The Effect of Household Earnings on Child School Mental Health Designations: Evidence from Administrative Data

Lauren Jones, Mark Stabile, Kourtney Koebel, Jill Furzer*

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Abstract

We investigate the impact of household earnings shocks on in-school mental health designations in the context of the Great Recession using a unique data set of linked administrative educational and tax data, and propensity score matching. Relative to children who did not experience recessionary earnings losses, the rate of new mental health designations among children with earnings losses was 0.5 percentage points higher (20 percent) during the recession. The effect of experiencing a recessionary earnings loss is persistent and grows, especially among children who experienced the loss when they were aged 10 or younger.

*Lauren E. Jones is an associate professor in the Glenn College of Public Affairs at The Ohio State University. Mark Stabile is the James M. and Cathleen D. Stone Distinguished Chair in Wealth Inequality and Professor of Economics at INSEAD and CEPR (corresponding author: mark.stabile@insead.edu). Kourtney Koebel is a postdoctoral fellow in the Department of Economics and the Institute for Gender and the Economy at the University of Toronto. Jill Furzer is a Senior Economist at Keystone Strategy.

Data Availability Statement

This paper uses confidential data from the Statistics Canada Research Data Centres. The data can be obtained by applying directly to the RDC. The authors are willing to provide all code (Kourtney Koebel).

Disclosure Statement

The authors have nothing to disclose.

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I Introduction

Prevalence and severity of mental health conditions among children and adolescents continue to worsen. The OECD suggests that between 10 and 20 percent of children worldwide suffer from mental health challenges, with increasing prevalence of certain conditions like anxiety and depression (Burns and Gottschalk 2019). Beyond the direct health challenges of mental illness, experiencing a mental health disorder during childhood and adolescence can have persistent effects on educational attainment and labor market outcomes (Currie et al. 2010). As such, understanding external triggers of mental health conditions among children is vital. One possible trigger may be sudden changes to family earnings. In this study, we use a unique administrative dataset covering the entire population of children enrolled in public schools in the Canadian province of British Columbia (BC) to estimate how fluctuations in household earnings impact in-school mental health designations. Our empirical approach makes use of the Great Recession of 2007 to 2009 as an unanticipated shock to household earnings.

There are relatively few studies that estimate the effect of income on child mental health (see Cooper and Stewart (2021) and Jones and Stabile (2023) for reviews). Those employing causal research strategies generally find evidence of a direct relationship between increases in household income and reductions in reports of social, emotional and behavioral development (Costello et al. 2003; Akee et al. 2010; Milligan and Stabile 2011; Hamad and Rehkopf 2016). A second line of literature, focusing on the Great Recession in particular, has demonstrated that aggregate measures of local economic conditions like unemployment and foreclosure rates were negatively associated with mental health symptoms and diagnoses among children (Cotti and Simon 2018; Currie and Tekin 2015; Gassman-Pines, Ananat, and Gibson-Davis 2014; Golberstein, Gonzales, and Meara 2019; Page, Schaller, and Simon 2019). Finally, several studies show that parental job loss is associated with worse parent-reported child mental health symptoms (Schaller and Zerpa 2019; Cooper and Stewart 2021). However, because of data limitations, these studies tend to use survey data with relatively small samples, self-reports of mental health symptoms, and/or self-reports of household resources, all of which may bias estimated associations between income fluctuations and child mental health. No previous studies have used administrative data on *both* household earnings and mental health conditions to estimate the effects of household earnings fluctuations on children's mental health.

We address this gap in the literature by using a unique administrative dataset that links administrative school records for every child in BC public and independent schools to parental tax records. The linked dataset encompasses longitudinal mental health designations and household income for over 250,000 children between 2002 and 2015, along with select child and household demographics. The use of these data distinguishes our study from existing work along several dimensions. First, we can measure and track annual household earnings accurately using tax records, thus mitigating issues associated with self-reported measures. Second, we can accurately identify in-school mental health designations from administrative school records, allowing us to track a student's mental health status over time without relying on parental reports. Third, we can link these two data sources together, allowing us to estimate the effect of household earnings losses on individual diagnoses. These advantages present an important advance in the literature on household earnings and child mental health conditions, where existing studies use survey-based, self-reported, or aggregate measures of either mental health conditions, economic conditions, or both. Our large sample size also allows us to identify changes in officially recognized mental health designations in schools, an event that remains relatively rare in our data. Finally, the long time horizon of our study – 14 years – allows us to track mental health trajectories for individual children over many years.

We derive our mental health measures from thirteen categories of special education need within our linked school administration files. These include moderate mental health or behavioural issues (i.e., aggression or hyperactivity) and severe mental health or behavioural issues requiring intensive support (i.e., extremely disruptive behaviour in most environments that is persistent over time). In-school mental health designations have increased substantially over time in BC. As displayed in Figure 1, the proportion of children ever having received a designation for a moderate or severe mental health condition increases from a total of around two percent in 2002 to a total of nearly seven percent in 2015. Figure 1 also reveals a distinct increase in the rates of these designations starting in the 2007/2008 school year and continuing through the 2010/2011 school year.[i] It is this anomaly, observable in the raw data, that we seek to explore further.

Our empirical approach involves examining differences in rates of in-school mental health designations among children in families that experienced an earnings loss in 2008 or 2009 relative to pre-recession earnings, versus children in families that did not. We use the Great Recession as an exogenous source of income variation given that it generated profound and acute economic stress within households across the world. For example, in the United States, nearly one in six workers lost their job between 2007 and 2009 (Farber 2011). In Canada, the unemployment rate increased 35 percent between 2008 and 2009, resulting in a net loss of 400,000 jobs (Larochelle-Côté and Gilmore 2009). The acute and sudden nature of job loss induced by the Great Recession thus provides an opportunity to study how a plausibly exogenous change in household earnings affects mental health among children. Moreover, because job losses during the Great Recession were concentrated in specific industries like manufacturing, construction and finance (Larochelle-Côté and Gilmore 2009), the particular mix of industries in a region will also impact the extent to which families experience economic hardship. In British Columbia, the unemployment rates in finance and related industries, manufacturing, forestry and other extractive industries, construction, and transportation more than doubled between 2008 and 2009 (Statistics Canada 2022) (see appendix Figure A1). The unanticipated timing of the recession, together with differences in the industrial composition of local labour markets, drive a sudden change in household earnings that should not be otherwise correlated with mental health incidence.

In addition to exploiting recessionary variation in household earnings, we use propensity score matching on pre-recession household covariates to create a cohort of treated children and comparable children who did not experience a loss. We then estimate a series of event study regressions to test for trend differentials in moderate and severe mental illness designations across children. To test the robustness of our result, we generate multiple measures of household earnings losses relative to both 2006 earnings, and to pre-recession permanent earnings (the average of household earnings between 2002 and 2006). We further conduct an analysis focusing on mothers' earnings losses and explore how our results differ across relevant child demographics, such as Indigenous identity, gender, home language, and child age. Finally, as a supplemental identification strategy, we report results of a Bartik two-stage regression that uses the 2006 employment shares across industries in the local labor market and the national trends in employment in these industries to predict household earnings.

Our event study estimates indicate that new, in-school designations of mental health disorders increased by 0.5 percentage points during the recession among children in families with an earnings loss. This effect is a 20 percent increase from the pre-recession mean. We also find that the rate of new mental health designations increased among treated children for both moderate and severe mental health designations. This phenomenon appears specific to mental health issues, as we do not find similar increases in physical health disorders.

We additionally find evidence of a persistent and increasing effect of recessionary household earnings losses on mental health designations. By 2015, rates of new mental health designations among children who experienced a household earnings loss in 2008 or 2009 are 0.7 percentage points, or 28 percent, higher than among comparable children having experienced no loss. The persistent effect of recessionary earnings losses on mental health designations is driven by children who were age 10 and younger at the time of the recession, who exhibit increased rates of diagnosis as they enter high school in 2011 at ages 12 to 14. This persistent effect is explained in part by the fact that the earnings of families who experienced a loss in 2008 or 2009 do not fully recover by the end of our sample period.

We conduct several heterogeneity analyses which reveal that the relative effects of income loss on child mental health are very large among girls who have a low baseline designation rate. We find that girls in households with recessionary earnings losses exhibit rates of new mental health designations that are more than 50 percent higher than comparable girls in households that did not lose earnings. We also find that Indigenous children – who have very high baseline rates of mental health designations – do not exhibit increasing rates of new mental health designations after experiencing a recessionary loss in household earnings. Earnings losses among mothers produce similar effect sizes as losses driven by either parent. Finally, the relationship between household earnings and in-school mental health designations is confirmed in our Bartik analysis, which reveals that an additional $1,000 in household earnings is associated with a 0.1 percentage point reduction in the rate of new mental health designations.

II Literature and Contribution

A. Previous Literature

There is a well-developed theoretical link between household economic conditions and child health (Currie 2009; Grossman 2000). Using a classic health production framework, health outcomes are a function of money devoted to health inputs – such as nutritious food and medical care – and time spent on producing health. Shocks to household income generated by economic downturns could impact both factors. In the case of mental health, a reduction in household income reduces the money available for health inputs like psychiatric care or enriching activities.[ii] Recessionary income losses – whether due to job loss, reduced working hours or wage cuts – are also stressful; such stress may trickle down to children, worsening mental health outcomes. By contrast, if household income losses are generated by job loss or reduced hours, families may have more time to spend with children, potentially improving mental health. Thus, the predicted effect of recessionary income shocks on child mental health is ambiguous.

Findings from the empirical literature on income and child mental health have not helped resolve this ambiguity. On the one hand, there is a strong, positive income gradient in mental health, with children from more affluent families exhibiting lower incidence of mental health conditions (Currie 2009; Johnston et al. 2014; Reiss 2013; Strohschein, 2005; Taylor, Dearing, and Mccartney 2004). Results of several causal studies also suggest that exogenous positive income shocks lead to improvements in mental health. Using changes in after-tax income generated by policy changes, researchers have demonstrated significant improvements in reported symptoms in a host of mental health and behavioral outcomes (Costello et al. 2003; Hamad and Rehkopf 2016; Milligan and Stabile 2011).[iii] These studies focus on the effect of income transfers, and therefore offer relatively strong evidence of a causal relationship between after-tax income and child mental health. However, as these studies focus only on *gains* in after-tax-and-transfer income, their external validity may be limited when trying to understand potentially asymmetric impacts of relatively larger negative income shocks. Additionally, income transfer studies do not shed light on the potential mental health responses to greater stress within the home due to income loss, or to sifting time use patterns generated by job losses.

On the other hand, evidence on the effect of transitory income changes within households on child mental health, while more generalizable than the studies above, demonstrates a weaker relationship between income and outcomes (c.f. Aughinbaugh and Gittleman 2003; Berger, Paxson, and Waldfogel 2009; Blau 1999; Mayer 1997). These studies suggest that positive associations between income and mental health are driven by factors associated with income – such as parental education or the home environment – rather than income itself (Berger, Paxson, and Waldfogel, 2009; Yeung, Linver, and Brooks–Gunn 2002). However, these studies tend to use fixed effects strategies that may not fully rule out endogeneity.

To help address these potential endogeneity concerns and understand the impact of negative income changes, some authors have focused on job loss. While transitory income changes could be the result of parental choice – or parental responses to pre-existing child mental health challenges – displacements are generally outside the control of workers and therefore an arguably exogenous shock to household earnings. Identification is therefore simpler in the case of job loss. A job loss, of course, represents a particular type of income change that may produce additional stress that also affects child mental health (Leana and Feldman 1988; Eliason and Storrie 2009; Kuhn et al. 2009). Job losses may also free up time to spend with children, thereby improving outcomes, particularly when mothers lose their jobs (Page, Schaller and Simon 2019).[iv,v] Studies of the effect of job loss on families therefore do not map perfectly to the literature on income and child outcomes more generally. Nonetheless, the job loss literature informs our analysis given its focus on a discrete event that is likely an important driver of negative income shocks – like a recession.

B. Contribution of this study

Our study falls at the nexus of these related lines of literature. We examine the effect of an earnings loss on child mental health, focusing on losses that occurred during the Great Recession. Our approach allows us to study a broad-based and large earnings change that affected tens of thousands of families – thereby improving the external validity of the study relative to existing studies that use small samples or idiosyncratic policy experiments. We argue that recessionary earnings shocks are more likely to be exogenous than general, transitory income changes, especially since our large sample size allows us to control for a rich set of fixed effects and demographics. Previous work has treated job loss as exogenous (Jacobson, Lalonde, and Sullivan 1993; Stevens 1997); recessionary job losses, in particular, are more likely to be prompted by industry- and business-level shocks rather than family characteristics or preferences (Page, Stevens, and Lindo 2009). However, we use both propensity score matching and a Bartik analysis to address remaining potential endogeneity issues.

To the best of our knowledge, we are the first study to use administrative records on both mental health conditions and household income to study the effect of income on child outcomes. The use of a large administrative dataset is especially important when investigating mental health conditions, many of which are relatively rare events and therefore require large sample sizes to explore effectively. The near-census sample also means that we are less concerned about sampling or attrition biases. More specifically, our follow-up period of (up to) eight years after the recession allows us to explore the dynamics of an income shock without the attrition problems often found in longitudinal surveys. Finally, using administrative records for a population of children may be relatively more generalizable than a sample of survey respondents or persons enrolled in a specific private or public health insurance plan.

We are also the first study to look at the impact of a recession on mental health as identified in school. This is important as educational settings are one of the most common entry points for children to receive mental health services (Farmer et al. 2003). An estimated 3.2 million students in the United States receive mental health services at school (Lipari et al. 2016), and just over one-third of students in need receive mental health services exclusively from school (Ali et al. 2019).[vi] As we detail below, the Canadian context also provides an ideal setting to study household earnings changes generated by macroeconomic fluctuations because of the structure of school financing, where budgets are relatively unaffected by recessions, and the universal health care system. Therefore, the estimates in our context provide evidence of the impact of household earnings on mental health through individual-level channels, exclusive of any impacts on school budgets or health care access (Jackson et al. 2021).

III Background and Context

A. Provincial School Context; In-school Mental Health Diagnoses and Special Education Funding

The elementary and secondary school system in British Columbia is comprised of public schools, private (for-profit) schools, and independent schools, which are private, not-for-profit schools. In 2006, approximately 90 percent of children in British Columbia between the ages of five and 19 were served by public schools (Statistics Canada 2021b). Both public and independent schools receive funding from the provincial ministry of education, including funding for special needs education.

Assignment of mental health designations in public and independent schools are directed by the BC Special Education Policy Framework, summarized in the *Special Education Services: A Manual of Policies, Procedures and Guidelines* (British Columbia Ministry of Education 2016a). The manual lays out the process that leads to a student being identified as having special needs, which include physical, intellectual, sensory, emotional, behavioral, or learning disabilities, as well as special gifts or talents. The identification process begins with a teacher or a parent, and in addition to a physician's diagnosis, requires that a student's difficulty is sustained and disruptive to their own or classroom learning (i.e., a medical diagnosis is not sufficient in the case of disorders such as ADHD). Students who are identified as having special needs are provided with an Individual Education Plan (IEP), as well as access to in-school learning assistance services, speech-language pathology services, or school and community counseling and psychology services, as needed.

The special needs identification process places students into one of 13 categories, which we list in Appendix Table A1. For our purposes, we focus on the moderate behavioral needs or mental illness (which we call *moderate mental health)* and the intensive behavioral needs and serious mental health categories (*severe mental health)*. Students classified in the moderate mental health category include those exhibiting aggression, hyperactivity, substance abuse, delinquency or child abuse and neglect; or those diagnosed by a medical practitioner with anxiety, depression, thought disorders, neurological or physiological conditions for whom the frequency, severity or duration of the behaviors or internalized states are very disruptive to learning. Students in the severe mental health category are those whose behavior is extremely antisocial or disruptive in most environments, or who have been diagnosed with a serious mental health condition and are considered "at-risk" without extensive support. Note that these mental health designations require diagnosis by a physician (British Columbia Ministry of Education 2016a). We also create indicators for *autism spectrum disorder* and *general physical health conditions* (including deaf-blind, physically dependent, deaf or hard of hearing, visual impairment, or physical disability).

Since 2002, most funding for special education needs (SEN) has been provided through the general, student-base funding mechanism in the form of Special Education Core Funding.[vii] However, some special needs classifications result in supplemental, per student, funding for schools (Appendix Table A1). Each type of special need is classified as Level 1, 2, 3 or no-funding. Students with Level 1 special needs include the Deaf-Blind and those who are completely physically dependent on others for meeting daily living needs. In 2015/2016, schools serving a student with a Level 1 need received $37,700 (Canadian dollars) in funding per academic year. Level 2 needs include autism spectrum disorder, deafness, visual impairments, as well as intellectual disabilities, moderate physical disabilities, or chronic health impairments; schools serving a Level 2 student received $18,850 in supplemental annual funding. Level 3 needs include serious mental health disorders, or those needing intensive behavioral interventions (*severe mental health)*, and schools received $9,500 in supplemental funding for these students. Finally, schools serving students with learning disabilities, mild intellectual disabilities, or moderate mental illness (*moderate mental health)* do not receive any supplemental funding for designated children.[viii]

Children and adolescents in BC also have several options for accessing publicly funded mental health care outside of school. Children in British Columbia registered with the BC Medical Services Plan (MSP) are eligible for free access to publicly funded physician and hospital services. Children diagnosed with neurological disorders regularly access both general practitioners and specialist pediatric services (Arim et. al., 2017). All Provinces also employ publicly funded child and youth psychologists, though these are often limited in number (Peachey, Hicks,

& Adams, 2013) and may have wait lists as long as 18 months (Mental Health Commission 2017). Child disability services are also available outside of school but appear to be more commonly used for disorders such as ASD rather than emotional and behavioral disorders (Russell et. al., 2021).

Private care through a child psychologist, counsellor, or social worker is also available in Canada and is covered through either out-of-pocket payment or supplemental private health insurance (Ronis, Slauwhite, & Malcom, 2017). This private health insurance is either purchased privately by a parent or obtained through an employer. Most plans set a dollar amount covered per visit up to a maximum dollar amount per year. The remainder of the cost for private mental health care must be paid out of pocket. Data on the precise proportion of private versus public mental health care use in Canada for either child and youth populations or the adult population is sparse. However, Canadians appear to spend substantially less out-of-pocket on mental health care than other similar countries. The most recent comparator data shows that only 7.2% of total private and public health care spending in 2015 was spent on mental health services in Canada. In the UK, this figure was 13% (Mental Health Commission 2017).

B. The Social Safety Net and Families with Children

The Canadian and British Columbian contexts are characterized by relatively strong social safety nets for families with children. While we focus on earnings changes, changes in total household resources will not vary as dramatically because of the insurance offered by these safety nets. In the era of our study, the largest programs available to insure against income loss for families with children were federal, tax-based programs like the Canadian Child Tax Benefit and Universal Child Care Benefit, federal Employment Insurance (EI), and BC-specific programs like Income Assistance (for unemployed families who are not eligible for federal EI). Programs such as EI offer immediate income loss insurance of up to 55% of wages. [ix] Others like the child tax benefit programs cannot insure against immediate income losses as they are based on last year’s earnings and therefore do not adjust until the year following a job loss. We conduct a robustness analysis using a measure of household income that includes benefits that families receive through the tax system.

IV Analytical Strategy

A. Data

1. Administrative School Files

Our data consists of longitudinal school administrative records for all students enrolled in a public or independent school in the province of British Columbia, Canada between the 2002/2003 and 2015/2016 school years. The school administrative files contain annual information for each child, each of whom is followed across years if they remain enrolled in a public or independent BC school. The administrative records note the child's birthdate, sex, home language, and self-reported Indigenous status. We are also able to observe which school the child attends every year, including information on whether the school is public or independent, and whether the school is a regular stream school or provides alternative education. We restrict our sample to children born between the years 1993 and 2000 and who are between six and 17 years of age in the data sample. This creates an unbalanced panel with students moving in and then out of the sample as they age. We also restrict the sample to students observed in the education file in either 2008 or 2009 to ensure that we have at least one recessionary observation for each child.

The school administrative files contain information on identified special education needs (SEN) every year. As detailed above, there are 13 categories of special education need across various physical, intellectual, mental, and other chronic health needs (See Appendix Table A1). Our outcomes are indicator variables for *moderate* and *severe mental health disorders*, as well as for *autism spectrum disorder* and *general physical health conditions* (including deaf-blind, physically dependent, deaf or hard of hearing, visual impairment, or physical disability). Each of these indicators is set equal to one on the first instance of a given SEN designation and remains equal to one for all years thereafter, creating indicators of a child having ever received the SEN designation.

Using SEN designation as a measure of mental health prevalence will likely result in an underestimation of true mental health disorders. In-school designations require first, a diagnosis by a qualified mental health clinician, second, that the behaviours be displayed in multiple settings, and finally, that the behaviour impacts their own learning and/or their classmates' learning (BC Ministry of Education 2016a, pg. 56). Given the requirement for a negative impact on learning, there may be many children with mental health disorders who do not require educational supports and therefore do not receive SEN designations, leading to an undercounting of the true prevalence. Furthermore, there is a significant administrative burden required to attach an in-school SEN designation to a child with a mental health need, which may further limit which children receive designations. Finally, our administrative data records only one main diagnosis per year. As many children will have multiple designations representing co-morbidities, this data feature may reduce the overall prevalence rate. Particularly because mental health disorders are associated with less funding versus some physical disorders, mental health may be more likely to be a "secondary" disorder and not recorded. Altogether, we find some evidence of undercounting in our data given the mental health designation rate of roughly four percent across all years. For comparison, data from BC's public health care system indicate that about seven percent of six to 19 year olds are diagnosed with ADHD, and about 14 percent are diagnosed with a depression or anxiety. There is significant overlap in these diagnostic groups, since 20 to 30 percent of affected children suffer from multiple mental health commodities (Gadermann et al. 2022).

2. *Administrative Tax Files and Linkage*

For each student-school year observation in the education data, we link parental administrative tax records for the corresponding tax year. The tax files are a subset of the Statistics Canada T1 Family File (T1FF) and contain information on annual earnings, annual total income, tax benefits, and select demographics as reported to the Canada Revenue Agency for tax filing purposes. We attach earnings data for tax year y to education data for the school year beginning in year y (e.g., 2003 tax data is linked to the 2003/2004 school year). Unlike the US system where children are included on parental tax returns using a Social Security Number, prior to 2010, Canadian federal income tax rules did not require parents to identify dependent children on their returns. This was changed beginning in 2010 when parents claiming the Canadian Child Tax Credit were required to note their child's name and birthdate on their tax return. Using this information, Statistics Canada staff linked parental tax records to the education data for BC. For tax years 2010 and later, the linking process is straightforward because claiming parents list their dependent children. For tax years prior to 2010, however, Statistics Canada used links from the post-2010 data and retroactively attached children to tax filers. Approximately 90 percent of children in the education data are successfully linked to at least one tax filer every year.[x]

We limit the sample according to availability of the tax data. We begin by dropping all children who are linked to five or more unique tax filers over the study period. We also drop children for whom we have no linked parent tax record for either 2008 or 2009 (since we have no measure of recession-era income). These sample restrictions cause us to drop fewer than one percent of children. Given the nature of our study, we also drop children whom we do not observe sufficiently prior to, or after the recession: those who have no linked tax records before 2004 or after 2010 (6% of the sample).

Because of the retroactive linkage process, each child is potentially linked to several tax filers across different households in a year – regardless of whether the child was meaningfully connected to the household in the year. For example, if a non-guardian parent lives with a parent and their child after 2010, the child might be linked to this person in pre-2010 years even if the child did not live with them at that point. To overcome this challenge, we identify what we call the *focal* household for each child in each tax year. For tax years where a child is linked to only one household, we set that household as focal. This constitutes about 90 percent of child-year observations in the data. For the remaining 10 percent of observations, we use a series of rules to identify the most likely focal household. First, we choose the tax filer that the child is most frequently linked to across years and attach their household earnings to the child in the questionable years. For children with no obvious frequent claimant – for example, children with two separated caregivers who take turns claiming the child and for whom we have tax records in every year – we choose the female filer as the focal parent and attach her household earnings to the child in each year. These rules allow us to assign all children to one household per tax year. We compute total household earnings in each year by summing earned income across tax filers in the household.[xi]

Because of the way we construct a child's household earnings, changes in this measure can be driven either by earnings changes among a fixed set of tax filers, or changes across years in the set of tax filers linked to the child. Since changes in household composition could also affect child mental health – and because household composition can respond to recessions (Schaller 2013) – we limit our main analysis to children in *stable households:* those who are linked to the same household composed of the same tax filers across all sample years. This constitutes about 78 percent of children and represents a sample of children where any observed earnings losses are due to earnings changes among a fixed set of filers. We confirm that our main results are robust to including "non-stable" households as well (results available upon request). Finally, we drop the very few children whose 2002 to 2006 permanent household earnings places them is in the top 1 percent of the distribution.

3. *Measuring Household Earnings Losses*

To estimate the effect of recessionary earnings losses, we use an event study framework where we examine outcome trends among children whom we identify as "treated" with an earnings loss. We create several measures of treatment using measures of total household employment earnings during the recession (2008 and 2009) relative to a pre-recession earnings measure. Our measures vary along two dimensions: which pre-recession earnings measure we use as a baseline, and how we characterize 2008/2009 earnings relative to the pre-recession baseline. To measure pre-recession earnings (baseline), we use either the child's 2006 household earnings, or permanent household earnings between 2002 and 2006 (which we call *permanent income*). We use three measures of earnings loss relative to baseline earnings: absolute loss in dollar terms, percentage loss, and standard deviation (SD) loss, where the loss is standardized by the SD of earnings between 2002 and 2006. This creates five different types of treatment definitions, since do not use the standard deviation measure with the 2006 baseline. For each of these five treatment definition types, we create several indicators that categorize a child as treated (experienced a loss) based on multiple thresholds (i.e., at least a $5,000 loss; at least a 50% loss; at least a 0.5SD loss, etc.). Table 1 shows the full list of treatment definitions we consider.

Previous studies have illustrated that the effect of job losses on children's outcomes may differ according to which parent loses their job. When mothers lose jobs, effects on outcomes may be muted, or even positive, as compared to when fathers lose their jobs (Rege et al 2011; Page, Schaller and Simon 2019; Schaller and Zerpa

2019). To test this hypothesis, we conduct a supplementary analysis focusing on recessionary earnings losses among mothers. To implement this analysis, we further limit our sample to households where mothers had positive employment earnings in the baseline income period (either 2002-2006 or 2006). This is roughly 90 percent of the sample for the permanent income measure and 80 percent of the sample for the 2006 income baseline measure. We then repeat the steps above using only the woman's earning in each focal household, and create a second set of parallel treatment variables.

4. *Sample Demographics*

Table 2 presents descriptive statistics for our analytical sample according to whether the child experienced any nominal household earnings loss in 2008 or 2009 relative to 2002 to 2006 permanent income. We present some characteristics averaged over all sample years (top panel), others averaged over the pre-recession years (2002 to 2006, middle panel), and others averaged in just 2006 (bottom panel). Across all years, 3.2 percent of children who did not experience a recessionary earnings loss received a mental health designation in school at some point, while 4.2 percent of children with a 2008/2009 loss received a designation. In the pre-recession years, the loss group had a designation rate of 2.5 percent, while the no-loss group had a rate of 2.0 percent. In both groups, about two thirds of mental health designations are for moderate rather than severe designations. In comparison, for both autism and physical health disorders, the rates of in-school SEN designations are similar across treatment groups, and less than 1 percent. Child age and grade, as well as enrollment in public school (versus in an independent school) are also similar across groups. Turning to characteristics in 2006, the children in the loss group have lower household earnings than those who will not experience a loss ($53,000 versus $66,000).[xii] Children in the loss group are also more likely to be Indigenous (14 versus 9 percent). Otherwise, the groups appear similar: both groups live with about 1.7 adults and about 1.5 earners, with total family size equal to approximately four in both groups. Parents are about the same age across groups. About 92.5 percent of children who will experience a loss live with a woman with some earnings in 2006, compared to about 89 percent of children without a loss. About 22 percent of loss children speak an Asian language at home, as compared to about 20 percent of no-loss children.

B. Methods

1. Main analysis

In our primary analysis, we utilize an event-study, difference-in-difference model to estimate changes in the incidence of new mental health designations pre- and post-the Great Recession across children with and without a household recessionary earnings loss. Our event study takes the following form:

$$(1)\quad MH_{it} = \boldsymbol{\beta_t} \sum_{t=2002}^{2015} I(year_t) * I(Loss_i) + \boldsymbol{X_{it}}'\boldsymbol{\gamma} + \mu_i + \pi_s + \lambda_t + \varepsilon_{it}$$

The outcome variable MH_{it} is a binary indicator for a mental health designation for child i, in the academic year beginning in calendar year *t*. $I(Loss_i)$ indicates children who experienced a household earnings loss according to our definitions above. Indicators for each year between 2002 and 2015 $I(year_t)$ are interacted with $I(Loss_i)$, and we estimate our event study coefficients of interest in the vector $\boldsymbol{\beta_t}$. We additionally control for year fixed effects (λ_t) to capture non-linear trends in mental health incidence common across all children, and school fixed effects (π_s) to control for unobserved factors leading to differing rates of mental health incidence, or propensity to designate a condition, across schools. We include individual child fixed effects (μ_i) to control for other unobserved heterogeneity across children. The inclusion of child fixed effects means that estimates of equation (1) will give us information about factors related to changes in designations, or new mental health designations, within child. Finally, the matrix $\boldsymbol{X_{it}}$ controls for time-varying, child-specific covariates including, family size, number of earners linked to the child, average parent age, child age fixed effects, and child grade fixed effects. For all regressions, we estimate robust standard errors clustered at the household level.

While income losses in 2008 and 2009 are driven by the recession and therefore less likely to be endogenous to mental health designations, we also use propensity score matching to identify a set of untreated children who are most like our treatment group. For each of our earnings loss treatment indicators, we use logit models to cross-sectionally predict propensity scores for each child based on measures of average parent age between 2002-2006, average family size between 2002-2006, average number of earners between 2002-2006, number of tax filing parents, indigenous status, child gender, birth year, pre-recession household permanent income, the standard deviation of pre-recession income, and indicators for speaking an Asian language at home, or speaking another language other than English at home. We then use the Nearest Neighbor without replacement algorithm to match treated children to similar control children based on the propensity score. This creates a distinct analytical sample for each treatment rule, composed of all treated children and their corresponding matches. We run our event study model above on these samples.

2. *Bartik Instrumental Variables Analysis*

We conduct a secondary analysis using a Bartik instrument for household earnings over the recessionary period. This approach provides estimates of the effect of household earnings on new mental health designations using variation driven by local exposure to changes in national-level, industry-specific employment growth. The Bartik instrument is created by interacting national, annual employment growth in each industry with the share of local workers employed in that industry in a baseline year. It is then used to produce a two-stage estimate of the effect of household earnings on new mental health designations. The Bartik estimates complement our main analysis since we use changes in household earnings over the recessionary period as identifying variation. These results have the advantage that we do not define children who experience a recessionary earnings loss using an arbitrary cut-off; instead, we use the full range of income changes over the recession (and subsequent years) to identify the treatment effect.

To create the Bartik instrument (B_{ft}), we begin by using 2006 Canadian Census data to measure the share of local employment in each of about 100 industries (d), defined by 3-digit North American Industry Classification System (NAICS) codes. We define locations by Forward Sortation Areas (FSA, denoted f below), the first three digits of a postal code. There are about 200 FSAs in British Columbia, each of which comprises about 25,000 people on average.[xiii] Next, we use Statistics Canada data on annual, national-level employment counts in each of the n industries, in each year t. Finally, we create a weighted average of the annual, national-level employment growth in each industry (g_{td}) and the 2006 FSA-level employment shares in each industry (s_{fd}). Formally, the Bartik is defined by Equation (2):

$$(2)\ B_{ft} = \sum_d s_{fd} g_{td}$$

We use the Bartik in a two-stage model, first predicting household earnings ($\underline{E_{it}}$) in year t for each child i, and then using the predicted earnings variable in a second-stage regression of new mental health designations. Formally, we estimate Equations (3) and (4):

$$(3)\ E_{it} = \delta B_{ft} + \boldsymbol{X}'_{\boldsymbol{it}}\boldsymbol{\gamma} + \mu_i + \lambda_t + \eta_f + \varepsilon_{it}$$

$$(4)\ MH_{it} = \beta\widehat{E_{it}} + \boldsymbol{X}'_{\boldsymbol{it}}\boldsymbol{\gamma} + \mu_i + \lambda_t + \eta_f + \varepsilon_{it}$$

In addition to time varying characteristics of children and families (X_{it}), child (μ_i) and year (λ_t) fixed effects, we also control for FSA-fixed effects (η_f) in these models. We cluster standard errors at the household level.

V Results

A. Main Analysis

We present our main results in the form of event study graphs. In each graph, we plot residual year effects for the treatment group relative to the matched control group after regressing our mental health indicators on the set of controls included in Equation (1) (i.e., we plot the estimates of $\boldsymbol{\beta_t}$, the coefficients on the treatment variable interacted with the year indicators). In all regressions, 2006 is the omitted year, meaning that the coefficients express the annual residual difference between the treatment and control group outcomes, relative to the 2006 difference. For our main results (Figures 2 and 3) we present all income loss definitions across both measures of pre-recession, baseline income. For the sub-group analyses, in the interest of space, we limit our results in the main text to the \$5,000 loss thresholds for both the 2002-2006 permanent income and 2006 income baselines. Results using additional treatment definitions are reported in the appendix.

1. Household earnings trajectories

To validate the construction of our treatment indicators, we begin by showing in Table 3 comparisons in earnings statistics across several of our treatment definitions. The first row of the table shows that the proportion of the total sample of children classified as treated varies from about 15 to 31 percent of children depending on the measure of income loss we use. The remaining earnings statistics in Table 3 are estimated after propensity score matching. As such, the sample for each comparison differs according to the size and characteristics of the treatment group and its matched controls. Across all treatment definitions, the average baseline earnings (either 2006, or 2002 to 2006 permanent income) remains similar across treatment children and their propensity matched control group, with differences of less than four percent in all cases. For the treatment groups measured relative to permanent income, the pre-recession standard deviation of earnings is also very similar across treatment and control households.

We note that the different treatment definitions capture different sets of children based on household earnings. For example, the $5,000 loss treatment definitions, which identify 23 to 31 percent of children as treated, have higher baseline earnings as compared to the other loss definitions (about $60,000 in the permanent income baseline case, and about $75,000 in the 2006 baseline case). The 50 percent loss definitions, which define only about 15 percent of children as treated, capture a sample of children with much lower baseline earnings: only about $33,000 in the permanent income baseline case, and about $50,000 in the 2006 baseline case. Across treatment definitions, treated children live in households where earnings in 2008 or 2009 were about $25 to $30,000 lower than the relevant baseline earnings measure. This is compared to the matched controls, whose 2008/2009 earnings were about $10,000 to $20,000 higher than baseline (in nominal dollars). The average 2008/2009 earnings losses are also largest for the $5,000 treatment definitions. As such, we prefer the $5,000 treatment definitions since they capture a large fraction of children who experience large losses in household earnings, and whose baseline earnings are comparable to the full sample (see Table 2).

We detail these trends further using our event study framework. We estimate Equation (1) on annual household earnings and graph the event study coefficients by year in Figure 2. The resulting graphs show the trajectory of the difference in annual household earnings between the treatment group and the propensity score matched control group, relative to the 2006 difference. Each of the five panels of the figure show the event study graph using a different treatment definition, and within each figure we vary the magnitude of the loss (for example, for the dollar loss event study we show $5K, $10K and $15K in one graph).

Confirming the statistics in Table 3, each graph illustrates a precipitous drop of about $30,000 to $40,000 in annual household earnings over the recessionary period for treatment households relative to matched control households. When we use 2002 to 2006 permanent income as the baseline measure (top row) – and match on permanent income – the figures reveal that, relative to the 2006 difference, treatment households earned roughly $10,000 more in the pre-recession years than control households; alternatively, the 2006 baseline (bottom row) shows that treatment households earned about $5,000 less in the pre-recession period relative to matched control households.

The permanent income baseline treatment definitions reveal a slight pre-trend in household earnings, with the trends in employment earnings across groups beginning to deviate in 2005. In Appendix Figure A3, we show the unconditional average earnings across treatment status using the $5,000 loss/permanent income treatment definition. The raw means illustrate that up to 2004, treatment and control children live in households with nearly identical earnings trends. The deviations in earnings beginning in 2005 is generated by gradually increasing income in the control group; average treatment group earnings do not begin to drop until 2007, the first year of demonstrable increases in unemployment in BC (see Appendix Figure A1 for annual unemployment rates). The pre-trend is not apparent when we use 2006 earnings as a baseline. Finally, we illustrate that the earnings of households experiencing a recessionary loss do not recover to their pre-recession levels. In 2015, six years after the worst spell of unemployment, families with recessionary income losses still earn about $20,000 to $30,000 less than those who did not experience a loss.

2. Household income losses and mental health designations

Figure 3 presents our event study estimates of Equation (1) on mental health designations for the same five treatment definitions we use above. For each treatment, we graph the results of estimating the model on new designations of a combined measure of moderate and severe mental health conditions (we show disaggregated results below). As with Figure 2, Figure 3 shows all configurations of earnings losses and baseline income to provide as comprehensive a picture as possible. All panels in Figure 3 show that relative to children whose families did not experience an earnings loss in 2008 or 2009, children in loss households experience increasing rates of new mental health designations following the recession. Some figures also indicate pre-trends in new mental health designations among treated families relative to control families.

The first row presents results using treatment defined relative to the 2002-2006 permanent earnings baseline. The first panel reports results for the dollar loss measures of treatment. For the $5,000 loss (our preferred specification, panel 1A) there is little evidence of statistically significant pre-trends and, starting in 2009, we begin to see a trend break in new mental health designations for treatment households relative to control households. Then, starting in 2012, we observe a second trend break with an additional increase in the rate of new designations among treated children relative to control children. By 2010 mental health designations are 0.2 percentage points higher among treated children relative to control children. By 2013, the rates of new mental health designations among children whose families experienced at least a $5,000 loss in 2008 or 2009 are 0.5 percentage points higher than among children whose families did not experience a loss. Relative to the 2006 population average rate of new mental health designations, this amounts to a 20 percent increase.

The results are similar (with varying magnitudes) for our other dollar loss measures. For instance, using the 50% percent loss (2A) and either standard deviation loss (3A) treatment definitions with the permanent income baseline also show similar results, with little evidence of statistically significant pre-trends and increasing mental health designations for the treatment group starting in about 2008. It is also the case that with some of our treatment definitions, children whose families will eventually experience a recessionary earnings loss are designated with new mental health conditions at a faster rate than comparable children without a loss even before the recession. This is especially true for the 90 percent loss definition. However, relative to the other treatment definitions, the 90 percent loss definition captures a much smaller share of children (6-9 percent of the full sample) with much lower baseline earnings ($20,000 to $30,000 annually, as compared to $60,000 to $70,000 in the full analytical sample).

The bottom row of Figure 3 presents our results using the 2006 baseline income definition. The graphs illustrate stronger evidence of pre-trends: the dollar loss treatment (panel 1B) definitions, for example, show increasing rates of new designations prior to the recession for treated children. For the 50% percentage loss group (panel 2B), however, there is less evidence of pre-trends and an increase in designations consistent with our permanent income measure reported above.

In Figure 4 we decompose our mental health designation measure into severe and moderate designations. As noted above, we focus now on our preferred loss specification of an absolute loss of $5,000. As in the combined measure above, we find little evidence of pre-trends and an increase in designations of around 0.1 to 0.2 percentage points for both moderate and severe mental health by 2012. Relative to the 2006 population averages, these increases represent increases of 6 percent for moderate mental health designations, and 14 percent for severe designations. Again, the estimated differential designation rates by treatment status continue to increase, such that by 2014, both the moderate and severe designations rates are about 0.3 percentage points higher among treated children relative to control children. These increases represent 14 and 20 percent increases, respectively. In panel B of the figure, we confirm that using 2006 earnings rather than permanent income as a baseline in treatment definition produces similar results.

3. *Alternative earnings: Mothers' earnings and transfer income*

We also report results using alternative definitions of earnings: mothers' earnings and total household income including transfer income. First, we limit our sample to households where mothers had earned income during 2002-2006, about 90 percent of the sample for the permanent income measure and 80 percent of the sample for the 2006 income baseline measure, and create a parallel set of treatment variables based on 2008/2009 changes in maternal earnings. Appendix Table A2 illustrates that when we define losses based on mothers' earnings, we capture about 20 to 30 percent of children with working mothers. Relative to our primary household earnings analysis, we capture children with similar levels of total household earnings when we focus on maternal losses. However, we also capture households with smaller total earnings losses in 2008 and 2009 (i.e. $15,000 in the maternal earnings treatment versus $25,000 for the household loss treatment, using the $5,000/permanent income definition). In Appendix Figure A4 we use our event study framework and illustrate that when we use maternal losses rather than household losses to define treatment, the differential trajectories in household earnings across treatment status are very similar.

In Figure 5, we show event studies of new mental health designations using maternal earning loss to identify treated children. We report results for the $5,000 treatment variables (full results for all treatment variables are reported in Appendix Figure A5). The results suggest that new mental health designations respond similarly to women's earnings losses as compared to household earnings losses. Both Panel A, using 2002-2006 permanent income and Panel B, using 2006 baseline income, show no statically significant evidence of pre-trends and an increase in both moderate and severe mental health designations of 0.2 to 0.3 percentage points by 2011.

In addition to using employment earnings as our primary measure, we also conduct our analysis using a total household income measure that includes both employment earnings and transfer income that we can measure in our data. As we note above, we can observe transfer income delivered through the tax code in our data. These additional sources of income may provide some buffer against effects of income loss on child mental health, although the average family in our analytical sample only receives about $4,000 per year in transfer income. Our findings using total income are reported in Appendix Figure A6 for our preferred loss specifications. We continue to see very similar patterns of negative effects on mental health, with no evidence that receipt of transfer income tempers the effects of earnings losses on new mental health designations.

4. *Stratifications Analysis*

To explore which populations are driving the substantial increase in new mental health designations following the recession, we stratify our population across four dimensions and estimate Equation (1) separately for each subgroup. We split the sample by: Indigenous status, children who speak English at home versus those who do not, child gender, and age of exposure to the recessionary loss (those who were 10 or younger versus those older than 10 in 2008). These groups exhibit differing rates of baseline mental health. For example, the baseline mental health SEN rate for Indigenous children is 5.6 percent, compared to 1.8 percent among non-Indigenous children. The baseline mental health SEN rate for boys is about 3.4 percent, while the rate for girls is only 0.8 percent. Earnings shocks in households may have differing effects on mental health outcomes for (marginal) children with lower baseline levels of mental health designations who had not previously sought in-school services for care.

After splitting the sample, we use the same propensity score matching technique described above to find similar children within each subgroup who did not experience an earnings loss. We plot the estimated coefficients for each sub-group in Figure 6 for our preferred specification of a $5,000 loss relative to permanent income (results for other treatment variables reported in Appendix Figure A8). In Appendix Figure A7, we also show how household earnings vary over time according to treatment status for each subgroup. To compute magnitudes, the relative effect sizes must be scaled by these first stage estimates, since income losses across demographics – especially those that vary systematically across families like Indigenous and language status – may not be equivalent.

Panel A of Figure 6 shows the results of our stratification analysis for Indigenous status. About ten percent of our full analytical sample is identified as Indigenous in the administrative data, which is slightly more than the province-wide average of six percent. Most people who identify as Indigenous live in BC's largest cities (Vancouver region, Victoria, and Kelowna) (Statistics Canada 2017). Indigenous families are also overrepresented among lower income families in Canada (18% versus approximately 10% overall) (ESDC 2021). Panel A of Figure 6 suggests that post-recession mental health designation changes are concentrated among non-Indigenous children. We find no evidence of any change in mental health designations among

Indigenous children, despite that Indigenous children who are in our treatment group experience significant household earnings losses of up to $24,000 in 2009. Appendix Figure A8, Panel A reveals that regardless of treatment definition, we find no statistically significant impact on new mental health designations among Indigenous children.

Panel B of Figure 6 presents results by language spoken in the home. About 30 percent of children in the full analytical sample do not speak English at home. The largest sub-group of non-English language speakers are those who speak an Asian language at home (Mandarin, Cantonese or Punjabi, 20 percent of the analytical sample). The baseline mental health SEN rate for non-English language children is 1.4 percent, and the rate for English language children is 2.5 percent. Post-recession, English-speaking, treated children experience increases in the rate of new designations of about 0.2 to 0.3 percentage points, with the estimated effect increasing to about 0.5 percentage points by 2015. Among children who speak a language other than English at home, we find limited evidence of differential rates of mental health designations across treatment status using the $5,000 treatment. However, using some of our other treatment definitions (Appendix Figure A8), we do find evidence of muted differences in mental health trajectories between treated and control children in the other language group, especially in the later years of our sample.

In Panels C and D of Figure 5, we show results after partitioning the sample by child gender and age. These estimates are easier to interpret than those based on race and ethnicity since treatment does not vary systematically across these demographics: boys and girls, and younger and older children, are equally likely to be treated, and treated children experience nearly identical earnings losses (Appendix Figure A7). In panel C, we show the results by child gender. The figure shows a significantly lower mental health designation rate among treated boys in the pre-recession years, making inference for this group difficult. However, for girls, there is little evidence of pre-trends and by 2013 we find increases in the order of 0.3 percentage points relative to their control group, albeit with large standard errors. Analyses using the alternative treatment definitions in Appendix Figure A8 confirm these findings: evidence of pre-trends in mental health designations among treated boys, with minimal pre-trends and large treatment effects, especially after 2012, among treated girls. The low baseline mental health designation rate among girls also implies large relative increases for treated girls, in the order of 50 to 60 percent.

Finally, in Panel D, we show the results after partitioning the sample by treatment age: those who were older than 10 in 2008 versus those 10 and younger in 2008. For the older age group, we are only able to consistently estimate coefficients until 2013, at which point most older children have left secondary school. Among the younger group, we can estimate trends in mental health designations starting in 2004, when the oldest children in this sub-sample are six. The results – especially those of alternative treatment definitions in Appendix Figure A8 – show that both younger and older children experience a small, immediate effect of recessionary earnings loss on mental health designations. By 2008, both younger and older children who experience a recessionary loss exhibit rates of new mental health designations that are about 0.2 percentage points higher than comparable children with no loss. However, the figures also show that among children who were younger when they were treated, relative to other young children whose family did not experience a loss, the rate of new designations continues to increase well beyond the recession. By 2013, relative to children with no loss, children who experienced a recessionary earnings loss when they were young had rates of new mental health designations up to 0.8 percentage points higher.

5. *Bartik Results*

We report results from our two-stage estimates of household earnings on child mental health designations in Table 4. We report results of a Bartik analysis on the full analytical sample in column (1) of the table, as well as after portioning the sample according to 2006 earnings quartile. Using the FSA-level Bartik Instrument, we first predict annual household earnings for each child. We find that the Bartik is a good predictor of changes in household earnings in the full sample, with an F-stat of over 50. In the second stage, we regress the indicators for mental health designations on the predicted annual earnings for each child (expressed in \$1,000), as well as the rich controls we detail above. We find that a \$1,000 increase in household earnings is associated with a statistically significant 0.1 percentage point reduction in the rate of new mental health designations. On the average pre-recession mental health designation rate of 2.5 percent, this represents a four percent effect size.

In columns (2) through (5) of the table, we report the results of the Bartik analysis after portioning the sample by quartile according to 2006 household earnings. We find that the Bartik instrument is a good predictor of household earnings in the top half of the earnings distribution. However, in the second quartile, the instrument does not predict earnings, and in the bottom quartile, we find that growth in the Bartik is negatively associated with household earnings, a relationship that is contrary to expectations. In the second stage analysis, we find that household earnings are associated with new mental health designations among children in the third quartile (mean earnings in the third quartile is $75,000). We estimate that a $1,000 increase in earnings is associated with a reduction of about 0.2 percentage points in new mental health designations.

6. *Placebo Tests*

Finally, in Figure 7 we plot the results obtained by estimating Equation (1) on two placebo outcomes. The placebo outcomes we create are indicators for other SEN designations that we do not expect to be largely affected by recessionary earnings losses. The first is autism spectrum disorder. While ASD is a psychological condition, it is not a mental health disorder, but rather a developmental and neurological disorder (National Institute of Mental Health 2022). Autism diagnoses grow over our sample period. In 2002, only about 0.4 percent of children in our sample had ever been designated in-school with autism. By 2015, the proportion had grown to 1.6 percent of children. The next placebo outcome we consider is an indicator for physical health disorders, including deafness, blindness, and physical disabilities. About two percent of children receive one of these SEN classifications in our data. In theory, neither autism nor these physical conditions should respond to household earnings changes.

For physical disorders, we estimate no discernable effect of treatment on new designations.[xiv] For autism, we find some evidence of increasing designations rates post-recession among treated children. In all post-recession years, however, we estimate coefficients of less than 0.1 percentage points, indicating relative effects of 10 percent or less. We also estimate effects of household earnings on these outcomes using our Bartik Instrument and find statistically insignificant estimated coefficients that are close to zero (available upon request).

6 Discussion and Conclusion

The concentrated increase in mental health concerns in children and youth over the past several years is still not fully understood. In this paper, we explore one important potential pathway to help explain and mitigate such concerns: household income. We examine the effect of recessionary declines in individual household earnings on children's mental health using a novel administrative dataset of school records linked to parental tax records. We focus on changes in mental health designations in-school following the Great Recession, which generated profound and acute economic stresses in households in our sample (and around the world). Combining propensity score matching with an event study analysis, we find that by 2013 new in-school designations of mental health and behavioral disorders increased by 0.5 percentage points among children experiencing a family income loss relative to children whose families did not. This effect represents a 20 percent increase in mental health designations from the pre-recession mean. By 2015, seven years after the recession, rates of new mental health designations among children whose families experienced a household earnings loss are 0.7 percentage points, or 28 percent, higher than matched control group children.

Our results show this effect is especially persistent among children who were 10 or younger when the recession hit. Beyond immediate increases in the mental health designation rate, the analyses for this younger group reveal a secondary increase in the mental health designation rate among treated children starting in 2013, at ages 13 through 15. This coincides with high school entry for this early exposure cohort. The persistence of our treatment effects among this group is not surprising given our findings that earnings among affected families do not rebound to pre-recession levels by the end of our study time frame. We also find evidence of particularly large relative effects among girls, who have low baseline designations rates. The opposite is true for treated Indigenous children, who exhibit essentially no change in mental health designations post-recession despite experiencing large reductions in household earnings.

We conduct several robustness analyses, including the use of a Bartik instrument to estimate the effect of household earnings on new mental health designations. We find that $1,000 in household earnings is associated with a 0.1 percentage point reduction in the rate of new mental health designations. While this estimate is an order of magnitude larger than the effects we estimate using the event study framework, we do confirm with the Bartik that the effects appear concentrated among the third quartile of the earnings distribution. The finding that the effect is concentrated among moderate income families is consistent with our preferred results from the propensity score matching models where we find the most robust effects for those who experienced a $5,000 loss - among families that have baseline earnings (2006) averaging $76,000. We also show that the effect of recessionary earnings on in-school child health designations is not similarly present in other special needs classifications like physical health disorders, although we do find some evidence of effects on autism.

Our study results align with existing work showing that regional recessionary impacts are related to mental health among children (Gassman-Pines, Ananat, and Gibson-Davis, 2014; Golberstein, Gonzales, and Meara, 2019; Page, Schaller, and Simon, 2019). For instance, Gassman-Pines, Ananat and Gibson-Davis (2014) found that a one percentage point increase in state unemployment is associated with a two to three percentage point increase in suicide-related behaviors among girls. Page, Shaller and Simon (2017) show that a one percentage point increase in state unemployemnt rates is associated with about a 10 percent increase in cases of severe emotional difficulties, while Golberstein, Gonzales and Meara (2019) find that a one percentage point increase is associated with an 11 percent increase in psychological problems. Schaller and Zerpa, (2019) find that fathers' job losses are associated with a 0.08 standard deviation increase in children's mental health index scores. Our study builds on this previous work by using administrative measures of both mental health and household earnings, and by estimating the effects of recessionary losses in a child's own family on their mental health designations.

Our study differs from the existing literature in that we find similar effects of mother's and household earnings losses on mental health. Previous work has found evidence that when mothers lose jobs (Schaller and Zerpa 2019), or when employment opportunities for women worsen (Page, Schaller and Simon 2019), children's outcomes can improve. We do not find evidence to support more moderated effects on mental health when mothers lose earnings. Our estimates also suggest that while mental health among boys and girls may have responded similarly to earnings losses, the baseline estimate for girls is much lower and hence the effect correspondingly larger, consistent with previous work that has shown that mental health among girls is more responsive to income changes (c.f. Milligan and Stabile, 2011).

This study complements the work of Jackson et al. (2021), which shows that, in the US context, recessionary school spending cuts led to large reductions in student achievement, along with Stuart (2022) finding that exposure to a recession as a child has far reaching, negative impacts on educational attainment and earnings. As Canadian schools have looser connections between local tax bases and school funding, we demonstrate that recessions negatively affect students even in contexts where they have no discernable impact on school budgets. Our results show that recessionary income losses affect designation rates for conditions that are attached to additional per student funding (severe mental health), as well as those which do not garner additional funding for schools. Overall, our evidence suggests that earnings shocks can have a strong and lasting effect on mental health. These results provide support for programs that would a) mitigate the effects of such shocks on vulnerable families and b) support those students most at risk in school.

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Table 1. Summary of Treatment Variables

	Treatment Defined Using Baseline Permanent Income	Treatment Defined Using Baseline 2006 Income
Absolute Loss (at least)		
$5,000	X	X
$10,000	X	X
$15,000	X	X
Percentage Loss (at least)		
50%	X	X
90%	X	X
Standard Deviation Loss (at least)		
0.5SD	X	-
0.75SD	X	-

Notes. Summary of treatment definitions. Dollar values are in Canadian dollars.

Source: Authors.

Table 2. Summary Statistics

	No Loss		Any Loss	
	Mean	SD	Mean	SD
Average over all years				
Any mental health illness	0.032	0.177	0.042	0.202
Moderate mental health	0.021	0.144	0.027	0.163
Severe mental health	0.018	0.132	0.024	0.153
Autism diagnosis	0.008	0.091	0.009	0.094
Physical disorder	0.005	0.073	0.006	0.076
Child age	11.727	3.225	11.735	3.221
Grade	6.695	3.220	6.691	3.212
Attends public school	0.889	0.314	0.883	0.321
Average over 2002-2006				
Any mental health illness	0.020	0.139	0.025	0.157
Moderate mental health	0.012	0.110	0.016	0.124
Severe mental health	0.011	0.105	0.014	0.118
Autism diagnosis	0.005	0.071	0.005	0.070
Physical disorder	0.005	0.070	0.005	0.072
Transfer income (tax system)	$3,500	$4,000	$3,700	$4,200
2006 average				
Average household earnings	$66,300	$50,000	$53,200	$53,400
Number of household earners	1.517	0.613	1.387	0.652
Number of parents	1.738	0.440	1.671	0.470
Family size	4.142	1.151	4.101	1.271
Mom working	0.890	0.313	0.925	0.263
Average age of parents	40.764	5.654	40.754	6.329
Asian language at home	0.200	0.400	0.222	0.415
Non-English or non-Asian language at home	0.092	0.289	0.092	0.289
Indigenous	0.094	0.291	0.130	0.336
Birth year	1996.303	2.277	1996.278	2.277
Gender (Male)	0.512	0.500	0.515	0.500
Number of Children (rounded to base 10)	172,000		79,660	
N (rounded to base 10)	1,859,630		863,930	

Notes. The sample includes children born between 1993 and 2000, and aged 6 to 17 in years 2002 through 2015. The *No Loss* group includes children whose families did not lose any income in 2008 or 2009 relative to 2002-2006 permanent income, and the *Any Loss* group includes children whose families did lose. Dollar values (in nominal CAD) rounded to base 100 as per vetting rules.

Source: BC Ministry of Education Public School Administrative Data File

Table 3. Summary of Earnings across Loss Variables

	Treatment Defined Using Baseline Permanent Income			Treatment Defined Using Baseline 2006 Income	
	5K Loss	50% Loss	0.5 SD Loss	5K Loss	50% Loss
Share of HH with loss	0.2293	0.1497	0.2456	0.3134	0.1412
Average baseline earnings, control group	$57,400	$33,300	$50,800	$73,200	$47,600
Average baseline earnings, treatment group	$58,400	$32,300	$50,900	$76,200	$49,400
Average SD perm earnings, control group	$16,300	$13,300	$13,600	-	-
Average SD perm earnings, treatment group	$16,900	$13,500	$13,600	-	-
Average 2008/2009 earn change (rel. baseline), control group	$22,900	$14,800	$18,700	$14,500	$6,800
Average 2008/2009 earn change (rel. baseline), treatment group	-$25,200	-$25,800	-$23,000	-$28,600	-$37,700
Average earnings across all years, control group	$79,100	$48,200	$69,000	$85,600	$55,400
Average earnings across all years, treatment group	$55,500	$27,500	$48,100	$65,400	$35,100

Notes. Average earnings are computed for the matched samples. Dollar values (in nominal CAD) rounded to base 100 as per vetting rules. Sample includes children born between 1993 and 2000, aged 6 to 17 in years 2002 through 2015.

Source: BC Ministry of Education Public School Administrative Data File

Table 4. Effect of household earnings on any new mental health designation using Bartik instrument

	(1) Overall	(2) Bottom Quartile	(3) Second Quartile	(4) Third Quartile	(5) Top Quartile
$\widehat{Earnings_{it}}$ ($1,000)	-0.0011**	0.0019	0.0041	-0.0023**	0.0001
	(0.0005)	(0.0019)	(0.0062)	-0.0011	(0.0005)
First Stage					
Bartik Instrument	30.9336***	-18.7471***	-5.8796	22.7483***	38.6872***
	(4.2429)	(4.3107)	(5.5387)	(6.4020)	(13.9048)
Average Household Income (2006)		$14,800	$43,700	$75,300	$133,400
First Stage F-Stat	53.15	18.91	1.13	12.63	7.74
N	2,677,080	606,401	619,640	626,860	626,950

*** p<.01, ** p<.05, * p<.1

Notes. The sample includes children born between 1993 and 2000, aged 6 to 17 in years 2002 through 2015. Results of estimating Equations (3) and (4). Covariates include average age of tax filers, indigenous status, home language other, home language Asian, and gender. The model also includes kid, FSA, year, age, grade, school, family size, number of earners, number of tax filers and school type fixed effects. Standard errors are clustered at family level. Quartiles are defined using 2006 household employment income. Dollar values rounded to base 100 as per vetting rules.

Source. BC Ministry of Education Public School Administrative Data Files and linked T1FF tax file.

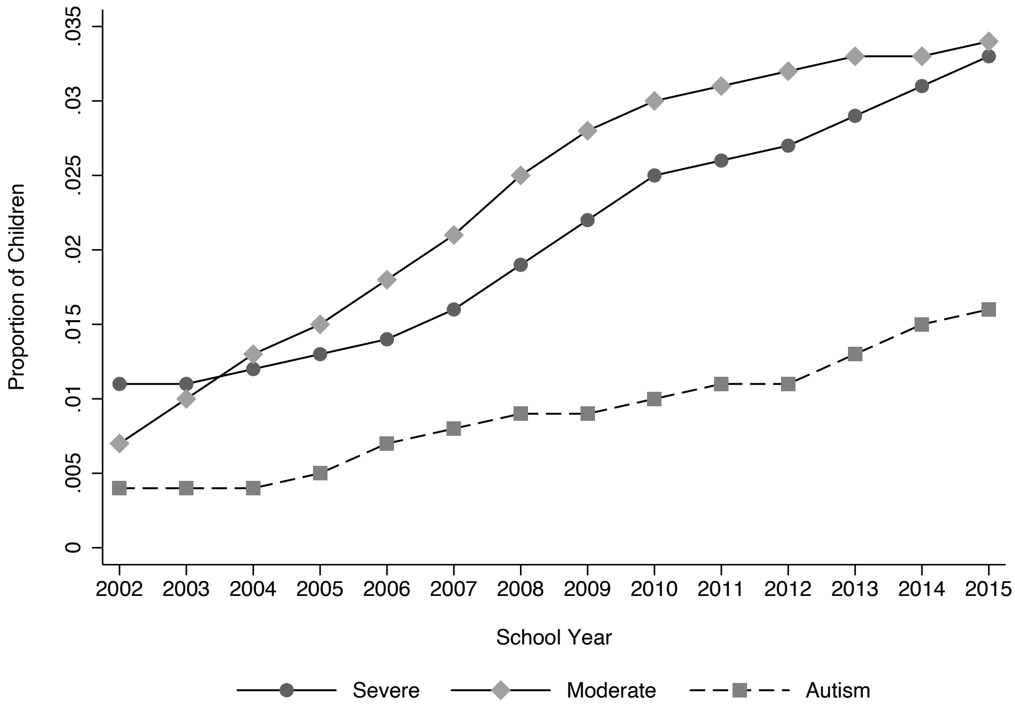


Figure 1. Proportion of British Columbia School Children with an In-school Mental Health Special Need, by Year

Notes. The sample includes children born between 1993 and 2000, and aged 6 to 17 in years 2002 through 2015. Indicators created by authors according to the Special Education Needs (SEN) classification, and equal one if a child has ever been classified as having the corresponding SEN.

Source: BC Ministry of Education Public School Administrative Data File.

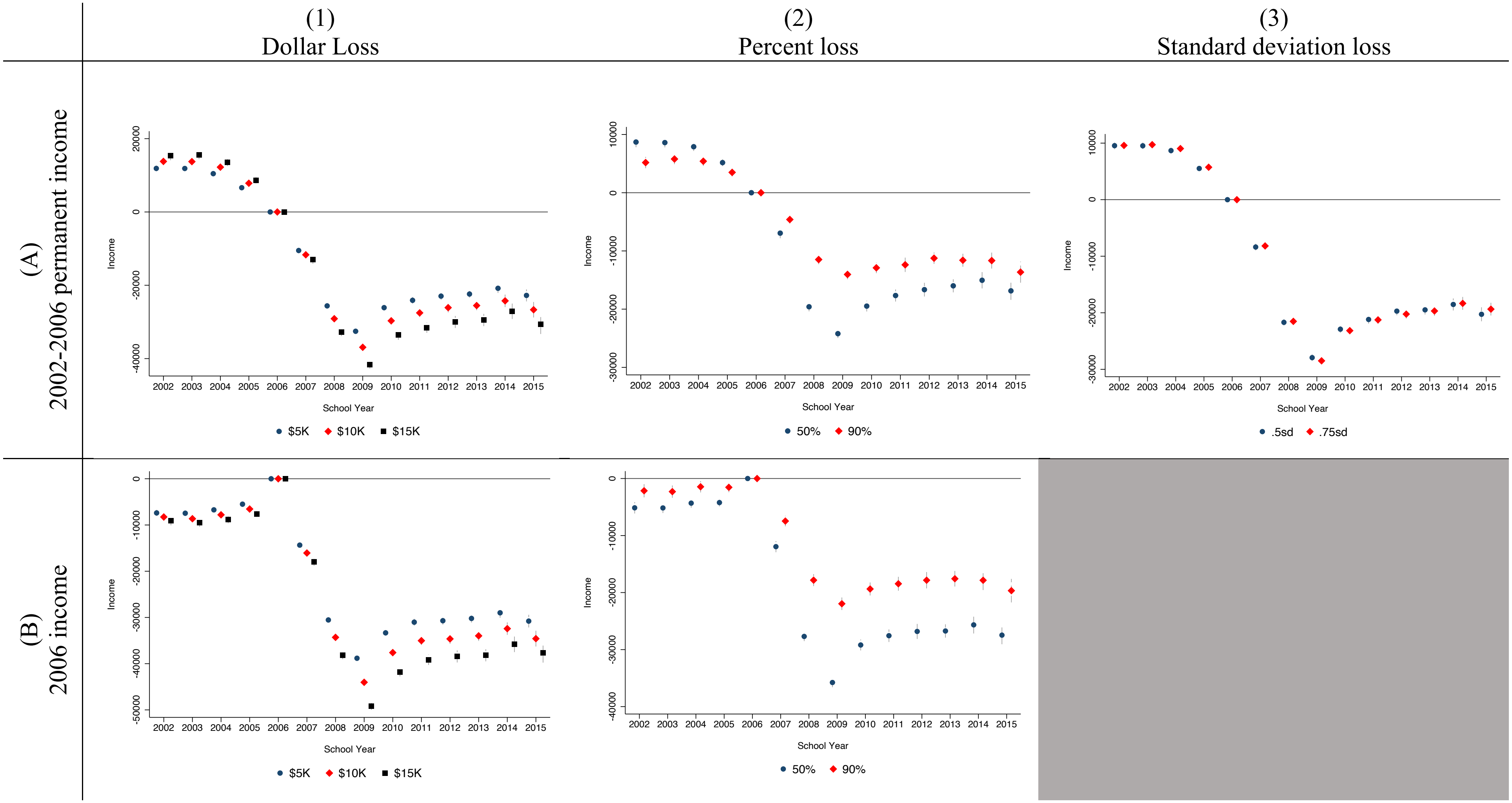


Figure 2. Event study estimates of the trajectory of earnings among children in households with a household earnings loss

Notes. The sample includes children born between 1993 and 2000, and aged 6 to 17 in years 2002 through 2015, after propensity score matching. Residual values derived from regressions including controls for family size, number of earners, average parent age, child age fixed effects, child grade fixed effects, as well as child, year, and school fixed effects. The grey vertical bars represent the 95 percent confidence intervals, which are based on within-household cluster-robust standard errors.

Source. BC Ministry of Education Public School Administrative Data Files and linked T1FF tax file.

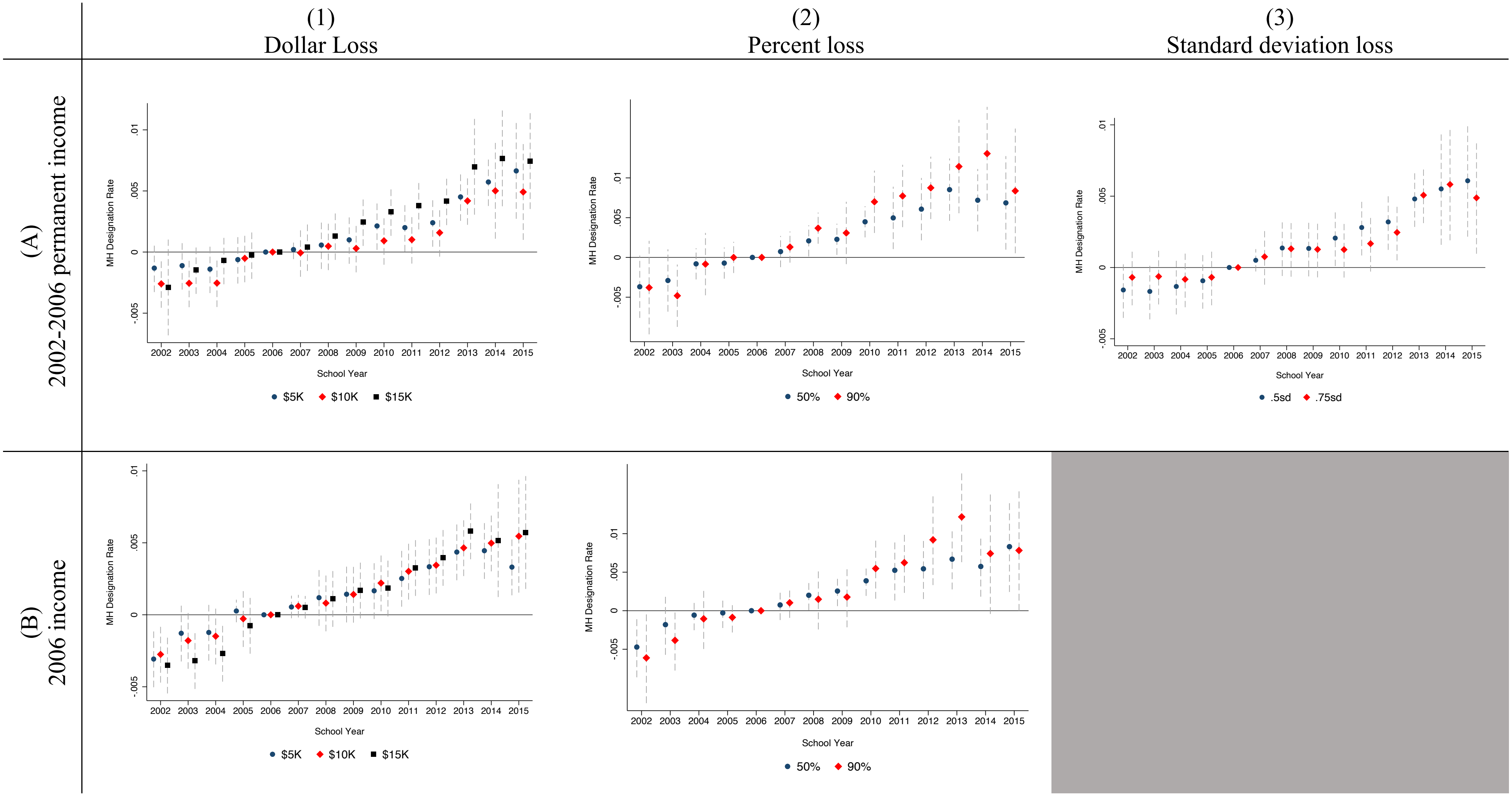
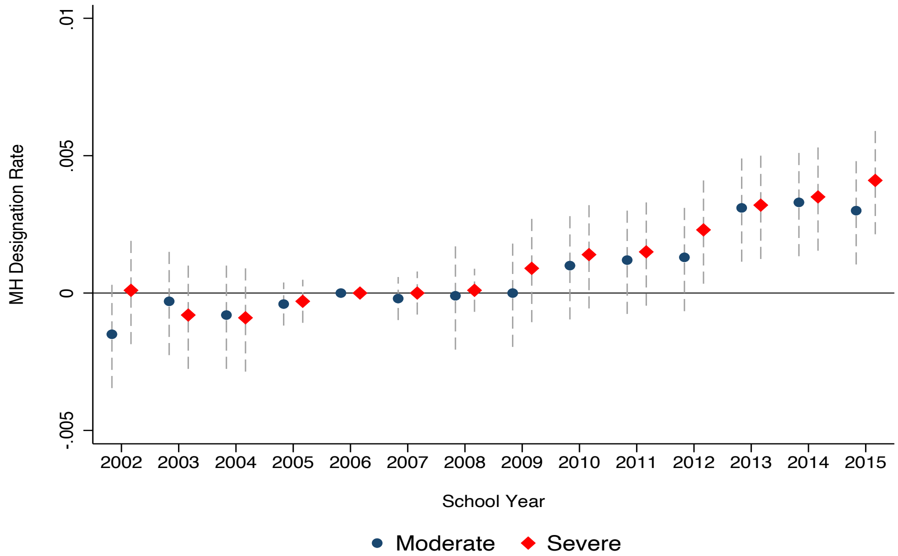


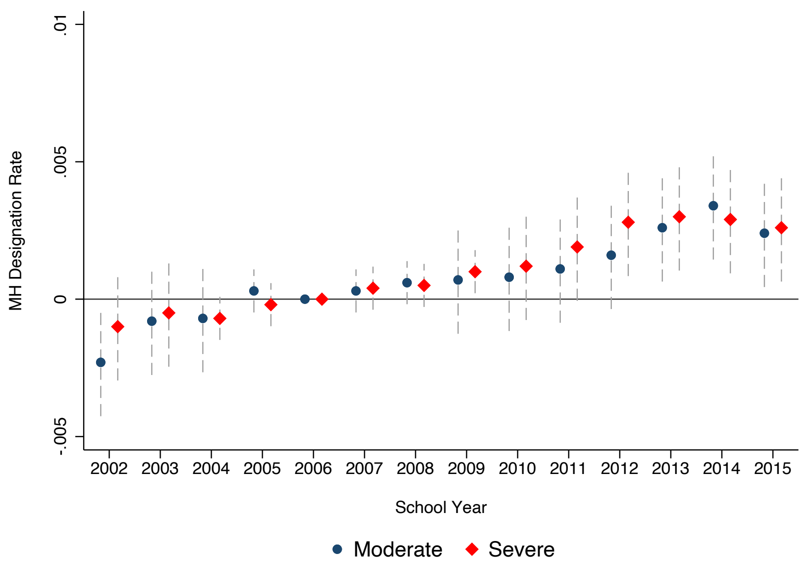
Figure 3. Event study estimates of the trajectory of mental health designations among children in households with a household earnings loss

Notes. The sample includes children born between 1993 and 2000, and aged 6 to 17 in years 2002 through 2015, after propensity score matching. Mental health indicators created by authors according to the Special Education Needs (SEN) classification, and equal one if a child has ever been classified as having a mental health condition. Residual values derived from regressions including controls for family size, number of earners, average parent age, child age fixed effects, child grade fixed effects, as well as child, year, and school fixed effects. The grey vertical bars represent the 95 percent confidence intervals, which are based on within-household cluster-robust standard errors.

Source. BC Ministry of Education Public School Administrative Data Files and linked T1FF tax file.



Panel A: 2002-2006 permanent income baseline, 5,000CAD loss

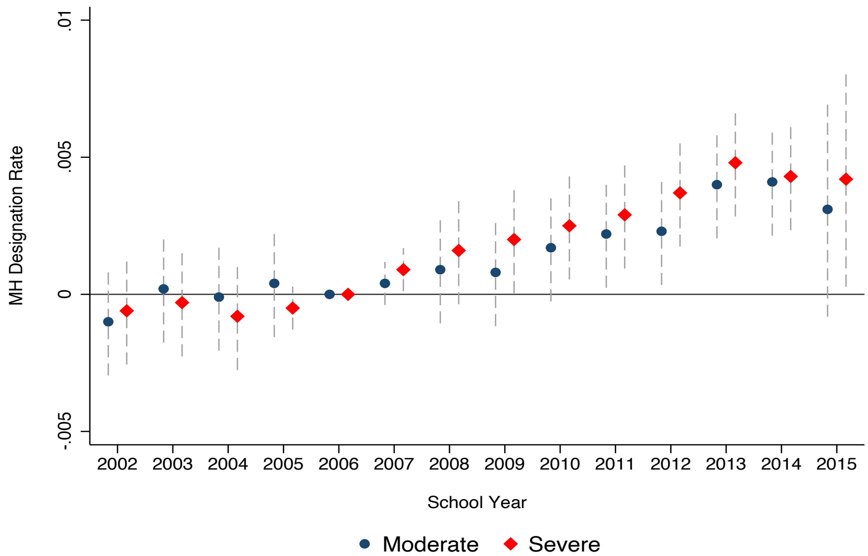


Panel B: 2006 income baseline, 5,000CAD loss

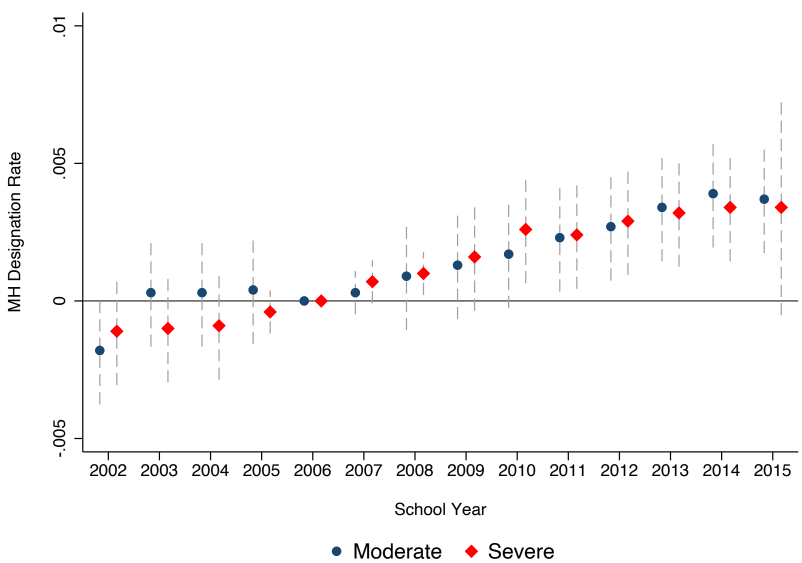
Figure 4. Event study estimates of the trajectory of mental health designations among children in households with a household earnings loss

Notes. See Figure 2. *Moderate* reflects ever having received a designation for Moderate Behavior Support or Mental Health Conditions, while *Severe* reflects ever having received a designation for Intervention or Serious Mental Health Illness.

Source. BC Ministry of Education Public School Administrative Data Files and linked T1FF tax file.



Panel A: 2002-2006 mothers' permanent income baseline, 5,000CAD loss

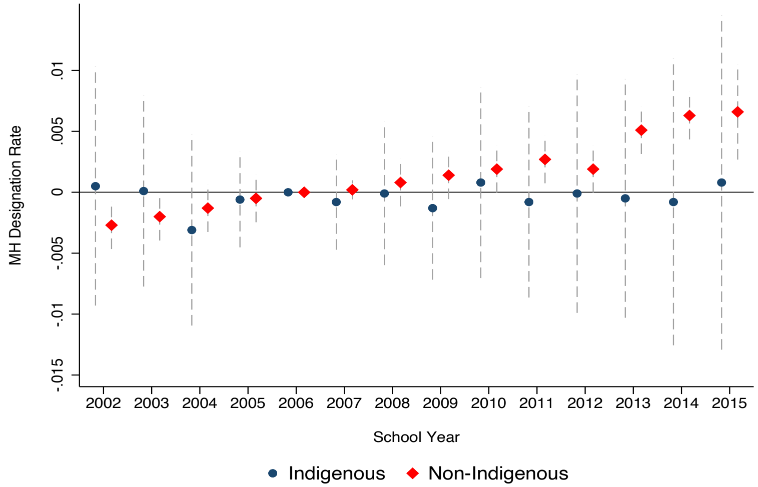


Panel B: 2006 mothers' income baseline, 5,000CAD loss

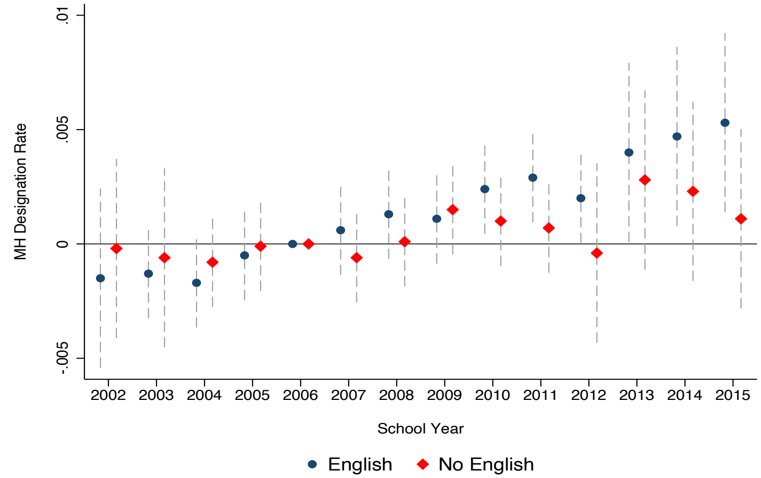
Figure 5. Event study estimates of the trajectory of mental health designations among children in households with a maternal earnings loss

Notes. See Figure 4. Panel A includes children whose mothers had positive permanent earnings. Panel B includes children whose mothers had positive earnings in 2006.

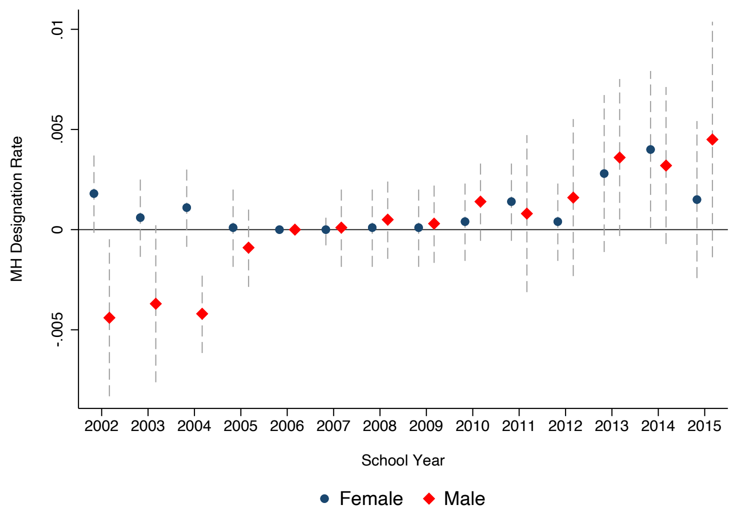
Source. BC Ministry of Education Public School Administrative Data Files and linked T1FF tax file.



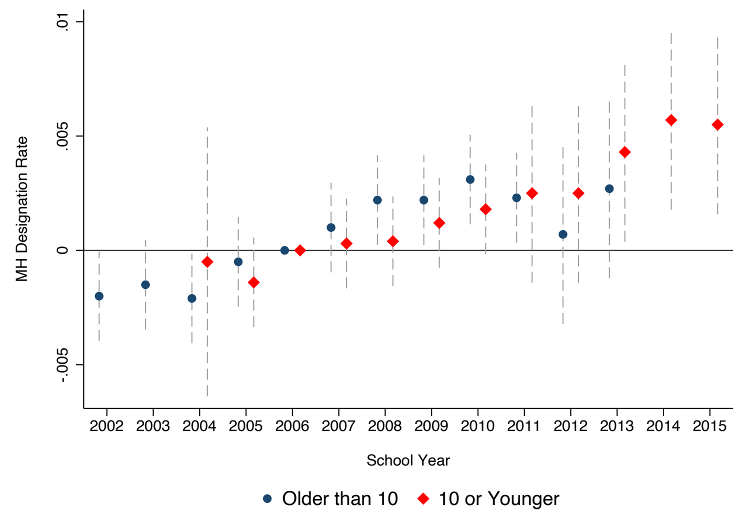
Panel A. Indigenous status



Panel B. Language spoken at home



Panel C. Child gender

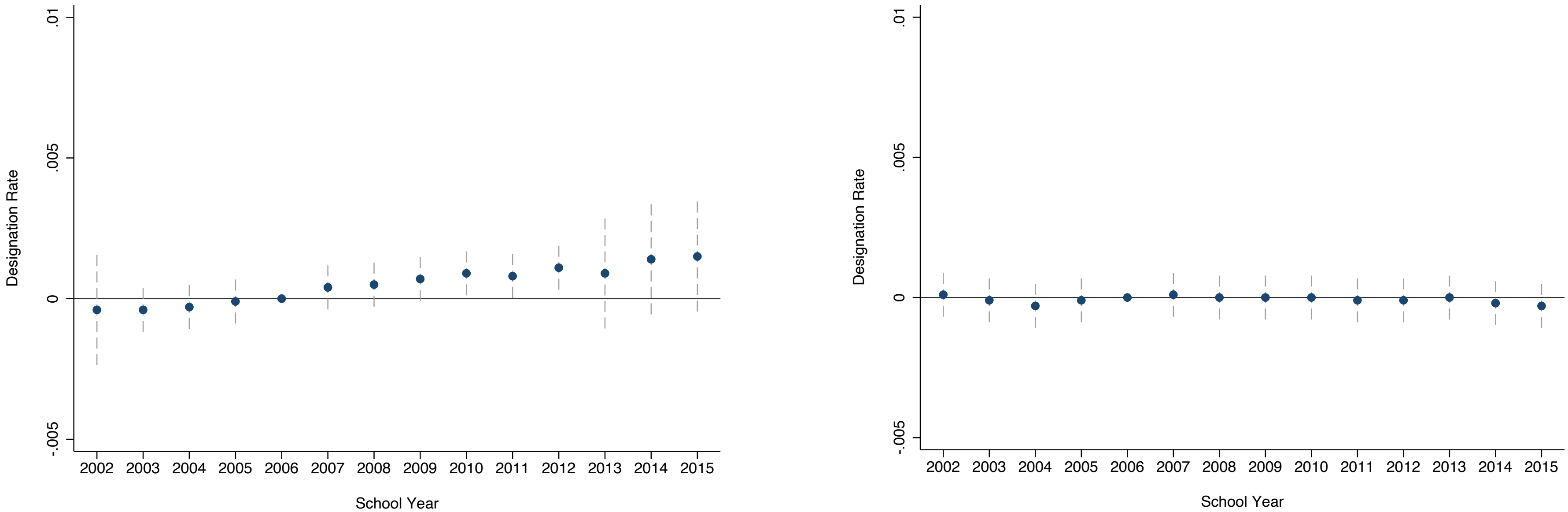


Panel D. Age in 2008

Figure 6. Event study estimates of the trajectory of mental health designations among children in households with a household earnings loss, by child demographics

Notes. See Figure 4; Treatment is 5,000CAD loss relative to 2002-2006 permanent income.

Source. BC Ministry of Education Public School Administrative Data Files and linked T1FF tax file.



Panel A. Autism **Panel B.** Physical health

Figure 7. Event study estimates of the trajectory of placebo health designations among children in households with a household earnings loss

Notes. See Figure 4. Treatment is 5,000CAD loss relative to 2002-2006 permanent income.

Source. BC Ministry of Education Public School Administrative Data Files and linked T1FF tax file.

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[i] As a comparator, we do not see increases in new designations of autism spectrum disorders (ASD) over the recessionary years.
[ii] Affordability of care is considered less of an issue in the Canadian context given free access to physician and hospital services.
[iii] One exception is a recent study of the short-run effect of receiving a lump-sum EITC credit, which found no relationship between EITC receipt and mental health outcomes among children (Batra and Hamad, 2021).
[iv] Using parent-reported survey data, Schaller and Zerpa, (2019) find evidence that fathers' job losses are associated with a 0.08 standard deviation increase in children's mental health index scores, as well as increases in children's reported visits to the doctor for mental health concerns. Schaller and Zerpa (2019) also find that mothers' job losses may lead to improvements in mental health outcomes among children, especially among low-SES families, pointing to a time-use mechanism. While the authors do not focus exclusively on job losses generated by a recession, they note that their study time frame includes two economic downturns (including the Great Recession).

[v] There are also several studies showing that parental job losses are negatively associated with children's educational outcomes (Stevens and Schaller 2011), educational attainment, and later life earning (Oreopoulos, Page and Stevens 2008; Page, Stevens, and Lindo 2009), especially among children from lower income households. One exception is Shea (2000), which uses variation in parent's income generated by job losses and does not find any relationship between parents' and children's incomes.

[vi] A total of 58 percent receive services either from school alone or in conjunction with other non-educational settings; children from lower-income and minority households are also more likely to obtain mental health services exclusively in educational settings (Ali et al. 2019).

[vii] Approximately 95 percent of funding for British Columbia schools comes from provincial – rather than local – sources. Approximately 80 precent of all school funding is distributed through the basic student-base allocation, with the remaining 20 percent split between grants for unique district needs and grants for unique student needs, including supplemental SEN funding (Herman 2013).

[viii] Over our study period, the nominal per-student funding levels incrementally increased from $30,000 to $37,700 (Level 1), from $15,000 to $18,850 (Level 2), and from $6,000 to $9,500 (Level 3) (see Appendix Figure A2). Note that school funding for special education (or overall) did not decrease during the recession as it did in some US states (Jackson et al. 2021). Appendix Figure A2 shows total funding to BC schools for children with special needs in each category in every school year from 2002/2003 through 2015/2016 (dotted lines). Total funding for Level 1 and Level 3 special needs did not change dramatically over our study time frame. However, total supplemental funding to support students with Level 2 special needs doubled between 2002 and 2015. This increase was driven by increasing numbers of students identified with autism.

[ix] We unfortunately do not observe employment insurance benefits in our tax files and note this as a limitation of our study.

[x] Note that this feature of Canada's tax code means that we do not explicitly know the relationship between claiming tax filers and their dependent children, especially prior to 2010 – we can simply observe tax filers who at some point lived in a household where someone claimed the child. Nonetheless, for convenience we refer to linked tax records as parental tax records.

[xi] Another difference between Canadian and American tax filing rules is that in Canada, married couples do not file jointly. This means that we must compute household earnings for cohabiting couples by summing individual earnings across tax filers.

[xii] All dollar figures are rounded to the nearest 100CAD as per Statistics Canada vetting rules.

[xiii] Due to data limitations, we do not use the leave-one-out approach for constructing our Bartik instrument. However, with so many FSAs and industries, using the leave-one-out approach would generate results that are unlikely to differ much from those reported below (Goldsmith-Pinkham et al, 2020).

[xiv] Note that the plotted coefficients appear equal due to Research Data Centre rounding rules. In actuality, the estimates fluctuate slightly.