Heterogeneous Disability Shocks and the Dynamics of Income, Employment, and Partial Insurance

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Abstract

This study examines the longitudinal effects of disability, distinguishing disability types by the activities they impair. Using linked Canadian survey and tax data, I estimate impacts on personal income components over ten years and identify gaps in partial insurance across types. Mental-cognitive disabilities cause larger, more persistent market income losses than physical disabilities. Although the tax-transfer system provides partial income insurance, its effectiveness varies, with minimal support for mental health-related disabilities. A welfare analysis reveals that disability benefits are suboptimal for several types, especially mental health-related conditions, underscoring the need for improved policy targeting.

JEL classifications: H30, I10, I14, I38, J14

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I Introduction

The onset of a work-limiting disability impedes the ability to execute essential tasks in work and daily life, hampering one's financial independence and posing significant societal costs for supporting these individuals. Consequently, disability-related economic inequalities are widespread 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%).[1] Disability is a prominent risk to income stability for working-aged adults, many of

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This paper uses confidential data that is administered by Statistics Canada and can not be made publicly available. Steps for data access can be found at https://www.statcan.gc.ca/en/microdata/data-centres/access. Supplementary files are provided to replicate the analysis provided access to these data. The author declares that he has no relevant or material financial interests that relate to the research described in this paper. I extend many thanks to Audra Bowlus, Nirav Mehta, Christopher Robinson, Todd Stinebrickner, Rory McGee, Naoki Aizawa, Baxter Robinson, David Wiczer, Kathleen McGarry, Steven Stern, Tom Triveri, Cecilia Diaz-Campo, and Marco Pariguana, seminar participants at the University of Western Ontario, Stony Brook University, St. Francis Xavier University, and participants at the 55th Annual meeting of the Canadian Economics Association, and the 2023 Stata conference in Stanford for helpful comments and questions, and for excellent RA help from Shafira Widjaja.

[1] Low-income is defined as 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).

whom will experience some form of disability before retirement.[2] 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 allocate scarce resources to those bearing the greatest burden from their disability.

This paper conducts a comprehensive analysis of heterogeneity in the effects of different types of disability on disaggregated components of personal income, where types are defined based on activity limitations. I analyze how sources of partial insurance available for disability shocks mitigate declines in market incomes, highlighting disparities across the types in each of the ten years following its onset. I employ two separate estimators in my empirical strategy, each addressing a different bias inherent to disability as a treatment. First, I apply the Interaction-Weighted (IW) estimator, recently proposed by Sun and Abraham (2021) to address bias related to unobserved heterogeneity in the effect of disability when the timing of onset is staggered. Second, I employ a Propensity Score Matching (PSM) approach to mitigate bias related to the non-randomness of disability onset.

Differences in the sorts of tasks and functions that are impaired by a disability are a primary factor driving the variation in its effects. Disabilities stem from one or multiple physiological ailments and differ markedly in how they impede daily life 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. 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 the importance of limited functions for work and daily life.

I start by distinguishing disabling conditions that affect physical activities from those affecting mental-cognitive activities. While this distinction is commonplace in the related literature, it masks important heterogeneity within these "aggregated" disability types.[3] I conduct a second analysis of more granular mutually exclusive 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 related exclusively to pain.[4] 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

[2]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, 2011).

[3]This sort of distinction is often seen in the literature on multidimensional health, such as Mori (2019); Wen (2022), and in the literature on multidimensional human capital, such as Poletaev and Robinson (2008); Yamaguchi (2012); Sanders, Taber et al. (2012); Lindenlaub (2017); Robinson (2018); Lise and Postel-Vinay (2020).

[4]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.

disorder).

A more granular distinction of disability types is essential for understanding which components of health capital are driving income losses. Moreover, this differentiation is particularly policy-relevant, as it helps clarify the composition of beneficiaries in partial insurance programs. For example, in the U.S., mental health and pain-related disabilities have been identified as significant contributors to the increasing number of disability insurance recipients (Autor, 2011). Mental health, in particular, has gained recognition for its profound impact on economic security—often surpassing the effects of physical disabilities (Frank and Glied, 2023; Prinz et al., 2018). This paper examines the role of various sources of partial insurance in mitigating these impacts and highlights how these effects vary across different disability types.

Fluctuations in the level and composition of one's income post-disability onset offer valuable insights into one's 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, 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 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 less susceptible to measurement error and under-reporting, two issues 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 related to drawing comparisons across samples, datasets, methodologies, and studies.

Lastly, Canada grants universal health insurance, unlike the US, where health insurance access is intertwined with disability policy. The Canadian setting allows for a cleaner analysis of the incentives from disability policies that are unconfounded by the added value of health insurance (Deshpande and Lockwood, 2022).

This paper presents several novel findings, highlighting substantial heterogeneity in the dynamic effects of different types of disabilities on components of personal income, as identified using both the IW and PSM estimators. The discussion is framed around short-run effects (five years or less post-onset) and long-run effects (six years or more post-onset). In the short-run, the decline in wages, salaries, and commissions (WSC) is similar in magnitude between physical and mental-cognitive disabilities. However, in the long-run, the impact of mental-cognitive disabilities doubles in magnitude, whereas the effect of physical disabilities remains relatively stable. On the extensive margin, individuals with physical disabilities experience a persistent 10-percentage-point decline in labour market participation post-onset. In contrast, those with mental-cognitive disabilities exhibit continued exits from the workforce, reaching a 19-percentage-point drop ten years post-onset. These findings suggest that mental-cognitive skills may have a higher market valuation, leading to greater wage penalties when disability-induced skill mismatches occur (Yamaguchi, 2012; Mori, 2019; Lise and Postel-Vinay, 2020; Humlum, Munch and Jorgensen, 2023). In a service-based economy like Canada, substitution to relatively scarce and lower-compensated physically intensive jobs after the onset of a mental-cognitive disability may amplify negative effects. Conversely, substitution to productive activities that favor mental-cognitive skills may be more feasible following the onset of a physical disability, mitigating its adverse impact (Humlum, Munch and Jorgensen, 2023).

The effects of market income following the onset of a disability are accompanied by an equivalent increase in total government transfers. However, point estimates are larger for physical disabilities, indicating a relatively lower proportion of income being insured after the onset of a mental-cognitive disability. Instead, the reduction in taxes paid plays a more substantial role in mitigating the financial effects of a mental-cognitive disability compared to a physical disability. I find no significant effects on the income of family members, suggesting limited spillover effects on household earnings. Despite these sources of partial insurance, after-tax income—which represents the resources available for consumption—declines significantly for both disability types. Notably, this decline is nearly double in magnitude for mental-cognitive disabilities.

The second set of results examines the specific activity limitations driving the effects observed for the aggregate disability types. For physical disabilities, the impact on market income and government transfers is primarily driven by disabilities affecting kinetic abilities. Additionally, kinetic ability disabilities negatively affect total household income in the years following their onset, including the income of family members. In contrast, disabilities exclusively related to pain show no significant effects on WSC or government transfers, although they are associated with some labour market exits. These findings highlight the importance of distinguishing between subtypes of physical disabilities. Disabilities related solely to pain introduce variability into the estimates, potentially obscuring the effects of aggregate physical disabilities.

Mental health disabilities follow a similar post-onset trajectory in their effects on market income as disabilities affecting kinetic abilities. However, the sources of partial insurance differ between the two groups. Individuals with kinetic ability disabilities experience a significant increase in government transfer payments. In contrast, those with mental health disabilities do not receive substantial income from these programs after onset. Instead, the decline in their market income is partially mitigated by a reduction in marginal tax rates, which helps buffer the income shock. Long-run income from family members also declines for individuals with mental health disabilities, though these estimates are imprecise. Notably, this group receives relatively little partial insurance from and sources and after-tax income experiences a persistent drop in the post-onset years.

For individuals with cognitive functioning disabilities, market income experiences the steepest decline in the years following onset. However, these individuals also benefit from the largest increase in government transfers and the greatest reductions in net taxes paid. Additionally, family members' incomes appear to offset some of the lost market income in the long-run, though these estimates are not statistically significant. While the decline in total after-tax income is the largest in magnitude for this group, it is not statistically significant.

The results can be interpreted through the lens of recent literature on task-based human capital. For example, Guvenen et al. (2020) demonstrate that skill mismatches in math and verbal abilities are more detrimental than in social skills. This helps explain why disabilities affecting cognitive functioning, which more severely impact math and verbal skills compared to mental health disabilities, result in larger estimated effects on earnings. Similarly, Lise and Postel-Vinay (2020) show that manual skills offer moderate returns and adapt relatively quickly, cognitive skills yield much higher returns but adjust more slowly, and interpersonal skills provide slightly higher returns than manual skills but remain largely fixed throughout life.

These findings align with the observed patterns: disabilities related to kinetic ability are closely linked to manual skills, cognitive functioning to cognitive skills, and mental health to interpersonal skills. However, the relationships are more complex due to cross-linkages between disability types and skill sets. For instance, mental health disabilities likely affect cognitive skills, while cognitive functioning disabilities may influence interpersonal skills. A comprehensive analysis that maps disability types to a complete range of skills and considers effects of disability in multiple areas 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). While the empirical analysis reveals differences in the extent of partial insurance across the various types of disabilities, the optimality of benefits depends on pre-onset income levels. This framework suggests that the optimal level of disability benefits hinges on several key parameters: the percentage change in consumption following the onset of a disability, the coefficient of risk aversion, and the elasticity of time spent receiving disability benefits in response to the level of benefits provided. The core idea underlying this framework is the trade-off between the work-disincentive effects of disability benefits and the welfare gains achieved through consumption smoothing. Assuming that changes in after-tax income closely align with changes in consumption post-disability onset, I assess the optimality of current benefits using elasticity estimates from the related literature. The findings indicate that current disability benefits are only optimal for individuals with lower risk aversion than is typically reported in the literature, particularly for those with mental-cognitive disabilities or impairments to kinetic ability. Individuals affected by mental health-related disabilities show the a notable deviation from the optimal benefits predicted by the framework.

This paper makes a significant contribution by providing a comprehensive analysis of the heterogeneous effects of disability shocks on market incomes and the broad array of partial insurance mechanisms. First, it introduces a nuanced distinction between disability types based on the specific activities they limit, offering an intuitive framework to understand the substantial variation in the magnitude and persistence of these effects. By linking multidimensional health, human capital, and the tasks that constitute work, this analysis suggests key mechanisms driving these differences.[5] Second, this paper offers a detailed exploration of the diverse channels through which individuals partially insure their income following a disability shock. By comparing insurance gaps across disability types, it highlights the roles of government transfers, family income, and the progressive tax system in mitigating the adverse effects of disability. The granular disaggregation allows for a deeper examination of the specific components of market income and the effectiveness of various insurance mechanisms. Finally, the paper provides fresh insights into the economic consequences of mental health disabilities, which are often understudied. It underscores the pressing need for improved income insurance for individuals in this group, addressing a critical gap in current social support systems. The next section situates these contributions within the broader literature, further clarifying the paper's unique insights and implications.

The remainder of my paper is structured as follows. Section II discusses the contribution to the related literature, Section III details the institutional details of the disability policy in Canada. Section IV describes the dataset used in my analysis and summarizes its key features, highlighting the demographic composition and differences across the disability types. Section V describes the empirical framework and its suitability for this analysis. Section VI analyzes the empirical model's results. Section VII explores the welfare implications of the results in Section VI, and Section VIII concludes.

[5] A description of an economic model formalizing heterogeneity in the effects of disability considered in this analysis is presented in Section 1 of the Appendix.

II Literature Review

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 sources of the underlying heterogeneity of these shocks on earned income. Additionally, I assess the completeness of partial insurance in smoothing consumption across types, identifying relative insurance gaps. 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 in the PSID and Consumer Expenditure Survey. Unlike such previous studies using survey measures of income, my analysis uses administrative data from annual income tax filings, offering important advantages in data quality. Related studies employing administrative data include Blundell, Graber and Mogstad (2015), who investigated 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. Additionally, the social insurance infrastructure allocates resources to programs that exclusively insure against disability shocks. This analysis can thus identify sources of inequality through magnitude of impact on market income, and discrepancies in partial insurance.

This research contributes to the broader literature on the longitudinal effects of health and disability shocks on labour supply, income, 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). My analysis is distinguished by its use of rich disaggregated personal income measures from administrative tax records, robust empirical design, and its focus on heterogeneity in effects by disability types.

Several related studies also employ administrative data. For instance, Lundborg, Nilsson and Vikström (2015) use Swedish administrative registry data to demonstrate how the consequences of health shocks vary by education level. While they also interpret the source of heterogeneity through skills, I focus on variation across disability types and broaden analysis beyond labour market outcomes by considering responses from multiple partial insurance channels. Autor et al. (2019) use Norwegian administrative data to study the insurance-incentive effects of disability insurance on incomes and consumption, but their analysis focuses on disability insurance applicants. Fadlon and Nielsen (2021) use Danish administrative data, but narrow their analysis on family labour supply responses following health shocks. More recently, Humlum, Munch and Jorgensen (2023) also use Danish administrative records to investigate the dynamic effects of workplace injuries on re-education and disability insurance applications but focus their analysis on physical injuries. Collischon, Hiesinger and Pohlan (2023) use German administrative data to investigate how workplace task characteristics influence the effects of disability onset. My analysis focuses on a similar mechanism driving heterogeneity in disability shock but complements their study with the comprehensive analysis of the partial insurance system.

In terms of methodology, the workhorse approach in these studies is an event study or dynamic difference-in-difference strategy, implemented with a TWFE model (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 recent 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 likely 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. I use the IW estimator proposed by Sun and Abraham (2021) gives longitudinal estimates of the treatment on the treated that are robust to such biases. Moreover, to mitigate bias from the nonrandomenss of disability onset, I follow the literature in adopting a quasi-experimental matching approach (Polidano and Vu, 2015; Fadlon and Nielsen, 2021; Collischon, Hiesinger and Pohlan, 2023). The combination of these approaches provides a robust depiction of the effects of disability shocks.

The second key contribution of this paper is the analysis of heterogeneity in effects by categorizing disabilities into distinct, mutually exclusive types. Related work on health shocks emphasize the role of type-based heterogeneity in the consequences of distinct disabling or medical conditions.[6] However, the mechanisms underlying the effects of a specific health condition on behaviour 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.[7] 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

[6]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. (2024) study heterogeneity in the relationship between disability insurance and mortality by types of medical conditions.

[7]For instance, 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.

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.

The distinction between physical and mental-cognitive is common practice in both disability and human capital literatures. For instance, Yi et al. (2015) define a capability vector compromising physical health, mental health, and cognitive functioning; Deshpande (2016) examines how discontinuing youth from disability support affects those with physical versus mental or intellectual disabilities; Mori (2019) models health capital in two categories, mental and physical, linking both to the accumulation of manual and cognitive skills. These studies focus on disabilities present in childhood and adolescence, whereas I examine disabilities that develop during individuals' working lives after most education investments have occurred.

Other related work also highlights this distinction: Wall (2017) groups mental-cognitive and physical in their analysis of poverty and persons with disability in Canada; Wen (2022) separates physical and cognitive health in studying older workers' retirement decisions, Humlum, Munch and Jorgensen (2023) concentrate on physical work accidents and how individuals compensate by investing in their cognitive skills; and Collischon, Hiesinger and Pohlan (2023) partition disabilities into physical, sensory, or psychological in analyzing labour market effects. Furthermore, studies on multidimensional human capital often differentiate physical and mental-cognitive skills to capture how these distinct capacities influence earnings and skill accumulation (Poletaev and Robinson, 2008; Yamaguchi, 2012; Sanders, Taber et al., 2012; Lindenlaub, 2017; Robinson, 2018; Lise and Postel-Vinay, 2020). This study contributes by considering more granular heterogeneity in how individuals fare in the face of different disability shocks. To the best of my knowledge, no prior research has conducted a longitudinal analysis of both physical and mental-cognitive types across market income components and a complete set of partial insurance mechanisms within a unified framework.

Finally, this study contributes to a growing literature studying the economic consequences of mental health. Mental health's impact is increasingly recognized as a crucial determinant of economic success, particularly in the labour market.[8] Much of the existing economic research focuses on the costs and consequences of mental health conditions on employment, job selection, and earnings capacity (Moser, Biasi and Dahl, 2021; Wang, Frank and Glied, 2023; Jolivet and Postel-Vinay, 2024). Compared to other disability types, mental health can be equally or even more detrimental to these outcomes. For instance, Frank and Glied (2023) note that while advances in the treatment and accommodations of mental illnesses have sharply increased in cost, they have only modestly reduced functional losses, unlike other medical conditions where improvements in care have resulted in sizable reductions in functional losses. Further, little is known about how and where individuals smooth their consumption following the onset of a mental health disability. This paper fills that gap by examining how individuals with mental health disabilities cope with

[8]For an overview of this literature, see (Prinz et al., 2018).

income losses, identifying which sources of partial insurance are most important, and comparing insurance gaps to those observed for other disability types. The findings suggest that, outside of the buffering effect of the progressive tax system, these types are underinsured by traditional programs.

III 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.[9] 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 reintegrate (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.[10] 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.[11] 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.[12]

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

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

[10] 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.

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

[12] 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.

equal to 25% of the earnings index that summarizes an applicant's bounded average earnings over their contributory period.[13] 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.[14]

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 provincially 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.[15] Beneficiaries of social assistance typically receive monthly financial transfers equaling 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

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

[14] 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).

[15] Individuals may receive social assistance while earning from other sources, but this may reduce benefits according to the program's replacement rate. SA may be revoked if sufficient effort is not taken on the beneficiary's part to receive income support from other sources.

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.[16] 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.

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.

IV 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 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

[16] Benefits may also be paid out for rehabilitation or for dependent spouses of people who died on the job.

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.[17]

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 if they report any positive WSC in that year. 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. I use these measures to construct a measure of net taxes paid. 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. Refer to Section 3 of the Appendix For additional details of the income measures.

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, I consider after-tax income dynamics as 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).[18] 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

[17] Confidentiality of data requires adherence to a set of restrictions for extracting statistics from the data center. Of note, it requires any statistics to be generated by a minimum number of observations.

[18] 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).

in the administrative tax records (Attanasio and Pistaferri, 2016).

IV.1 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.[19] 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.[20] Mental health conditions encompass many emotional, psychological, and mental health conditions, including anxiety, depression, bipolar disorder, substance abuse, and anorexia. Additional details of the survey questions can be found in Section 2.1 of the Appendix.

The activity limitations are self-reported in LISA. Disability status is identified in two steps. First, respondents report whether they are limited in each of the separate activities.[21] Those reporting an activity limitation are then asked about how frequent they are limited in the respective activity. I flag a individual as having a disability of that type if they respond "sometimes," "often," or "always" for the frequency of that activity limitation.[22]

For each respondent flagged for a disability type, I derive the age of onset from a self-reported question: "At what age did you first start having difficulty or an activity limitation?" Because disability status is not recorded in the income tax data, I assume that once a disability is flagged, it remains present from the reported onset year through all subsequent survey years. In other words, I do not directly observe transitions in disability status between its reported onset and its identification in the survey. However, if a respondent indicates they began experiencing a limitation "x" years in the past, it is reasonable to assume they were in some way limited during that intervening period. Due to the retrospective nature of this question and the panel structure of the survey, there are instances in which respondents report different ages of onset in different waves. In such cases, I follow Meyer and Mok (2019) and take the minimum reported age of onset as the actual onset age.[23]

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

[19] 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.

[20] 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.

[21] For instance, "are you limited in walking on a flat surface for 20 minutes without rest?" Some cognitive limitations, such as those related to learning conditions or developmental disabilities, are initially flagged based on diagnosis from medical professionals.

[22] I take this approach as the frequency questions is delivered in a consistent way for all survey waves and types of activity limitations.

[23] I do not observe additional disabilities that may have existed prior to those identified in the survey.

from those impacting cognitive or socio-emotional activities is common in the literature on the heterogeneous effect of disability. In the data, labour market and demographic descriptive statistics are more similar among activity limitations within physical than within mental-cognitive. However, this aggregation can mask underlying heterogeneity across the specific activity limitations within these categories.

The second step 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. 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, 2011). 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). There are instances in the data where respondents report limitation in multiple areas of activity limitation concurrently. However, I am unable to determine whether the limitations began simultaneously, or if one preceded the other. Because of this, I focus the analysis on mutually exclusive types and will leave the analysis of interaction effects for future research.

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.

The rate of disability in the population and the distribution of types is reported in Table 1. I find that 18.4% of the sample reports the onset of any activity limitation during their working life.[24] The majority of these are physical in

[24] I capture a relatively broad notion of disability in the population. For comparison, Meyer and Mok (2019) report disability rates between 11%

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, 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.

Studies on the variation in the effects of disability often consider heterogeneity by the severity of their impairment.[25] Unfortunately, severity is only observed when respondents take the survey but not when the disability onset occurs. I flag disability based on any positively reported frequency of limitation, capturing a relatively broad coverage of the disabled population. This approach minimizes the type II error of incorrectly flagging someone as not disabled. However, the disabled sample will include individuals with milder conditions that may not be considered disabled in other settings or by policymakers. 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 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.[26]

The disability measure in this paper 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,

and 15% in the calendar years of their empirical sample (1968-2015) from the PSID.

[25]Some examples of studies estimating the heterogeneous 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).

[26]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)

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.[27] 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, as described in Section 5 of the Appendix. 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.

IV.2 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.[28] 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. 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 drop observations that are missing key demographics. 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

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

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

sample to increase the size of the ever-disabled sample, and I include rich controls for sex in the empirical framework. 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.

V Empirical Framework

I use two separate models to analyze the dynamic effects of disability types. Each model shares a similar two-way fixed effects (TWFE) structure, but are reweighted in order to address different identification barriers. First, I apply the Interaction-Weighted estimator of Sun and Abraham (2021), which addresses bias in TWFE models when treatment effects are heterogeneous and treatment timing is staggered. Second, I use a propensity score matching (PSM) approach, as in Collischon, Hiesinger and Pohlan (2023), to address bias related to the non-randomness of disability onset. For each model, I use an event window of five pre-onset and ten post-onset periods, as in Meyer and Mok (2019) and Collischon, Hiesinger and Pohlan (2023).

V.1 Interaction-Weighted

I first 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).[29] 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).

To build intuition, I describe the estimand of interest and the identifying assumptions.[30] 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

[29] I obtain my estimates using the Stata command `eventstudyinteract` (Sun, 2021).

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

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 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,

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

where $CATT^g_{e,l}$ 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 $CATT^g_{e,l}$ 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_{le}, with the following two-way fixed effect regression,

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

where indicator variables for the l periods relative to treatment interacted with cohort indicators estimate $CATT_{e,l}$ for all e and l. A^g_{lit} is an indicator variables equaling one in year $t \in \{1982, \ ..., \ 2017\}$ with $l \in \{-5, ..., 10\}$ years relative to onset, and zero otherwise. A^g_{eit} are indicator variables equaling one in year t if i is in treatment cohort e, and zero otherwise. 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, weights are calculated for each $CATT_{e,l}$, $Pr(E_i = e | E_i \in \{-l, T-l\})$. Last, the IW estimator for the effect of treatment in relative period l is simply the average of $CATT_{e,l}$ over e weighted by $Pr(E_i = e | E_i \in \{-l, T-l\})$. The standard errors are clustered at the individual level.

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. The estimation sample includes a large control group of individuals that never become disabled.[31] The control group remains the same for each disability type. Causal interpretation of estimates is valid when satisfying a set of assumptions to ensure the control group's outcomes serve as a valid counterfactual to never being treated. These include assumptions on parallel trends

[31] A large control sample can mitigate collinearity in dynamic event study designs, which can arise when using pre-treatment observations as the control group (Borusyak and Jaravel, 2017).

before onset, the anticipation of disability onset, and heterogeneity in the treatment effect.[32]

The empirical specification accounts for various dimensions of treatment effect heterogeneity. First, the dynamic design separately estimates treatment effects in each period relative to disability onset, capturing their heterogeneity over 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.

Individuals experiencing a disability are a selected group. There exist differences in pre-onset characteristics between the ever- and never- disabled samples, as seen in Table 2 and Table 3 in Section 4 of the Appendix. To address the pre-onset differences, I include a rich set of time-varying control variables. First, the effect of a disability depends on one's pre-onset skills and the skill requirements of their work, as formalized by the model presented in Section 1 of the Appendix. While controlling for occupation is preferred, this variable is unavailable in the panel of incomes. Instead, I control for education level to capture differences in pre-disability skill types.[33] I interact education level with a second-order polynomial in age to control for life-cycle effects, and with a second-order polynomial of time since 1989 to control for trends in the effect of skills over time. Further, I control for marital status, sex, and number of children under the age of eighteen, which are determinants of government transfers and tax rates. Each of these are interacted with a second order polynomial's in age and time since 1989 to account for trends in the effects of these variables over the life-cycle and over time. Finally, I control for provincial fixed effects.

Last, identifying a causal effect involves a restriction on how respondents anticipate onset of their disability, as they may change behaviour prior to the year of reported onset. I remain agnostic about anticipatory effects before disability onset, and note where this assumption appears to be violated.[34] 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.[35]

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

[33] Education is measured as the highest completed certificate, which are grouped into high school dropout, college graduate, bachelor's degree, and degrees above a bachelor's.

[34] Violations in this assumption may be addressed by adjusting the treatment period such that the start of anticipatory effects (if known) becomes the new treatment date. However, in my data, it is not known when anticipatory effects may have began.

[35] This is described by the model in Section 2 of the Appendix, which formalizes how a gradual increases in extent of disability may occur prior

Due to the nature of my data, I cannot distinguish between these phenomena.

V.2 Propensity Score Matching

The onset of a disability is a nonrandom event and may depend on ones characteristics and past choices. To address the bias from the non randomness of disability onset, the second empirical model employs a propensity score matching (PSM) strategy. PSM mitigates this bias by ensuring that the treatment and comparison groups are similar regarding the observed characteristics that influence the likelihood of disability onset. By matching on the propensity score, PSM mimics a randomized experiment within the observational data, reducing the confounding effect of those characteristics. However, PSM can only control for observed and measured confounders, and bias from unobserved factors may still remain.

Specifically, I use a 5-nearest-neighbor PSM algorithm similar to Collischon, Hiesinger and Pohlan (2023). First, I calculate propensity scores, which give the probability of experiencing treatment (disability onset) conditional on a set of observed characteristics. Second, each individual in the ever-disabled group is matched to a set of individuals who do not experience a disability but have a similar propensity score. This ensures that the treatment and control groups are balanced on the observed characteristics that predict the onset of a disability. With the matched sample, I estimate

$$Y_{it} = \alpha_i + \gamma_t^g + X_{it}'\beta + \sum_l \delta_l^g A_{lit}^g + \epsilon_{it},$$

where i is individual, t is year, l is year relative to onset, and g is the disability type under consideration. This specification is similar to that specified above, and X_{it} contains the same set control variables as described above.

The specific matching procedure is as follows. First, I split sample by future disability status two years prior to the reported onset of a disability in the data. The control group is obtained based on the propensity score for disability onset occurring two years in the future. To calculate the propensity scores, I use a logistic regression to estimate the likelihood of disability onset two years in the future. Next, I find the five closest matches (nearest neighbors) based on the propensity score for each person in the treatment group. The outcomes of the five nearest neighbors are then used to construct my comparison group. I do this separately for each disability type using the same pre-matched sample and matching variables. I recover a unique set of propensity scores and matching weights for each disability type.

For matching variables, I use a set of pre-disability average income measures and individual characteristics. To control for labour market factors that affect one's disability risk, I match the previous five-year average participation rate and employment income. I match individuals' education level interacted with age and time since 1982 to control for skill differences. Given the well-known socioeconomic status-health gradient, I control for socioeconomic and

to its report in the data.

family factors using the average government transfer income and family total income in the previous five years. Additionally, I control for family composition, marital status, and sex, each interacted with age and number of years since 1982. Finally, I match based on the province of residence. The results of the matching procedure for each disability type, including the balancing of covariates and the t-scores for the matched and unmatched samples, are shown in Section 7 of the Appendix.

V.3 Robustness

As robustness, models for each dependent variable and disability type were estimated using the traditional unweighted TWFE specification. The results from these models almost exactly mirror the result's from the IW estimator. For brevity, I did not extract these additional results from the data center or include them in the paper.[36]

I conduct several robustness exercises using the traditional TWFE model. I examine how the estimates vary under alternative sample selection criteria and model specifications. The main empirical findings remain robust when (1) selecting a balanced panel of post-treatment, (2) excluding work-related disabilities, (3) conditioning on sex (longitudinal paths and cross type comparisons mostly hold, although magnitude of point estimates differ by sex), and (4) specifying the estimating equation as in Collischon, Hiesinger and Pohlan (2023) (for both for PSM and IW weighting procedures). More detailed descriptions of the robustness exercises and implications for the results are found in Section 5 of the Appendix.

VI Results

I begin the analysis by examining the effects of different disability types on market income in the years following onset. I then explore how government transfers and family members' income partially mitigate the impact on market income. Last, I assess the role of the tax system as an alternate mechanism for smoothing consumption after disability onset. I frame the discussion around short-run (corresponding to five or fewer years post-onset) and long-run effects (referring to six to ten years post-onset).

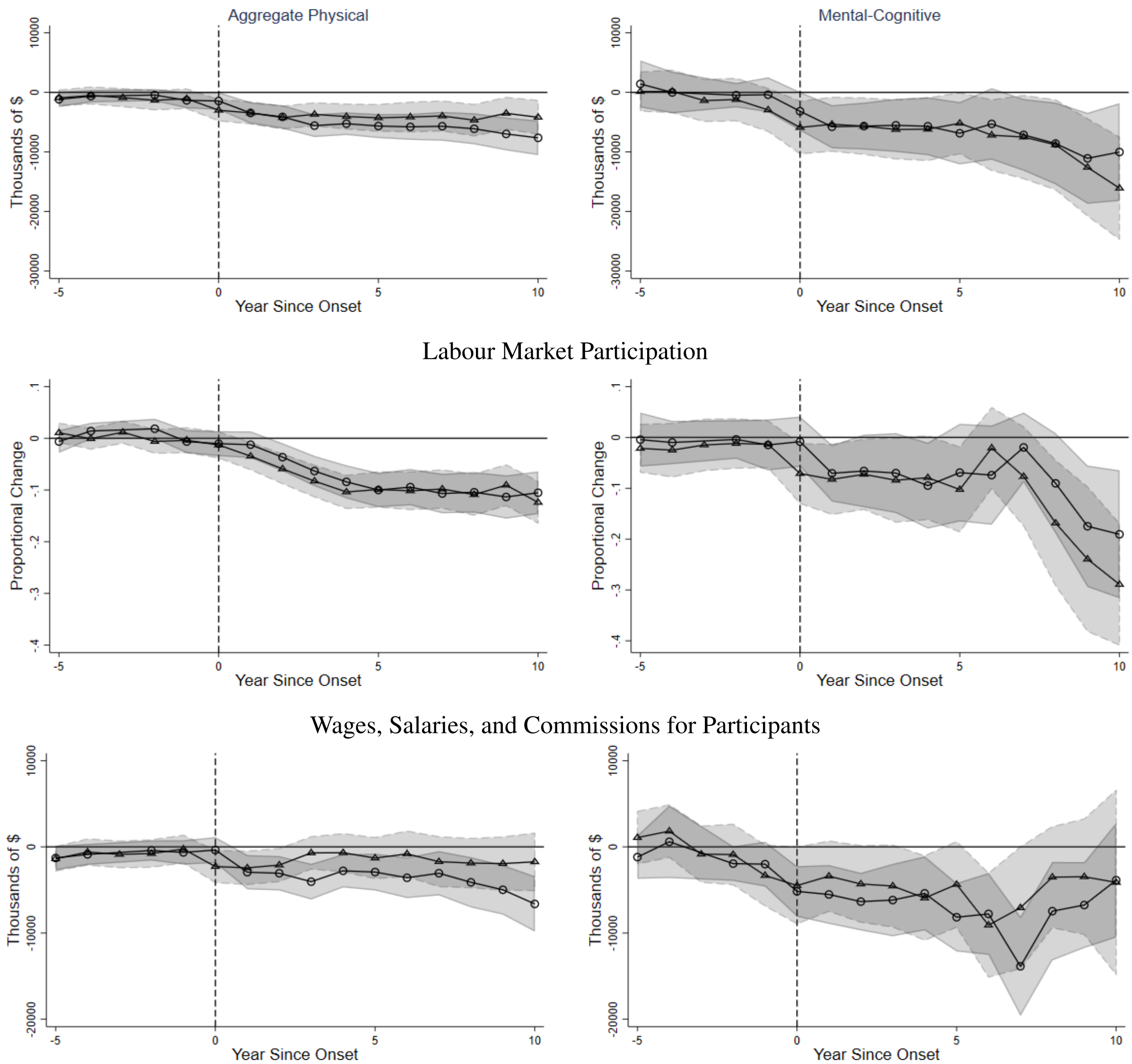
To illustrate the results, I present figures displaying the point estimates of the average effect of each disability type over the years $l \in \{-5, ..., 10\}$, relative to the reported onset year. In each figure, triangles represent the point estimates from the IW model, and circles represent the point estimates from the PSM model. The dashed shaded region indicates the 95% confidence interval for the IW model, and the solid edged shaded region indicates the 95% confidence interval for the PSM model. I discuss the differences in estimates from the IW and PSM models when apparent.

[36]Estimates from these models may be made available upon request.

VI.1 Market Income

Figure 1: Effect of Aggregate Disability Types on Market Income

Wages, Salaries, and Commissions (Level)



Notes: Figures present point estimates of the effects of disability onset in the $l \in \{-5, ..., 10\}$ periods relative to its reported onset. The triangles correspond to estimates from the IW model and the circles correspond to estimates from the PSM model. The 95% confidence intervals for the point estimates is represented by the dashed and solid edged shaded region for the IW and PSM model, respectively. Data on WSC is top-coded at the 99th percentile. Estimates and standard errors used to generate these figures are reported in Section 8 of the Appendix.

Market income includes all earnings from market activities, with the largest component being paid employment income in the form of WSC.An individual's employment income is directly tied to their productivity. A change in this measure following the onset of a given type reflects the impact on the corresponding type of human capital, and the importance of impaired functions in their work. Figure 1 presents estimates from models where the dependent variables are: unconditional WSC (top row), labour market participation (middle row), and WSC conditional on participation (bottom row).

The results for total WSC reveal distinct differences in the longitudinal effects of physical and mental-cognitive disabilities following onset. The onset of an aggregate physical disability results in modest but significant reductions in WSC that persists into the long run. WSC drops by -$5,623 on average in the post-onset years. In contrast, the onset of a mental-cognitive disability results in an immediate decline of $5,902 in the short run and this effect doubles in magnitude in the long run. To better understand the scale of these effects, it is helpful to express them as a percentage of pre-onset earnings. I calculate percentage effects where average pre-onset WSC is taken from Table 2 in Section 4 of the Appendix.[37] The onset of a mental-cognitive disability results in a greater loss in both the level and proportion of pre-onset income compared to the onset of an aggregate physical disability, with a substantial difference in the long run. The implied percentage changes for aggregate physical and mental-cognitive are plotted in Section 6 Appendix Figure 1. Focusing on the PSM model, the percentage effect of a mental-cognitive disability grows from -14% in the year following onset to -26% nine years onset. This percentage decline is 8 pp larger than physical disability nine years after onset.

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. Disabilities can distort work incentives in several ways; it can reduce productivity, raise the reservation wage through eligibility to disability programs in the social insurance environment, and impose additional costs and barriers to working, such as the need for workplace accommodations. The second row of Figure 1 examines the extensive margin by plotting the estimated effects of onset on labour market participation. The third row of Figure 1 plots the estimated effect of onset on WSC for participants, which reflects the combined effect on wages and the intensive margin. In the short run, the extensive margin effects of onset are of similar magnitude for both types, although labour market exit is more gradual for physical types. The effect of a physical disability remains relatively constant into the long run, 10 percentage points lower than the pre-onset rate. Mental-cognitive types show continued exit, reaching a 19 percentage point decrease ten years post-onset.

The effect of disability onset on WSC for participants is nearly twice as large for mental-cognitive compared to physical disabilities, both in the short run (-$3,150 vs -$6,320) and long run (-$4,472 vs -$7,943). WSC for participants rebounds for mental-cognitive disabilities seven years post-onset, which aligns with the sharp labour market exit

[37] A more direct approach involves a log transformation of the dependent variable or an estimation using a Poisson regression. However, both methods result in a loss of observations across each dependent variable. This causes the small differences in the estimation samples, creating a residual disclosure risk that prevents extracting results from the Statistics Canada Research and Data Center, as dropped observations are not consistent across the different income measures.

observed for this group. This suggests that the decline of unconditional WSC over time is driven by lower earnings for participants in the short run, and the exit of the least productive individuals from the labour market in the long run.

The estimates are mostly similar for the IW and PSM specifications. The estimated effect of physical on WSC is attenuated in the IW model relative to the PSM model, which appears to be driven by effects on participants. The implication is that the unbalanced control group are lower earners conditional on participation. For mental-cognitive disabilities, the IW model estimates a greater long-run effect on participation, suggesting that the unbalanced control sample have higher participation rates.

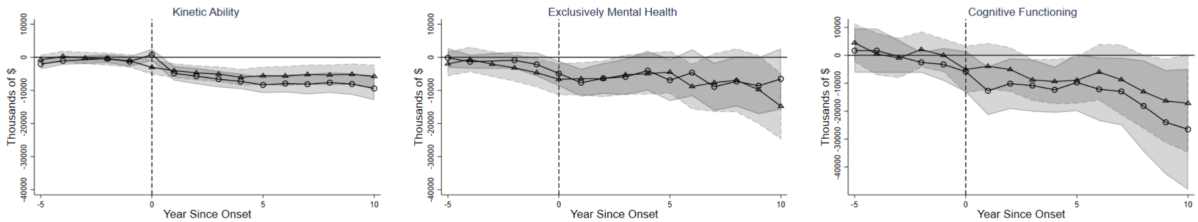
Relating these findings to the conceptual framework described in Section 1 of the Appedix, the results for market income are consistent with a higher market valuation for mental-cognitive skills (π) or a higher implicit skill price (θ) of mental-cognitive skills. These findings align with much of the 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.

The next set of results examines more granular types of physical and mental-cognitive disabilities. Figure 2 plots the point estimates for disabilities related to kinetic ability (left), exclusively mental health (center), and cognitive functioning (right). The impact of physical disabilities on market income is primarily driven by kinetic ability impairments. Point estimates on unconditional WSC, labour market participation, and WSC for participants mirror those of the aggregated physical disability group but are larger in magnitude. In contrast, the estimated effect of exclusively pain types (Figure 7 in Section 6 of the Appendix) are both noisy and insignificant. Disabilities affecting kinetic ability have a more intuitive link to productivity, as mobility and flexibility limitations hinder manual labour tasks, while dexterity impairments reduce productivity in hands-on work such as carpentry, landscaping, or musicianship. In comparison, the specific impact of pain-related disabilities on productive tasks is less clear. Including individuals whose limitations stem exclusively from pain attenuates the estimated effects of physical disabilities overall.

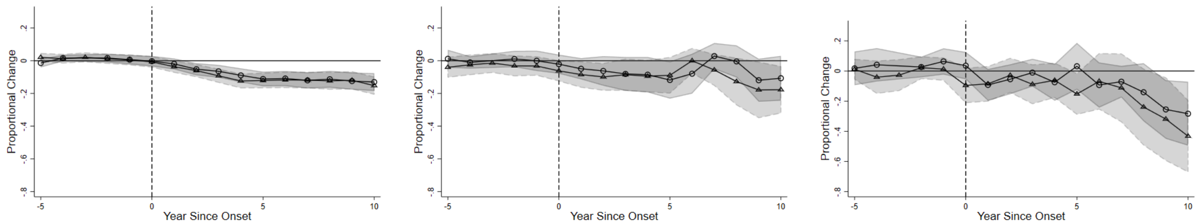
Cognitive functioning disabilities have substantial and worsening effects on WSC over time. In the short run, income declines by an average of \$11,153, deteriorating further by \$26,502 ten years after onset. Labour market participation falls by 17 percentage points in the long run, though there are no significant short-run effects. For participants, WSC declines by \$4,590 on average in the short run but rebounds in the long run, coinciding with the

Figure 2: Effect of Disability Types Within Mental-Cognitive on Market Income

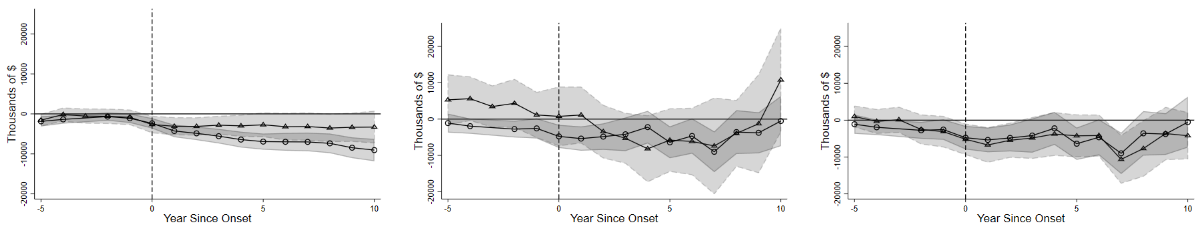
Wages, Salaries, and Commissions (Level)



Labour Market Participation



Wages, Salaries, and Commissions for Participants



Notes: Figures present point estimates of the effects of disability onset in the $l \in \{-5, ..., 10\}$ periods relative to its reported onset. The triangles correspond to estimates from the IW model and the circles correspond to estimates from the PSM model. The 95% confidence intervals for the point estimates is represented by the dashed and solid edged shaded region for the IW and PSM model, respectively. Data on WSC is top-coded at the 99th percentile. Estimates and standard errors used to generate these figures are reported in Section 8 of the Appendix.

increased in labour market exits.

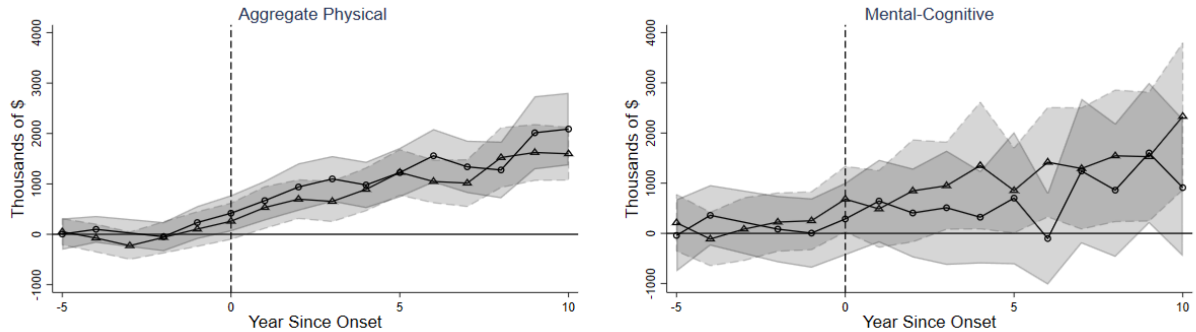
The estimated effects of exclusively mental health on WSC are similar in magnitude to those of kinetic ability impairments, averaging -\$6,172 in the short run and -\$7,188 in the long run. Labour market participation decreases by approximately 10 percentage points, though estimates are imprecise. WSC for participants in the short and medium terms but begins to rebound seven years post-onset. This pattern is similar to that observed with cognitive function disabilities, where declines in unconditional WSC are initially driven by lower earnings among participants and later by labour market exits.

VI.2 Government Transfers and Family Income

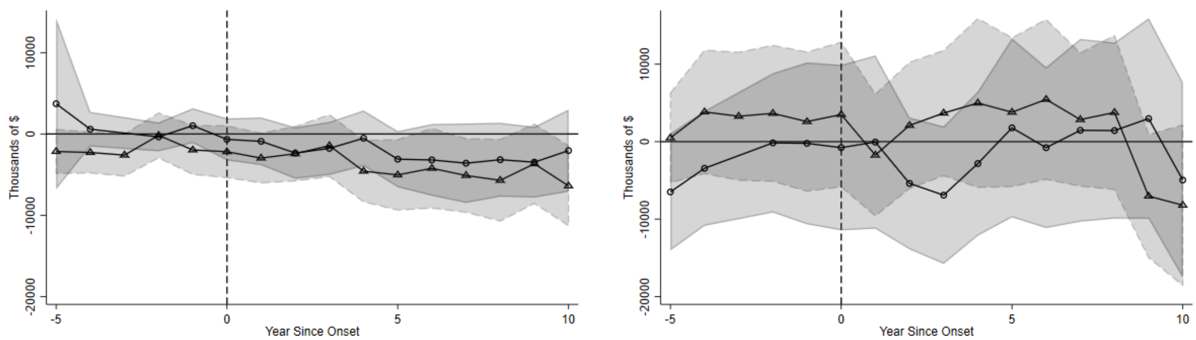
The results for market income find significant and varying effects on WSC and labour market participation for the different types of disabilities. This section examines how government transfers and family members' income respond

Figure 3: Effect of Aggregate Disability Types on Government Transfers and Family Income

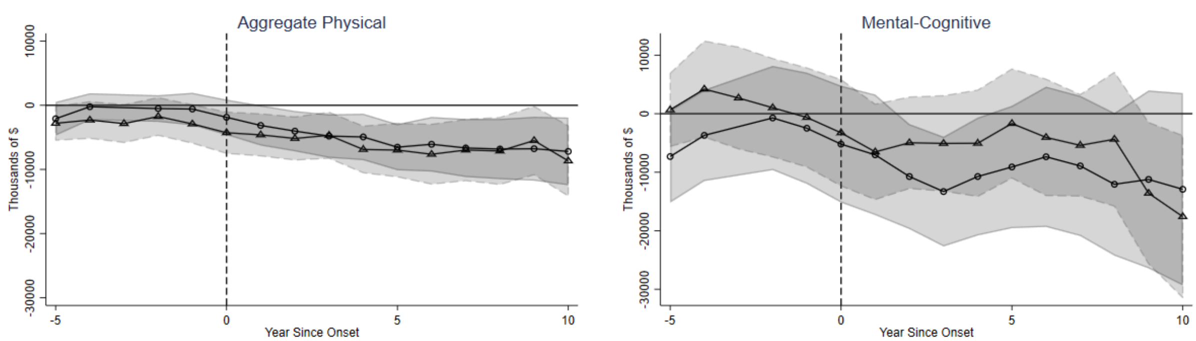
Total Government Transfers



Income of Family Members



Total Family Income



Notes: Figures present point estimates of the effects of disability onset in the $l \in \{-5, ..., 10\}$ periods relative to its reported onset. The triangles correspond to estimates from the IW model and the circles correspond to estimates from the PSM model. The 95% confidence intervals for the point estimates is represented by the dashed and solid edged shaded region for the IW and PSM model, respectively. Data on Total Family Income is top-coded at the 99th percentile. Estimates and standard errors used to generate these figures are reported in Section 8 of the Appendix.

to disability onset. Government transfers, which form the backbone of Canada's social safety net, provide income assistance and tax credits to individuals facing barriers to their economic independence. As productivity declines after the onset of a disability, labour market exit is often influenced by the uptake of these programs, which are designed to mitigate the financial impact of disability-related shocks. Differences in the uptake of government transfers, relative to a given income decline, reflect differences in coverage and eligibility criteria across types of disabilities. Moreover, the earnings of household members can act as an additional layer of financial insurance. To analyze this dynamic, the analysis estimates the effect of disability onset on both the total income of family members and the combined income of all household members.

Figure 3 shows results from models where the dependent variables are total government transfers (top row), income from family members (2nd row), and total family income (3rd row). The rise in total government transfers following the onset of a mental-cognitive disability is approximately two-thirds of the amount observed for physical disabilities. For physical disabilities, government transfers show an immediate and significant rise, averaging \$981 in the short run and increasing to \$1,650 on average in the long run. In contrast, mental-cognitive types yield significant increases only in the long run, with an average rise of \$903. For both types of disabilities, these increases primarily come from disability-specific transfer programs. Other family-relevant transfer programs, which are typically means-tested and triggered by declining income levels, do not appear to play a significant role, as shown in Figure 4 of Section 6 of the Appendix.

Following the onset of an physical disability, there is a significant reduction in the income of other family members in the IW model. This aligns with the hypothesis that family members substitute work for home care, as discussed in Fadlon and Nielsen (2021). However, while the point estimates from the PSM model are negative, they are not statistically significant. The lack of significance may be due to income support provided by family or friends -such as siblings or adult children- who are not dependents and, therefore, not linked through tax records. Total household income declines significantly after the onset of a physical disability, with the average reduction closely mirroring the decline in unconditional WSC. Similarly, the onset of a mental-cognitive disability results in significant short-run declines in total family income, averaging \$1,018. While the magnitude of this effect remains steady into the long run, the point estimates become increasingly noisy over time.

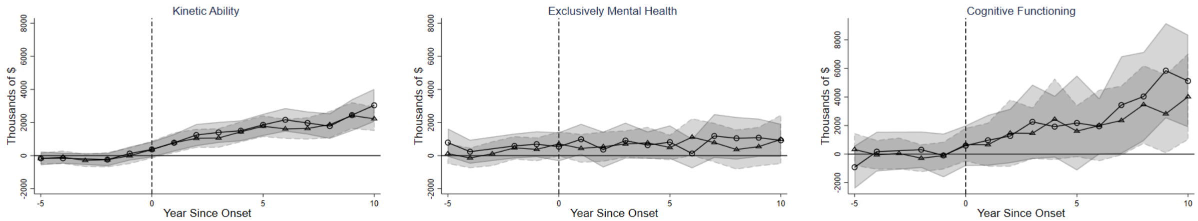
Results for the granular types of disabilities are presented in Figure 4. The increase in government transfers is driven entirely by disabilities related to kinetic ability. In contrast, as shown in Figure 8 of Appendix Section 6, the onset of a disability caused exclusively by pain does not significantly increase government transfers from either source.[38] For kinetic ability, government transfers increase by an average of \$1,357 in the short run and \$2,281 in the long run. However, neither type within aggregate physical disabilities significantly affects family-relevant transfers. Similarly, as observed with aggregate physical disabilities, there is no significant impact on family members' income. The decline in total family income closely matches the reduction in unconditional WSC.

In the long run, the onset of a disability related to cognitive functioning leads to a substantial increase in government transfers, peaking at \$5,839 nine years after onset. Short-run estimates are noisy and insignificant in both

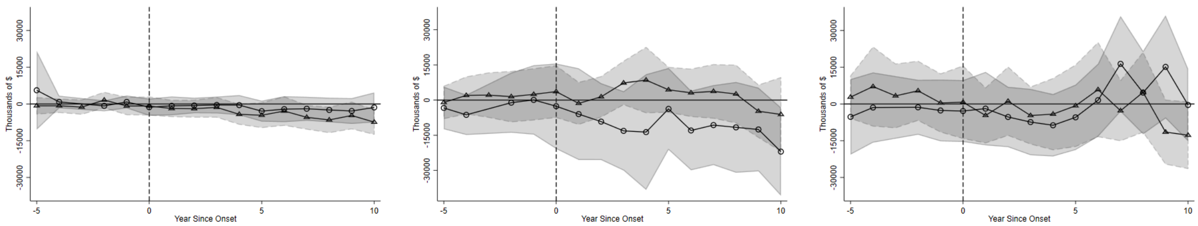
[38]The lack of significance for exclusively pain-related disabilities aligns with results for total WSC. These findings may also reflect challenges in verifying pain-related disabilities.

Figure 4: Effect of Disability Types Within Mental-Cognitive on Government Transfers and Family Income

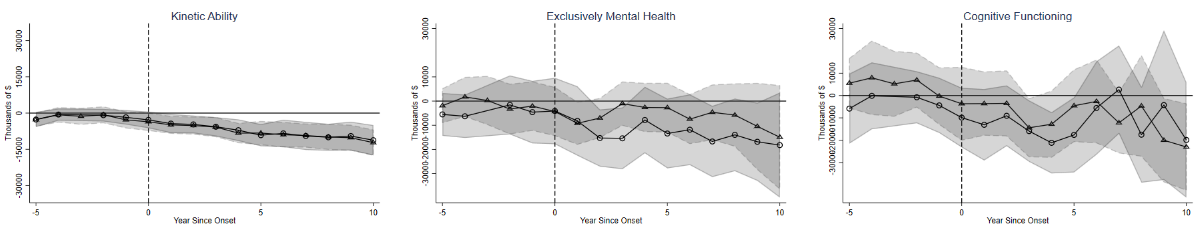
Total Government Transfers



Income of Family Members



Total Family Income



Notes: Figures present point estimates of the effects of disability onset in the $l \in \{-5, ..., 10\}$ periods relative to its reported onset. The triangles correspond to estimates from the IW model and the circles correspond to estimates from the PSM model. The 95% confidence intervals for the point estimates is represented by the dashed and solid edged shaded region for the IW and PSM model, respectively. Data on Total Family Income is top-coded at the 99th percentile. Estimates and standard errors used to generate these figures are reported in Section 8 of the Appendix.

model specifications, likely due to the small sample size of this group. As with other disability types, the increase in government transfers is primarily driven by disability-specific programs (Figure 3 of Section 6 in the Appendix). In the short run, total family income declines significantly by $15,380, but it rebounds over the long term. The recovery is accompanied by an increase in family members' income, which, though statistically insignificant, supports the hypothesis that family members may increase their labour supply over time to support individuals with cognitive disabilities—particularly in light of the significant labour market exit observed in the previous section.

In contrast, the onset of a mental health disability does not result in a significant increase in total government transfers. This finding is notable given its effects on WSC and labour market participation are comparable to those observed for kinetic ability. Additionally, total household income declines by an average of $8,662 in the short run and $12,030 in the long run. Family members' income also decreases, with a significant effect observed in the tenth period, averaging a drop of $9,141 in the short run and $12,957 in the long run. For exclusively mental health disabilities, the estimates from the IW model for family income and family members' income are higher than those from the PSM model, suggesting that family members in the unbalanced control sample have lower average income.

These findings indicate substantial gaps in the partial insurance provided by government transfers for mental health-related disabilities. Unlike kinetic disabilities, which present observable impairments, mental health conditions can be more difficult to verify, and their impact on work is often less clear. Only recently has mental health received broader acknowledgment for its economic and labour market implications. Consequently, individuals who develop mental health disabilities during their working years may need to seek alternative ways to smooth their consumption.

VI.3 Total Income Before and After Taxation

Table 2: Effect of Disability on Before and After-Tax Incomes

	Physical	Mental Cognitive	Kinetic Ability	Cognitive Functioning	Mental Health
Short Run					
Total Before-Tax ($)	-3318	-6595	-5290	-9100	-7538
Total After-Tax ($)	-2463	-5408	-4022	-5261	-6612
% Reduced	0.26	0.18	0.24	0.42	0.12
Long Run					
Total Before-Tax ($)	-4997	-9891	-7183	-16337	-7003
Total After-Tax ($)	-3987	-7382	-5472	-9316	-5787
% Reduced	0.20	0.25	0.24	0.43	0.17

Notes: Figures present the average of point estimates of the effects of disability onset in the short run ($l \in \{1, ..., 5\}$ periods relative to its reported onset) and long run($l \in \{6, ..., 10\}$ periods relative to its reported onset). Point estimates are obtained from the PSM model. Data on total before-tax and after-tax income is top-coded at the 99th percentile. Estimates and standard errors used to generate these figures are reported in Section 8 of the Appendix.

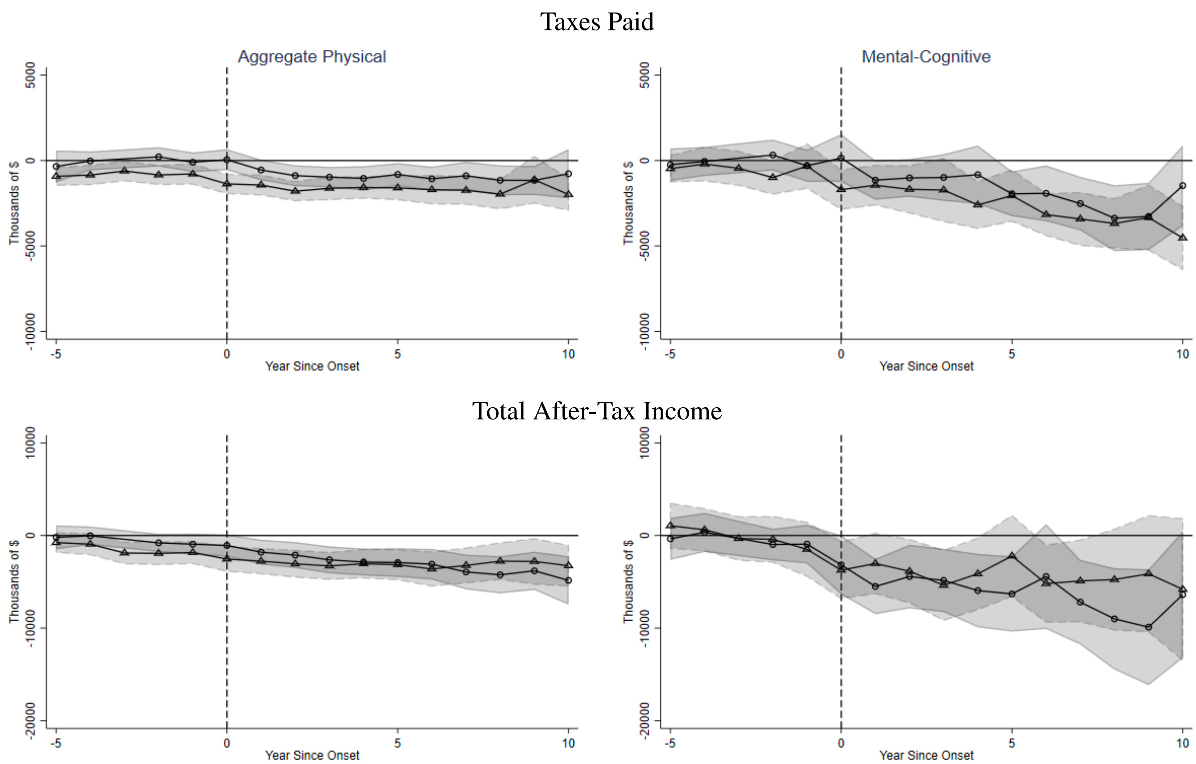
The final set of empirical results examines effects on total before-tax and after-tax income. Canada's tax and transfer system is progressive, which mitigates the impact of negative income shocks on take-home resources. First, the tax system exempts various sources of income, including many government transfers, thus reducing individuals' tax burden when they substitute to these nontaxable sources following an income shock. Additionally, because the tax system is progressive, any decline in income that places individuals in a lower tax bracket also lowers their marginal tax rate, further cushioning the impact of income shocks.

Table 2 reports the average total before-tax and total after-tax income in both the short and long run. Comparing these measures provides insight into the overall buffering effect of the total tax and transfer system. To quantify this for each disability type, I calculate the percentage reduction in the income-shock effect resulting from the tax and transfer system.[39]

[39] Specifically, this is calculated as; *% reduced = 1 - (total after-tax)/(total before-tax).*

Overall, the tax and transfer system reduces the income effects of disability for every type examined. For physical types, it offsets about a quarter of the before-tax income loss on average in the short run, and in the long run about one-fifth. However, cognitive disabilities experience a smaller short-run reduction of around one-fifth but a larger long-run reduction of about one-quarter. Examining more granular disability categories reveals stark differences in how the system mitigates these effects. For kinetic disabilities, roughly one-quarter of the negative impact on before-tax income is consistently offset, whereas cognitive disabilities benefit from a reduction of over 40% in the short run. In contrast, individuals with mental health disabilities see only a 12% offset in the short run and 17% in the long run.

Figure 5: Effect of Disability Types on Taxes Paid and Total After-Tax Income



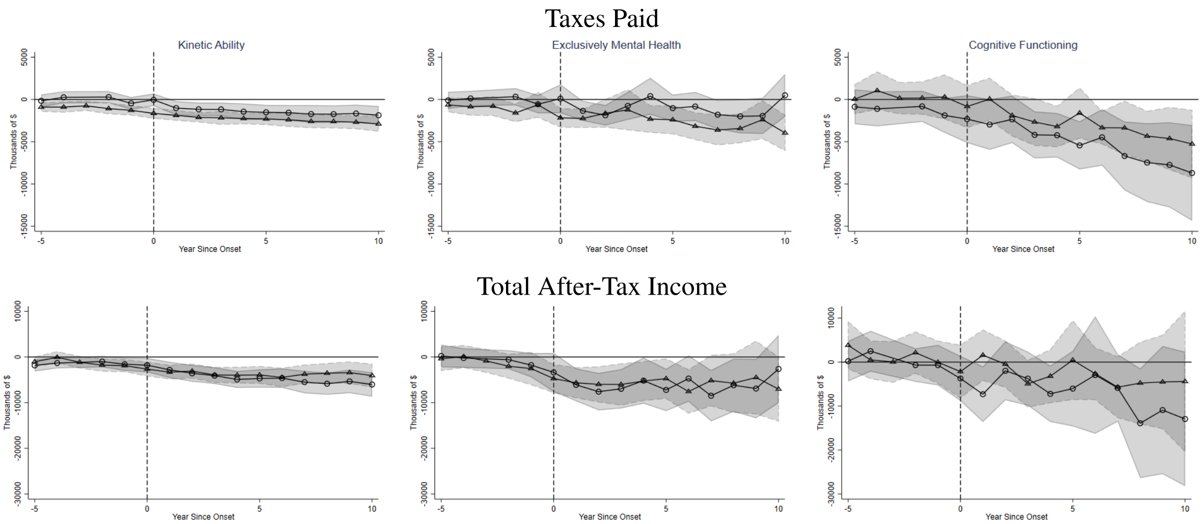
Notes: Figures present point estimates of the effects of disability onset in the $l \in \{-5, ..., 10\}$ periods relative to its reported onset. The triangles correspond to estimates from the IW model and the circles correspond to estimates from the PSM model. The 95% confidence intervals for the point estimates is represented by the dashed and solid edged shaded region for the IW and PSM model, respectively. Data on Total before-tax and after-tax income is top-coded at the 99th percentile. Estimates and standard errors used to generate these figures are reported in Section 8 of the Appendix.

To measure partial insurance from the tax system, Figure 5 presents the effects on net taxes paid.[40] The figure also presents estimated effects on total after-tax income, reflecting the impact of disability onset on take-home resources. Notable differences emerge in how the tax system smooths income between aggregate physical and mental-cognitive disabilities. Following onset, mental-cognitive disabilities result in an increasingly large decline in net taxes paid.

[40]Net taxes paid refers to total before-tax income minus total after-tax income.

Physical types show a more modest and persistent reduction in taxes paid of about $931 on average over the ten years post-onset. Estimates from the IW model are shifted downward for both disability types, indicating that the unbalanced control group, on average, pays higher taxes than the treatment groups—consistent with summary statistics showing these disability groups generally have lower earnings than the non-disabled sample. Although both physical and mental-cognitive groups receive partial insurance from the tax and transfer systems, each still experiences a persistent decline in total after-tax income following onset.

Figure 6: Effect of Disability Types on Taxes Paid and Total After-Tax Income



Notes: Figures present point estimates of the effects of disability onset in the $l \in \{-5, ..., 10\}$ periods relative to its reported onset. The triangles correspond to estimates from the IW model and the circles correspond to estimates from the PSM model. The 95% confidence intervals for the point estimates is represented by the dashed and solid edged shaded region for the IW and PSM model, respectively. Data on total before-tax and after-tax income is top-coded at the 99th percentile. Estimates and standard errors used to generate these figures are reported in Section 8 of the Appendix.

The final set of results in Figure 6 presents the effects of the more granular disability types on net taxes paid and total after-tax income. The results for kinetic ability closely mirror those of the aggregate physical group, which has been the case for all dependent variables considered. Kinetic ability disabilities result in clear increases in non-taxable income, and the tax system buffers some of the effects as well.[41] As with the aggregate physical group, the IW model is shifted downward from the PSM model, suggesting the nonbalanced control sample are higher taxpayers on average. As with the aggregate physical group, the IW model is shifted downward relative to the PSM model, suggesting that the unbalanced control group, on average, pays higher taxes.

Individuals with cognitive functioning disabilities receive significant partial insurance through a combination of reduced net taxes and higher government transfers. Although their total after-tax income does decline, the change is

[41] Disabilities related exclusively to pain produce low-magnitude point estimates that are largely insignificant. See the Appendix table for tax results related to pain and the IW model results on non-taxable income.

statistically insignificant. In this case, the IW model estimates that the unbalanced control group pays less in taxes on average.

Finally, individuals with mental health disabilities receive minimal partial insurance from the progressive tax system in the years after onset.[42] Among the more granular disability types, this group experiences the largest average short-run decline in after-tax income and the second-largest decline in the long run. These findings suggest a troubling lack of insurance for income losses following the onset of mental health disabilities. The next section explores the policy implications of this result.

VII Welfare Implications and Optimal Benefits

The last section of this paper considers the welfare implications of the empirical results. To do so, I apply the optimal insurance framework of Baily (1978), generalized to accommodate disability benefits by Chetty (2006). The key idea of this framework is that the optimal level of benefits balances the moral hazard relating to the work disincentives from disability benefits with the value of consumption smoothing following an income shock. I give an intuitive description of the framework, and defer to Chetty (2006) for a more detailed description of this model and its extensions.

The setting is that of a worker who faces risk over two states of the world, good and bad, where the bad state is disability in my application. The time spent in the bad state is endogenously chosen given the level of benefits, *b*, paid 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 worker's welfare by partially smoothing consumption across states. In the framework, it's assumed that 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 that is derived from the optimality of the agent's utility-maximizing decision. Assuming that preferences are independent of the state, then the Bailey-Chetty optimal benefit condition can be expressed as,

$$\gamma \frac{\Delta c}{c}(b) = \epsilon_{D,b} \ . \tag{1}$$

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

[42] Additionally, the estimated effects on total non-taxable income for mental health types are insignificant (see Appendix figure).

I make several simplifying assumptions to interpret my findings using this framework. First, I assume the change in consumption is proportional to after-tax income. This assumption is reasonable if savings are not a large source of consumption smoothing in the face of a disability shock. This is reasonable given longitudinal path in estimated effects resembled a permanent income shock. Moreover, this assumption ignores any consumption smoothing from family members. I found little evidence of family members' income increasing following onset, except for cognitive functioning in the long run. For mental health types, I found the income of family members to decline, suggesting my approach serves as an lower bound to the decline in consumption. 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 $\frac{\Delta c}{c}$.

In the table below, I calculate the implied γ that is consistent with optimal benefits for different choices of $\epsilon_{D,b}$. I can then compare this to values of γ from the related literature and determine whether disability benefits are optimal or not. First, I consider the elasticity from Meyer and Mok (2019), who set $\epsilon_{D,b} = 0.174$.[43] This paper conducts a similar application of the Bailey-Chetty Framework for disability shocks. However, their empirical work uses the PSID, and there are important differences in the policy environment between Canada and the USA, notably the health insurance system, that may impact this elasticity. I consider the lower and upper bound of the elasticity of labour market nonparticipation with respect to disability insurance benefit level from Gruber (2000). This study exploits quasi-experimental variation in the disability insurance benefit level from a 1987 reform in Canada. The reform took place in all provinces except for Quebec, and the elasticity is recovered using a difference-in-difference framework. His estimates imply the $\epsilon_{D,b} \in (0.28, 0.36)$

The coefficient of relative risk aversion (γ) consistent with optimal benefits under the Bailey-Chetty conditions, as shown in Table 3, ranges from 1.1 to 4.11 across disability types and values of $\epsilon_{D,b}$. Most of these γ values are on the lower end of those typically found in the literature. Notably, the implied optimal γ for the mental health group suggests that these individuals would need to be relatively less risk-averse for benefits to be optimal.

In the related literature, γ values generally range from 1.5 to 4.5 (Chandra and Samwick, 2009; Lockwood, 2018; Deshpande and Lockwood, 2022). In a meta-study of empirical estimates of the intertemporal elasticity of substitution (IES), Havránek (2015) finds the mean estimate of the IES is in the range of 0.3-0.4, which implies a γ of 2.5-3.3. Within this range, benefits are less than optimal for all types based on the elasticity from Meyer and Mok (2019). For the aggregated physical group, benefits are within the range of optimality under the elasticities from Gruber (2000). However, a more granular analysis shows that individuals with kinetic ability disabilities are under-insured at the lower

[43] Refer to Meyer and Mok (2019) for a description of how this elasticity was calculated.

Table 3: Consumption Change After Onset and Coefficient of Relative Risk Aversion Consistent with Optimal Benefits for Select Disability Types

	Physical	Mental-Cognitive	Kinetic Ability*	Mental Health	Cognitive Ability
Pre-Onset Consumption (c)	36860	40318	35855	41314	39809
Mean Change in Consumption (Δc)	-3225	-6395	-4747	-6199	-7288
$\Delta c/c$	-0.09	-0.16	-0.13	-0.15	-0.18
γ Consistent with Optimal Benefits					
$\epsilon_{D,b} = 0.174$	1.99	1.10	1.31	1.16	0.95
$\epsilon_{D,b} = 0.28$	3.20	1.77	2.12	1.87	1.53
$\epsilon_{D,b} = 0.36$	4.11	2.27	2.72	2.40	1.97

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. For each elasticity, $\epsilon_{D,b}$, the γ that is consistent with optimal benefits is calculated using equation (1) and the calculated change in consumption for each disability type.

bound $\epsilon_{D,b}$, though they fall within the optimal range of γ at the upper bound. In contrast, mental health disabilities remain sub-optimal across all elasticities considered. Cognitive functioning disabilities have the greatest deviation from optimal γ. However, this group sees increases in family members' income for this group, which can partially offset the sub-optimality. Overall, the findings suggest that current benefits are less than optimal across disability types.

VIII Conclusion

This paper offers a comprehensive analysis of how disability dynamically affects the components of personal income. It categorizes disability into mutually exclusive types based on the specific productive tasks that are impaired. The onset of a disability induces a permanent shock to income, and the welfare implications of this shock vary considerably across these types. The mechanisms underlying these findings are interpreted through a framework that connects disability to multidimensional human capital. The empirical results provide fresh insights into the considerable variation in how disability impacts earnings, employment, and sources of partial insurance.

Disabilities that impair physical tasks cause significant declines in market income, driven by both labour market exit and lower earnings for those who remain employed. After onset, government transfer payments, primarily from disability-relevant programs, steadily rise, and individuals pay less in taxes, providing partial insurance against lost market income. In contrast, the onset of a mental-cognitive disability results in relatively larger declines in market income, and a smaller share of these losses is offset by government transfers. Instead, individuals with mental-cognitive impairments rely more heavily on Canada's progressive tax system for partial insurance. As a result, their overall take-home resources decline more than those of individuals with physical disabilities.

Among the aggregate physical types, disabilities that impair kinetic ability are the driving force in the effects on market income and government transfers. Disabilities exclusively related to pain do not significantly affects wages, salaries, commissions, or government transfers, although they do result in modestly exit from the labour market. Disabilities that hinder cognitive functions lead to the largest drop in market income and a considerable rise in transfer payments from disability-relevant programs, coinciding with a sharp long-run decline in labour force participation. In contrast, mental health disabilities do not receive significant partial insurance via transfers, the tax system, or household income adjustment from family members, despite having similarly large impacts on market income as kinetic ability disabilities.

Finally, a welfare analysis of these results suggests that gaps in optimal partial insurance exists across the disability types. In the case of mental health disabilities, current benefit levels are only optimal if affected individuals are less risk-averse than what much of the literature would suggest.

This analysis sheds light on how disability relates to the various skill components highlighted in task-based human capital research. Although it provides novel estimates of the effects of different disability types, the paper does not directly capture skill heterogeneity or the specific tasks performed at the time of disability onset. A more comprehensive examination that integrates skills, job requirements, and multidimensional disability types is left for future work. Furthermore, because the data cannot adequately support analyses of interaction effects across multiple dimensions, this study focuses on mutually exclusive disability types. Future research into such interaction effects remains crucial for understanding how health comorbidities reduce productivity across different aspects of human capital.

IX Declaration of generative AI and AI-assisted technologies in the writing process.

During the preparation of this work the author(s) used ChatGPT and Microsoft Pilot in order to copy edit the written text in the paper. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the published article.

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