794
	(230.73)	(221.85)	(51.55)	(431.501)	(361.536)	(311.727)
7	1047.416	1061.661	-20.742	1418.095	678.265	677.493
	(215.98)	(205.85)	(60.13)	(556.547)	(544.179)	(310.852)
8	1015.08	1010.68	2.737	1292.881	1085.367	149.494
	(237.13)	(227.94)	(61.82)	(616.348)	(574.885)	(215.984)
9	1522.181	1521.293	3.382	1545.495	1259.637	222.294
	(302.62)	(293.96)	(61.32)	(669.269)	(621.598)	(233.968)
10	1622.97	1600.652	8.369	1528.444	1159.884	231.654
	(282.98)	(277.98)	(62.23)	(655.317)	(609.852)	(189.517)
11	1597.555	1549.44	30.874	2331.56	2002.871	220.199
	(266.42)	(255.79)	(58.05)	(747.58)	(741.192)	(183.723)

Table reports the point estimates from estimation of models specified in Section 5 of the main text, whose dependent variable is reported at the column head. Standard errors are clustered by person and reported in brackets below the estimates.

Table 12: Estimated Effect of Disability Onset on Government Transfers: Types Within Mental-Cognitive

	Cognitive Functioning			Exclusively Mental Health		
Year Relative to Onset	Total Government Transfers	Disability Relevant Transfers	Family Transfers	Total Government Transfers	Disability Relevant Transfers	Family Transfers
-4	324.635	93.404	242.758	118.726	-270.429	387.959
	(569.774)	(495.827)	(231.67)	(305.613)	(282.214)	(239.155)
-3	-50.978	-302.778	274.782	-139.721	-552.089	428.824
	(513.845)	(475.605)	(201.256)	(303.611)	(304.585)	(216.677)
-2	50.558	-579.804	644.223	111.439	-342.552	448.378
	(550.421)	(488.634)	(302.347)	(368.636)	(310.833)	(216.064)
-1	-284.253	-844.832	570.066	469.962	-170.239	648.31
	(478.389)	(367.592)	(272.46)	(347.448)	(324.692)	(225.625)
0	-105.357	-593.989	495.459	377.384	-114.811	527.454
	(478.21)	(418.132)	(273.445)	(352.303)	(331.179)	(208.287)
1	663.507	158.903	471.25	709.309	71.566	658.862
	(582.881)	(530.014)	(255.407)	(369.555)	(326.833)	(221.222)
2	658.397	-33.388	645.546	437.379	-436.851	913.21
	(770.303)	(800.759)	(268.887)	(430.853)	(263.376)	(406.468)
3	1469.597	475.706	929.218	540.186	-26.869	553.124
	(1187.208)	(1206.459)	(383.23)	(451.735)	(469.825)	(311.069)
4	1456.965	562.182	826.022	705.148	-9.018	702.524
	(902.486)	(888.146)	(341.865)	(404.893)	(405.317)	(312.122)
5	2440.877	2148.049	238.345	775.284	-95.268	860.984
	(1437.605)	(1450.663)	(343.419)	(477.362)	(482.127)	(376.011)
6	1607.617	631.052	852.774	490.581	-307.232	779.962
	(908.513)	(714.053)	(513.834)	(377.798)	(397.164)	(412.437)
7	2001.787	1180.51	733.463	1117.497	430.943	648.59
	(1261.483)	(1195.394)	(438.462)	(566.536)	(626.929)	(450.909)
8	2352.792	2104.651	171.082	784.986	574.141	169.245
	(1228.694)	(1134.29)	(422.998)	(596.474)	(566.278)	(238.248)
9	3465.145	3110.568	255.506	368.144	99.019	232.442
	(1387.102)	(1332.79)	(378.848)	(604.023)	(522.584)	(268.186)
10	2821.919	2526.373	138.529	542.225	86.902	341.833
	(1393.309)	(1310.148)	(286.207)	(593.571)	(498.063)	(259.627)
11	4013.899	3763.138	111.042	981.162	669.549	232.71
	(1522.251)	(1509.628)	(321.277)	(746.67)	(641.781)	(203.046)

Table reports the point estimates from estimation of models specified in Section 5 of the main text, whose dependent variable is reported at the column head. Standard errors are clustered by person and reported in brackets below the estimates.

Table 13: Estimated Effect of Disability Onset on Government Transfers: Types Within Aggregate Physical

	Kinetic Ability			Exclusively Pain		
Year Relative to Onset	Total Government Transfers	Disability Relevant Transfers	Family Transfers	Total Government Transfers	Disability Relevant Transfers	Family Transfers
-4	-172.321	-144.057	-27.976	409.117	369.733	51.122
	(166.947)	(158.205)	(42.627)	(214.999)	(188.791)	(79.305)
-3	-95.268	-84.111	0.182	-58.951	-74.662	7.777
	(193.721)	(184.079)	(47.68)	(187.377)	(175.165)	(68.914)
-2	-290.717	-252.852	-36.097	-155.654	-107.61	-47.591
	(189.218)	(179.127)	(48.442)	(179.572)	(169.439)	(65.421)
-1	-248.408	-215.239	-25.611	187.688	123.969	46.134
	(221.147)	(210.083)	(54.321)	(191.253)	(182.343)	(70.411)
0	-6.597	-25.588	20.245	225.796	249.671	-39.539
	(243.296)	(231.001)	(61.54)	(217.077)	(208.146)	(62.483)
1	365.253	371.112	-7.366	31.847	16.111	-6.831
	(257.123)	(248.279)	(53.482)	(215.298)	(193.354)	(73.779)
2	779.409	802.664	-31.297	55.187	68.394	-30.995
	(302.937)	(293.151)	(55.154)	(206.606)	(185.634)	(72.448)
3	1045.492	1036.913	10.713	28.809	78.058	-57.435
	(277.824)	(258.703)	(80.729)	(206.692)	(188.691)	(74.041)
4	1065.41	1123.236	-54.903	-128.732	-91.444	-43.703
	(287.392)	(274.666)	(62.675)	(215.567)	(198.596)	(77.314)
5	1437.161	1471.341	-37.788	-132.414	-138.33	11.776
	(306.546)	(298.323)	(60.605)	(222.382)	(202.594)	(82.125)
6	1777.174	1816.872	-32.5	183.211	234.242	-40.483
	(320.145)	(310.712)	(58.678)	(244.985)	(221.084)	(91.319)
7	1615.311	1626.547	-21.518	-43.255	11.003	-54.48
	(295.089)	(284.936)	(69.824)	(229.894)	(204.938)	(103.925)
8	1641.607	1638.453	0.582	-164.386	-139.708	-25.808
	(329.612)	(320.093)	(67.408)	(236.652)	(207.738)	(114.856)
9	1872.093	1916.778	-43.478	835.413	790.929	48.316
	(405.332)	(396.933)	(61.284)	(393.593)	(367.885)	(122.883)
10	2421.483	2371.192	31.916	128.939	193.085	-71.939
	(398.276)	(395.779)	(80.396)	(277.593)	(251.22)	(89.094)
11	2224.855	2209.71	-9.161	377.243	306.64	64.516
	(362.761)	(355.682)	(64.041)	(314.551)	(264.318)	(105.65)

Table reports the point estimates from estimation of models specified in Section 5 of the main text, whose dependent variable is reported at the column head. Standard errors are clustered by person and reported in brackets below the estimates.

Table 14: Estimated Effect of Disability Onset on Government Transfers: Aggregate Physical and Mental-Cognitive

	Aggregate Physical					Mental-Cognitive				
Year Relative to Onset	Family Total Income	Before-Tax Income	After-Tax Income	Non-Taxable Income	Family Members Income	Family Total Income	Before-Tax Income	After-Tax Income	Non-Taxable Income	Family Members Income
-4	-4594.061	-1695.148	-767.604	54.604	-2150.693	75.209	571.958	1046.629	110.865	491.07
	(1686.14)	(677.6)	(537.42)	(78.67)	(1388.21)	(3776.882)	(1516.632)	(1237.747)	(138.184)	(2957.692)
-3	-4855.911	-1783.336	-933.413	10.533	-2278.335	2572.22	416.256	621.107	-205.478	3839.421
	(1676.39)	(743.88)	(579.92)	(80.84)	(1286.36)	(4417.099)	(1533.358)	(1161.226)	(124.064)	(4063.184)
-2	-5990.158	-2500.139	-1885.553	-122.206	-2598.232	1102.328	-781.082	-325.34	-189.719	3277.499
	(1762.47)	(779.84)	(592.68)	(65.78)	(1318.11)	(4610.755)	(1599.458)	(1197.384)	(113.088)	(4217.998)
-1	-4522.174	-2772.242	-1927.781	-96.672	-168.39	173.275	-1412.687	-415.212	-205.228	3653.147
	(1770.18)	(807.51)	(619)	(98.3)	(1408.82)	(4792.273)	(1656.854)	(1259.812)	(113.23)	(4478.739)
0	-5095.349	-2616.424	-1829.668	63.803	-1962.629	-1432.658	-1819.537	-1493.391	-163.035	2583.698
	(2163.64)	(808.59)	(607.53)	(118.2)	(1538.66)	(4929.357)	(2047.454)	(1485.419)	(107.388)	(4584.861)
1	-6209.273	-3909.785	-2540.401	226.986	-2181.143	-3488.763	-5444.96	-3741.602	17.571	3505.57
	(2414.89)	(875.99)	(678.02)	(130.91)	(1626.93)	(5237.19)	(2039.112)	(1561.773)	(179.976)	(4765.054)
2	-7196.028	-4199.992	-2766.936	421.463	-2963.807	-7970.074	-4472.532	-3025.723	183.453	-1740.526
	(2431.88)	(895.48)	(692.87)	(156.44)	(1558.67)	(4477.277)	(2137.625)	(1660.739)	(280.843)	(4002.357)
3	-7398.375	-4850.503	-3055.965	558.331	-2426.478	-5809.291	-5539.742	-3854.425	288.934	2094.245
	(2854.32)	(930.59)	(738.47)	(148.59)	(1711.31)	(4463.279)	(2202.487)	(1748.119)	(426.021)	(4156.235)
4	-5836.434	-4903.57	-3282.847	475.224	-1434.148	-6025.95	-7103.568	-5377.58	315.71	3690.193
	(3712.65)	(939.75)	(741.14)	(137.96)	(1938.66)	(4598.547)	(2380.358)	(1929.037)	(337.138)	(4124.394)
5	-7223.039	-4619.391	-3042.85	585.528	-4571.156	-4877.228	-6732.86	-4135.831	423.098	4987.38
	(4116.21)	(1000.8)	(783.26)	(153.46)	(1927.93)	(5822.805)	(2423.284)	(1971.637)	(550.156)	(5560.21)
6	-8249.256	-4750.334	-3150.939	673.063	-5030.624	-3635.922	-4260.417	-2209.592	-0.059	3802.19
	(4549.75)	(1078.34)	(830.5)	(172.91)	(2208.78)	(5155.276)	(2772.771)	(2232.362)	(239.691)	(4902.53)
7	-7557.311	-5318.876	-3612.849	576.686	-4220.665	-6967.141	-8360.021	-5197.984	-31.455	5455.83
	(5156.41)	(1250.51)	(944.07)	(146.51)	(2495.9)	(5613.047)	(2480.709)	(2125.225)	(211.031)	(5263.912)
8	-8683.912	-4973.242	-3230.766	652.85	-5105.508	-9756.873	-8328.385	-4910.202	260.34	2848.504
	(4837.17)	(1256.09)	(960.24)	(156.61)	(2311.99)	(4632.224)	(2847.143)	(2252.244)	(242.045)	(4388.652)
9	-7673.348	-4736.345	-2769.036	872.098	-5696.726	-9104.442	-8436.155	-4757.72	556.49	3768.525
	(5200.79)	(1304.33)	(1006.76)	(207.36)	(2564.32)	(5991.231)	(3307.894)	(2778.084)	(385.825)	(5073.623)
10	-4426.94	-3923.442	-2797.646	729.974	-3662.327	-18011.6	-7478.001	-4138.34	658.352	-7029.566
	(6218.06)	(1425.36)	(1258.46)	(164.98)	(2487.7)	(6190.798)	(3843.185)	(3203.658)	(443.151)	(4053.833)
11	-8204.408	-5251.802	-3264.249	633.845	-6381.975	-22657.1	-10348.11	-5818.406	781.696	-8204.155
	(6874.98)	(1446.11)	(1117.9)	(168.39)	(2503.74)	(7094.598)	(4362.706)	(3896.005)	(471.177)	(5284.828)

Table reports the point estimates from estimation of models specified in Section 5 of the main text, whose dependent variable is reported at the column head. Standard errors are clustered by person and reported in brackets below the estimates. Data on Total before-tax income, after-tax income, and family total income is top-coded at the 99th percentile.

Table 15: Estimated Effect of Disability Onset on Government Transfers: Types Within Mental-Cognitive

	Cognitive Functioning					Exclusively Mental Health				
Year Relative to Onset	Family Total Income	Before-Tax Income	After-Tax Income	Non-Taxable Income	Family Members Income	Family Total Income	Before-Tax Income	After-Tax Income	Non-Taxable Income	Family Members Income
-4	7025.931	3849.384	3821.492	349.761	2800.873	-3903.403	-1955.642	-1047.882	4.906	-743.951
	(7402.503)	(3346.594)	(2718.821)	(334.12)	(4422.964)	(1830.634)	(672.517)	(535.194)	(106.177)	(1728.89)
-3	7317.273	1542.983	491.746	-193.797	7123.281	-2947.032	-972.771	-70.865	-15.783	-730.58
	(8899.96)	(2918.257)	(2185.855)	(237.849)	(8255.458)	(1686.838)	(786.415)	(632.439)	(119.52)	(1412.623)
-2	3809.425	179.411	33.961	-339.347	3305.471	-4396.248	-1902.532	-1149.3	-187.31	-1271.056
	(7593.766)	(3093.613)	(2376.375)	(165.576)	(6652.557)	(1865.064)	(858.906)	(651.053)	(96.135)	(1496.794)
-1	6145.241	2313.857	2144.383	-378.81	5387.75	-3059.741	-2871.201	-1784.792	-208.903	1593.819
	(6548.154)	(3191.329)	(2409.269)	(158.509)	(6165.498)	(1967.452)	(891.094)	(682.736)	(148.927)	(1621.135)
0	-1335.539	252.613	-43.633	-230.572	429.699	-5112.373	-3186.68	-1897.42	-82.721	-813.516
	(6979.021)	(3565.73)	(2464.594)	(188.492)	(6062.545)	(2114.85)	(885.04)	(681.059)	(171.603)	(1835.09)
1	-3866.935	-2997.484	-2163.497	276.882	717.553	-5834.505	-4301.463	-2655.264	198.989	-823.967
	(9135.597)	(4095.156)	(3063.995)	(430.196)	(7560.688)	(2313.692)	(974.849)	(775.942)	(190.289)	(1892.27)
2	-3116.249	1615.699	1573.196	827.705	-4681.635	-8139.523	-5203.804	-3317.328	502.434	-1850.039
	(7900.29)	(3897.768)	(2926.324)	(732.073)	(5736.588)	(2042.606)	(979.41)	(775.323)	(235.31)	(1705.687)
3	-3112.974	-2364.672	-469.544	1227.565	1135.515	-8497.426	-5217.606	-3094.544	727.481	-1925.249
	(8416.382)	(3544.754)	(2685.655)	(1167.402)	(7126.51)	(2143.458)	(979.058)	(788.16)	(219.541)	(1774.538)
4	-15169.18	-7611.864	-4940.035	771.128	-4712.361	-8836.14	-6116.08	-3940.163	654.258	-1381.995
	(7229.601)	(3695.54)	(2718.564)	(797.34)	(5946.475)	(2449.576)	(1041.56)	(843.462)	(207.28)	(2053.733)
5	-13774.98	-6419.597	-3209.821	1553.233	-4146.668	-10634.63	-6242.722	-3985.57	837.605	-4217.969
	(8221.354)	(3677.403)	(3087.849)	(1338.031)	(7438.695)	(2902.082)	(1120.975)	(887.167)	(229.296)	(2092.622)
6	-5122.071	-1162.246	446.181	376.449	-733.04	-12288.35	-6230.359	-3924.928	991.957	-4598.228
	(8841.577)	(5492.795)	(4575.422)	(522.796)	(8495.55)	(2916.282)	(1201.484)	(948.558)	(254.658)	(2581.694)
7	-4832.127	-5987.98	-2645.613	228.341	5864.31	-11806	-6882.742	-4478.727	745.588	-2886.45
	(10282.67)	(3123.865)	(3009.775)	(334.452)	(9813.778)	(3390.53)	(1346.145)	(1036.832)	(207.129)	(2981.731)
8	-16644.8	-9082.027	-5712.727	844.222	-2756.2	-13966.85	-6358.125	-3759.994	892.674	-5440.797
	(6992.403)	(4748.162)	(3532.489)	(635.884)	(6264.293)	(2885.812)	(1322.511)	(1026.802)	(226.09)	(2478.204)
9	-9374.791	-9115.394	-4777.778	1507.42	4776.081	-12467.04	-6162.2	-3554.847	1197.78	-6507.728
	(11514.53)	(5801.624)	(4742.942)	(992.658)	(8315.685)	(3958.58)	(1381.994)	(1090.978)	(301.696)	(2657.431)
10	-24228.87	-9135.627	-4512.084	1450.945	-11478.44	-12978.71	-6111.533	-3422.682	1028.356	-4700.974
	(9712.675)	(6585.372)	(5424.303)	(1052.915)	(6673.857)	(3285.704)	(1506.77)	(1204.921)	(239.108)	(2792.219)
11	-27884.18	-9684.125	-4413.794	1618.249	-12759.76	-16551.81	-6975.96	-4074.296	869.56	-7422.203
	(10017.5)	(9039.008)	(8142.823)	(1125.244)	(6963.665)	(3114.73)	(1625.561)	(1284.278)	(244.386)	(2553.797)

Table reports the point estimates from estimation of models specified in Section 5 of the main text, whose dependent variable is reported at the column head. Standard errors are clustered by person and reported in brackets below the estimates. Data on Wages, Salaries, and Commissions is top-coded at the 99th percentile. Data on Total before-tax income, after-tax income, and family total income is top-coded at the 99th percentile.

Table 16: Estimated Effect of Disability Onset on Government Transfers: Types Within Aggregate Physical

	Kinetic Ability					Exclusively Pain				
Year Relative to Onset	Family Total Income	Before-Tax Income	After-Tax Income	Non-Taxable Income	Family Members Income	Family Total Income	Before-Tax Income	After-Tax Income	Non-Taxable Income	Family Members Income
-4	-3693.09	-1027.931	-388.432	-15.497	-1018.746	-5631.28	-1318.159	-340.487	124.683	-4387.267
	(3935.647)	(1619.182)	(1326.937)	(133.913)	(3528.87)	(3189.832)	(1399.775)	(1121.991)	(109.334)	(2234.524)
-3	-656.025	-774.19	89.306	-241.634	2006.135	-7628.274	-3165.476	-2416.761	31.847	-4471.372
	(4352.174)	(1599.15)	(1237.92)	(161.62)	(4031.562)	(3284.98)	(1459.639)	(1095.975)	(83.754)	(2337.248)
-2	-1697.29	-1656.628	-863.298	-154.311	2124.3	-8015.284	-3428.971	-3100.827	-36.704	-4429.004
	(5261.659)	(1734.08)	(1278.515)	(162.467)	(4854.836)	(3331.045)	(1471.61)	(1103.251)	(72.753)	(2257.288)
-1	-4493.04	-3619.023	-2026.44	-156.715	1464.544	-6441.676	-2647.295	-2237.164	56.866	-2715.746
	(5952.635)	(1755.379)	(1340.55)	(165.32)	(5490.973)	(3120.63)	(1505.021)	(1150.131)	(76.95)	(2348.94)
0	-3054.276	-3175.964	-2540.466	-175.727	2455.452	-4481.666	-1719.464	-1780.972	272.984	-3385.225
	(5944.038)	(2465.56)	(1804.952)	(147.709)	(5587.686)	(4252.112)	(1520.564)	(1113.974)	(131.527)	(2480.761)
1	-4842.226	-6914.239	-4735.371	-115.095	3613.176	-6370.233	-3302.739	-2419.599	243.299	-4059.127
	(5926.457)	(2024.526)	(1572.679)	(162.062)	(5633.009)	(4796.872)	(1616.676)	(1219.793)	(141.053)	(2723.137)
2	-11949.77	-7899.069	-5655.303	-152.159	-1411.569	-5065.564	-2552.273	-1921.392	256.71	-4392.846
	(4755.03)	(2145.319)	(1683.823)	(175.627)	(4568.278)	(5114.588)	(1672.31)	(1265.36)	(126.506)	(2704.224)
3	-8839.243	-7633.454	-5991.253	-177.459	1400.401	-5012.914	-4285.691	-3088.919	228.147	-2906.019
	(4503.368)	(2505.05)	(1972.959)	(197.168)	(4405.283)	(6405.626)	(1820.555)	(1430.728)	(132.201)	(3167.828)
4	-2429.396	-7246.171	-6019.37	57.577	7304.946	-123.441	-2799.947	-2201.834	135.995	-1115.875
	(5112.878)	(2775.427)	(2316.55)	(242.976)	(4726.942)	(8567.847)	(1762.723)	(1357.353)	(105.662)	(3494.506)
5	-2153.885	-7586.168	-5266.481	-264.205	8532.105	-716.502	-1797.636	-1461.868	111.32	-4692.95
	(7195.792)	(2816.026)	(2175.915)	(219.519)	(7128.863)	(9397.193)	(1851.44)	(1428.919)	(114.094)	(3359.175)
6	-5883.407	-7137.46	-4735.404	-290.426	4380.017	-424.816	-2106.771	-1823.725	71.732	-5216.084
	(5394.899)	(2911.304)	(2216.259)	(257.053)	(4901.028)	(10615)	(2031.86)	(1516.272)	(136.552)	(3440.799)
7	-11350.11	-10733.81	-7567.584	-225.648	3105.428	1089.88	-2503.126	-2142.818	233.346	-5672.61
	(5455.394)	(3005.497)	(2431.387)	(290.421)	(5161.437)	(12095.9)	(2430.185)	(1798.457)	(151.655)	(3881.936)
8	-8854.129	-8789.567	-5167.623	-84.029	3712.999	1462.103	-2487.183	-2339.583	198.635	-3678.45
	(6114.909)	(3579.506)	(2820.103)	(103.466)	(5845.709)	(11306.03)	(2497.073)	(1872.234)	(140.976)	(4023.374)
9	-10599.48	-9178.106	-5744.335	-55.268	2580.945	1448.288	-2206.76	-1485.692	275.535	-3432.4
	(6793.133)	(3986.816)	(3272.303)	(117.036)	(6291.584)	(11242.53)	(2558.31)	(1933.928)	(190.648)	(4552.27)
10	-15089.57	-6889.168	-4495.946	64.385	-4753.197	11147.34	25.351	-1730.043	170.834	-1185.434
	(8923.608)	(5036.945)	(4070.2)	(81.822)	(5706.079)	(14524.78)	(2675.652)	(2622.511)	(131.029)	(4116.939)
11	-20163.04	-10995.83	-7030.763	172.223	-6115.688	7150.658	-2172.037	-1923.51	162.165	-3752.383
	(10778.16)	(4397.518)	(3586.242)	(156.146)	(8031.837)	(16459.02)	(2626.322)	(1961.601)	(137.05)	(4499.118)

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