SSM - Population Health 23 (2023) 101451

Contents lists available at ScienceDirect

SSM - Population Health

journal homepage: www.elsevier.com/locate/ssmph

Beyond the mean: Distributional differences in earnings and mental health in young adulthood by childhood health histories

Emmanuelle Arpin [a,b,*], Claire de Oliveira [a,b,c,d], Arjumand Siddiqi [e,f], Audrey Laporte [a,b]

[a] Institute of Health Policy, Management and Evaluation, University of Toronto, 155 College St 4th Floor, Toronto, ON, M5T 3M6, Canada
[b] Canadian Center for Health Economics, University of Toronto, 155 College St 4th Floor, Toronto, ON, M5T 3M6, Canada
[c] Centre for Health Economics and Hull York Medical School, University of York, Heslington, York, YO10 5DD, UK
[d] Institute for Mental Health Policy Research, Centre for Addiction and Mental Health, 1000 Queen Street West, Toronto, ON, M6J 1H4, Canada
[e] Dalla Lana School of Public Health, University of Toronto, 155 College St 6th Floor, Toronto, ON, M5T 3M6, Canada
[f] Department of Health Behavior, Gillings School of Global Public Health, University of North Carolina – Chapel Hill, Chapel Hill, NC, USA

A R T I C L E I N F O

Keywords:
Child health
Distributional inequalities
Mental health/developmental disorders
Chronic conditions
Non-parametric methods
Educational attainment

A B S T R A C T

Research on the long-term effects of health in early life has predominantly relied on parametric methods to assess differences between groups of children. However, this approach leaves a wealth of distributional information untapped. The objective of this study was to assess distributional differences in earnings and mental health in young adulthood between individuals who suffered a chronic illness in childhood compared to those who did not using the non-parametric relative distributions framework. Using data from the Panel Study of Income Dynamics, we find that young adults who suffered a chronic illness in childhood fare worse in terms of earnings and mental health scores in adulthood, particularly for individuals reporting a childhood mental health/developmental disorder. Covariate decompositions suggest that chronic conditions in childhood may indirectly affect later outcomes through educational attainment: had the two groups had similar levels of educational attainment, the proportion of individuals with a report of a chronic condition in childhood in the lower decile of the relative earnings distribution would have been reduced by about 20 percentage points. Findings may inform policy aimed at mitigating longer run effects of health conditions in childhood and may generate hypotheses to be explored in parametric analyses.

1. Introduction

Childhood is a critical period for the accumulation of skills and the development of stocks of health, both of which can be expected to have lasting effects on later outcomes (Almond et al., 2018). The empirical literature is robust in finding that, on average, children who suffer from an illness which affects either their physical or mental/developmental health, fare worse with regard to both short- and long-term health and socioeconomic outcomes compared to those who do not (Andersen & Gunes, 2018; Case et al., 2005; Currie et al., 2010; Currie & Stabile, 2006). However, the reliance on parametric methods to examine differences between groups narrows the analytical focus to measures of the location (e.g., mean) and variation around it, leaving important distributional information untapped. This limits our ability to fully understand the extent of the effect of health in early life. Distributional insight can inform us as to where sub-groups of children may be concentrated across distributions, which can ultimately inform policy interventions to prevent conditions or mitigate their long-term effects.

This study investigates distributional differences in earnings and mental health scores in young adulthood (ages 18 to 28) between individuals who suffered an illness in childhood (ages 0 to 17) and those who did not. Specifically, non-parametric relative distribution methods developed by Handcock and Morris (Handcock & Morris, 1998, 2006) are used to characterize and quantify distributional differences. Our study is focused on the US with data from the Child Development Supplement and the Transition into Adulthood Supplement from the Panel Survey of Income Dynamics.

The relative distributions framework has been predominantly used in the income inequality literature (Contoyannis and Wildman, 2007; Rudoler et al., 2015). Though there are some applications in the health

* Corresponding author. Institute of Health Policy, Management and Evaluation, University of Toronto, 155 College St 4th Floor, Toronto, ON, M5T 3M6, Canada.
E-mail addresses: emmanuelle.arpin@mail.utoronto.ca (E. Arpin), claire.deoliveira@camh.ca (C. de Oliveira), aa.siddiqi@utoronto.ca (A. Siddiqi), audrey.laporte@utoronto.ca (A. Laporte).

https://doi.org/10.1016/j.ssmph.2023.101451
Received 17 June 2022; Received in revised form 9 June 2023; Accepted 10 June 2023
Available online 21 June 2023

inequalities literature (Bernhardt et al., 1995; Handcock & Morris, 1998; Hermeto & Rangel, 2009; Kabudula et al., 2017), there are none to our knowledge in the field of health in early life. The application of the relative distributions' framework represents a contribution to the field of research on health in early life for several reasons. First, the method examines distributional differences with greater detail than commonly used parametric tools. Rather than focusing on differences at the mean, differences across distributions of interest can be examined. By way of illustration, the method allows for identification and quantification of the density of a group of individuals who experienced an illness in childhood (comparison group) relative to those individuals who did not (reference group) at various points along a distribution of earnings in adulthood, for example. Additionally, as the derived relative distributional difference is represented as a ratio, the method draws on basic probability tools, which enhances ease of interpretation. Moreover, the approach allows for decompositions, which can be used to identify the contribution of individual characteristics to the overall distributional differences. Finally, as it is also a descriptive tool, the relative distribution method can support hypothesis generation by identifying variables that have an effect - both direct and indirect - in adulthood which can then be further explored using parametric approaches.

An objective of this study was to examine comparatively long-term effects of physical and mental health/developmental conditions in childhood. Although there has been an increase in interest in childhood mental/developmental health conditions, rarely have both physical and mental/developmental health conditions been considered comparatively (Case et al., 2005). In addition, this study also aimed to investigate the underlying pathways that mediate the relationship between health conditions developed in childhood and outcomes in young adulthood. The decomposition approach embedded in the relative distributions' framework allowed us to unpack underlying pathways in a novel way. This study focused on educational attainment as the primary pathway of interest for its relationship with both health conditions in childhood (i.e., inhibiting educational attainment due to time away from scholastic activities) and outcomes in young adulthood (i.e., low educational attainment is associated with lower earnings).

In what follows, we first present a theoretical and empirical background to motivate our research questions. We present an overview of the key findings from the literature with respect to the legacy effects of health conditions in childhood as well as a description of distributional approaches. Following this, we describe the data and methodological approach. We then present the main findings. We conclude with a discussion of the implications of the results as well as study limitations.

2. Background

It is well established in the empirical literature that health in childhood carries important legacy effects into adolescence and adulthood. The skills formation framework developed by Heckman and Cunha suggests that child development is a dynamic process with implications over the life-course, where "skills beget skills": if skills are developed early in life, the production of subsequent skills will be more effective as skills build on each other over time (Cunha & Heckman, 2007, 2008). The model further suggests that disadvantage or illness occurring in childhood will not only negatively impact the child contemporaneously in period t, but will also affect the accumulation and productivity of the skills in period $t+1$. This is predominantly due to the child's time away from regular skill-building activities which ensues from a health condition.

The characteristics of childhood chronic conditions align with the notion of time away from regular skill-building activities. Chronic conditions in childhood imply functional limitations on normal child activities, often that last more than 12 months, and require medical or specialized care (van der Lee et al., 2007). A chronic condition may be physical (e.g., asthma, epilepsy) or mental/developmental (e.g., autism, general anxiety disorder) in nature. The prevalence of childhood chronic conditions remains high and has been increasing over the last three decades in the US. The US Centers for Disease Control and Prevention report that about 40% of school-aged children and adolescents suffer from a chronic condition, relating to conditions affecting a child's physical health and/or behavioural/learning problems (Centres for Disease Control, 2021). In recent years, mental/developmental disorders have been increasing as well. Mental health problems relate to psychological and/or emotional well-being, such as general anxiety disorder, while developmental problems relate to neurodevelopmental disorders, such as attention deficit/hyperactivity disorder (ADHD) and learning disabilities.

The empirical literature has examined the long-term effects of both physical and mental/developmental chronic conditions on various later outcomes (Andersen & Gunes, 2018; Case et al., 2005; Currie et al., 2010; Currie & Stabile, 2006). In a seminal paper, Case and colleagues examined the effect of childhood chronic conditions on educational qualifications in early adulthood (O-level exams in the UK), self-reported health, employment (full- and part-time) and socioeconomic status (occupational role) (Case et al., 2005). Using the British National Child Development Study, the authors found that a higher number of total chronic conditions (physical, neurodevelopmental) in childhood was associated with a lower probability of higher socioeconomic outcomes and a lower probability of reporting good health in adulthood. When examining specific conditions, results differed slightly. Physical health conditions showed weaker long-term effects, whereas mental/emotional health conditions showed long-term effects, regardless of the age at diagnosis.

Mental health conditions and developmental disorders have increasingly been studied due to their increasing prevalence as noted above. Currie and Stabile examined the effect of ADHD on short-run outcomes in Canada and the US. The authors found that a one-point increase in a clinically validated hyperactivity scale at ages 4 to 11 was negatively associated with academic performance at ages 12 to 15 in both contexts (Currie & Stabile, 2006). Currie and colleagues confirmed that these negative effects persisted into later adulthood; children with a report of ADHD at ages 4 to 8 or later in childhood were less likely to be enrolled in grade 12 at age 17 and are more likely to be on social assistance later in life (Currie et al., 2010). Considering mental health more generally, Andersen and Gunes found that better self-reported mental health at age 16 was associated with a higher probability of college attendance, earnings and health in later adulthood (Andersen & Gunes, 2018), while Fletcher found that reports of mental health measured as depressive symptoms reduced labour force attachments in young adulthood (Fletcher, 2014).

The empirical literature on the relationship between health in childhood and outcomes in young adulthood continues to grapple with the identification of underlying pathways. Within the "health selection" perspective, which views health as a cause of later health and socioeconomic outcomes, there are two dominant classes of explanatory pathways (S. Haas, 2008; S. A. Haas, 2006). The first suggests that health conditions in early childhood exert a direct effect on future health and socioeconomic outcomes in adulthood. This literature is akin to the fetal origins hypothesis, which posits that conditions developed and shocks experienced in early life will have a direct and lasting impact on future skills and health, net of intermediary factors (Almond & Currie, 2011; Barker, 1990). This pathway also relates to the idea of "latent effects" proposed by social epidemiologists (Hertzman & Power, 2003; Kuh et al., 2003). The second suggests an indirect pathway. This perspective suggests that health conditions in childhood do affect intermediary factors in youth, such as high school completion or educational attainment, which in turn affect future health and economic outcomes.

This study focuses on educational attainment as an underlying pathway. Educational attainment is related to both child health conditions and outcomes in adulthood (i.e., earnings and mental health) (Ross & Wu, 1995; Zajacova et al., 2015; Zajacova & Lawrence, 2018). As alluded to above, child health conditions can influence outcomes in childhood and adolescence such as educational attainment. Both physical and mental/developmental health conditions imply time away from regular activities, including scholastic activities. For mental/developmental health conditions more specifically, resources may be more limited in the school environment to support children with these conditions thus significantly setting them back in comparison to their peers (DuPaul et al., 2011; Sibley et al., 2016). Educational attainment also influences job and occupational prospects, which subsequently influences earnings. Educational attainment has also been found to influence care seeking behaviours and health more generally. Educational attainment is thus a natural starting point to consider in a decomposition analysis.

3. Methods and measures

3.1. Data

We used data from the Child Development Supplement (CDS) and the Transition into Adulthood Supplement (TAS) from the US Panel Survey of Income Dynamics (PSID). Since 1968, the PSID has collected intergenerational data on socioeconomic factors and the health of families and individuals (Johnson et al., 2018). In 1997, the PSID launched the CDS, where the purpose was to collect detailed age-specific information on a cohort of children belonging to PSID families present in the survey in 1997. The children were between the ages of 0–12 years (born between 1984 and 1997). The CDS covered three waves of data over 10 years at five-year intervals – 1997, 2002 and 2007. Children were followed until the age of 17. In 2005, the PSID launched the TAS. The purpose of the TAS was to investigate the transition period between childhood and adulthood by collecting data from the children who aged out of the CDS (>18 years). The addition of the TAS thus effectively extended the original CDS cohort. Respondents were followed until the age of 28, after which they could enter the PSID as adults. There were seven waves of the TAS over twelve years, from 2005 to 2017, conducted at 2-year intervals. Together, the CDS and the TAS allow us to follow a cohort of children from early childhood into early adulthood.

For the purposes of this study, children who participated in at least one wave of the CDS (1997, 2002, 2007) and one wave of the TAS (2005–2017) were included. The period of childhood is defined as between the ages of 0–17, the ages covered in the CDS. The young adulthood period is between the ages of 18–28 years of age, the ages included in the TAS. There were 3563 children in the original CDS (1997). After excluding individuals who did not participate in at least one wave of both the CDS and the TAS, the analytical sample consisted of 2942 individuals.

3.2. Measures

We investigate distributional differences for two outcomes in young adulthood - earnings and mental health scores. We use annualized earnings from the TAS, which is a derived measure of earnings from wages and salaries from all jobs reported in a given year (i.e., up to five jobs). All earnings are adjusted to 2017 dollars, most recent year of TAS data. About 6% of the sample does not report any earnings ($0); thus, the log of the earnings variable was applied after adding $1 to the zero values. The highest reported value of earnings in this period (ages 18 to 28) is taken as an indicator of earnings in young adulthood. Much of the research on intergenerational income finds that permanent income in adulthood is determined when individuals are in their mid-forties (Haider & Solon, 2006), although more recent research by Chetty and colleagues (Chetty et al., 2014) suggests that income stabilizes when individuals reach their mid-to late twenties and thus can be an accurate reflection of their future earnings.

Mental health in young adulthood is measured using scores from the K-6 Non-Specific Psychological Distress Scale (Kessler et al., 2002, 2003). This validated screening tool captures undiagnosed mental health conditions of respondents based on answers to six questions (e.g., how often they felt nervous in the past month). Each question can receive a score from 0 to 4 points; points are then summed up to maximum of 24 points. A higher score represents poorer mental health and a score of 13 or higher indicates clinically significant nonspecific distress. The average K-6 score over the young adulthood period is used as an indicator of mental health status (ages 18 to 28).

Two groups of individuals are compared: those with a report of a child chronic health condition and those without a report of a child chronic health condition. The CDS consistently includes measures of chronic health conditions in childhood across its three waves. Conditions relate to both physical (e.g., asthma, diabetes, hypertension) and mental/developmental chronic health conditions (e.g., hyperactivity/ADHD, autism, learning disability). Of particular interest are chronic conditions that carry a lasting effect and imply time away from regular activities, so short-term infections, injuries and congenital disorders are excluded. These exclusions also acknowledge that health in childhood is distinct from health at birth. For each health condition of interest, an indicator is created to denote that an individual experienced at least one condition over the three waves of the childhood period as has been done by others (Case et al., 2005).

Relative distributions between individuals with a report of a child chronic health condition and those without a report of a child chronic health condition are generated based on the presence of two child health indicators. Specifically, results are presented for an indicator of at least one mental/developmental health condition and an indicator of at least one physical health condition. Said otherwise, one set of models will compare those without a physical condition versus those with a physical condition, and another set of models will compare those without a mental/developmental health condition versus those with a mental/developmental health condition. The indicator of at least one mental/developmental condition includes autism, emotional disturbance, learning disability and hyperactivity/ADHD. The indicator of at least one physical health condition includes heart condition, diabetes, anemia, asthma, epilepsy, orthopedic problems, allergies, and chronic ear infections (at least three in last 12 months). Although the aforementioned conditions are parent-reported, they are based on having been detected by a physician (i.e., "has a doctor or other health professional ever detected diabetes?") thus reducing some concerns around measurement error. Finally, we note that although the CDS does include other questions on child mood (i.e., anxiety and fearfulness), these are strictly parent-reported and have not been confirmed by a physician. For consistency across the conditions of interest, we focus on child health conditions that have been reported in a similar manner.

Finally, a number of covariates were included in the decomposition analyses. The primary focus in the analysis was on educational attainment. Educational attainment is measured as the maximum years of education achieved in young adulthood. As described above, educational attainment is emphasized in the extant literature as an important pathway for future health and socioeconomic outcomes because cognitive skills are developed and professional credentials are achieved, all of which influence employment, earnings and health (Case et al., 2005; Currie et al., 2010). Other covariates of interest include household income in childhood. This inclusion builds on the empirical literature finding that children from economically disadvantaged families report poorer health and that this relationship increases over time (Case et al., 2002; Currie & Stabile, 2003). Recognizing the greater importance of permanent household income compared to annual household income (Contoyannis & Li, 2011; Dahl & Lochner, 2008), average household income during the childhood period is used. Birth weight is used to represent baseline health and the intrauterine environment which can impact future health (Almond & Currie, 2011; Oreopoulos et al., 2008). Finally, maternal education is deemed to be an important marker of household socioeconomic status for children. As mothers have traditionally been primary care givers for children, their higher education or income is posited to influence child rearing practices and familial resource allocation, as stated by the "good mother hypothesis" (Dooley et al., 2005; Hsin, 2012).

3.3. Empirical approach

The relative distributions (RD) framework described below draws on Handcock and Morris' description (Hou & Myles, 2008; Hout, 2012). Let Y_0 be a random variable representing a given measurement for a population (e.g., income). The population that generated Y_0 is deemed the "reference group". The cumulative distribution function (CDF) of Y_0 is denoted by $F_0(y)$ and the probability density function (PDF) by $f_0(y)$. In addition, let Y represent another population deemed the "comparison group". It is assumed that Y has a CDF, F(y), and a density, f(y). For the purposes of this study, the reference group is composed of children who did not experience a chronic illness in childhood, whereas children who did experience a chronic illness in childhood represent the comparison group.

The relative distribution of Y to Y_0 is defined as the distribution of the random variable, R:

$$R = F_0(Y) \quad (1)$$

R is obtained by transforming Y (comparison group) by the CDF of Y_0, F_0. It is continuous over the outcome space [0,1] and the realization of R, r, is termed the relative data. This relative data thus captures the difference in distributions, between the two groups. As a random variable, r has both a CDF and a PDF. Of interest, the PDF of r can be obtained as the derivative of G(r), g(r):

$$g(r) = \frac{f(Q_0(r))}{f_0(Q_0(r))} \quad 0 \le r \le 1 \quad (2)$$

The PDF of r can be interpreted as a density ratio between the two groups. This can be seen more easily by expressing g(r) explicitly in terms of the original measurement scale, y. Let the rth quantile of r be denoted by the value, y_r on the original measurement scale, so the y_r corresponding to r is $Q_0(r)$. The relative PDF is then,

$$g(r) = \frac{f(y_r)}{f_0(y_r)} \quad y_r = Q_0(r) \ge 0. \quad (3)$$

Although the relative density can be interpreted as a density ratio, it is a proper PDF in that it integrates to 1 over the unit interval. Since the tools in the RD framework boil down to CDF and PDF interpretations, the RD framework provides results that are easily interpretable. Practically, the relative data can be interpreted as the percentile rank (position) of Y (comparison group) to Y_0 (reference group). Percentile ranks are presented graphically. If the ratio between the two groups falls at the horizontal reference line at the value of 1 on the y-axis, the two distributions in the ratio are identical. This implies no differences between groups at that point in the distribution. Where there are differences, this can be seen on the graph as deviations above or below the line at the value of 1. If the frequencies are denser above 1, then there are more observations at this point in the distribution for the comparison group. If the frequencies are denser below 1, there are more observations at this point in the distribution for the reference group. If a uniform distribution is observed (i.e., values concentrated at 1 on the horizontal line), then there is no difference between the two groups.

Location and shape decompositions can also be performed in the RD framework to examine if the concentration of one group at a particular point of the distribution is driven by their location (mean, median) or the broader dispersion of values in the upper and lower tails of the distribution of interest. In the location decomposition, a counterfactual distribution has the comparison group's location (i.e., mean) and the reference group's shape. The counterfactual distribution is then compared to the reference distribution, where the locations differ between groups. This allows for examination of the importance of the mean values from the overall distributional difference. A uniform distribution in the location decomposition would imply that no differences are explained by the mean. The shape decomposition takes the residuals from the former counterfactual distribution and compares it to the reference group's distribution. If there are no shape differences, the relative density will be uniform.

Covariate decompositions are conducted if it is suspected that the covariate composition of one group may be contributing to overall distributional differences. The method decomposes the relative distribution into a component that represents the effect of changes in the marginal distribution of the covariates (the composition effect from the covariates), and a component that represents the residual changes (a counterfactual assuming no covariate differences between groups). A uniform distribution in the composition effect means that differences are not explained by differences in the covariates between groups. Following this, the residual effect analysis considers the hypothetical case where the two covariate distributions are the same (covariate adjustment), thus removing the differences in covariates. These analyses are akin to the parametric covariate adjustments, by producing a counterfactual distribution where both groups have the same covariate composition with all else (shape and location) being distinct for each group. The covariate decompositions are particularly useful to identify pathway effects and moderating effects. For example, if there are no residual effects observed, then a direct pathway effect is suggested; if the residual effects indicate that there are differences between groups, an indirect pathway effect is suggested for the particular covariate being analyzed.

The RD framework generates nonparametric, entropy-based summary statistics to provide measures of the distributional differences, specifically the Kullback-Leibler measure of divergence. Such nonparametric summary measures are akin to the R^2 in regression analyses. These measures of entropy are indicated above the graphical displays for the location and shape decompositions to illustrate how much each decomposition is contributing to the overall distributional difference. RD analyses were conducted in R using the "reldist" package developed by Handcock and Morris (1998, 2006). The CDS-PSID weights from 1997 are used in analyses.

4. Results

4.1. Descriptive analyses

Table 1 presents descriptive statistics for the outcomes in young adulthood and covariates of interest by reports of child chronic health conditions. Individuals with a report of any of our health conditions of interest consistently report lower mean earnings compared to those who did not, except for the mean earnings for individuals with a physical condition in childhood. These individuals also report poorer mental health (i.e., higher mental health scores) in young adulthood by about one point on the K6 scale. Also consistent with the literature, individuals with a report of a mental/developmental health condition in childhood are more likely to belong to families with lower household income (Case et al., 2002; Currie & Stabile, 2003), with the exception of physical health conditions.

For comparative purposes, results for both parametric and non-parametric tests to assess differences between groups are reported in Table 2. Similarly to parametric t-tests, non-parametric tests are useful to indicate whether there are significant distributional differences. However, these are global assessments and cannot provide greater insight into the differences at particular points of a distribution, nor can they quantify them. As such, non-parametric test results are a useful first step towards a more fulsome distributional assessment.

The non-parametric tests employed are the Kolmogorov-Smirnov test, the Mann-Whitney rank-sum test and the Epps-Singleton test (Jones, 1997). The indicator of at least one mental/developmental condition in childhood shows significant differences for earnings and mental health in young adulthood for all tests. Having at least one

Table 1
Descriptive statistics by childhood health conditions.

	Full sample		Mental/develop. disorder		No Mental/develop. disorder		Physical Condition		No Physical Condition	
	Mean/Prop.	SD	Mean/Prop.	SD	Mean/Prop.	SD	Mean/Prop.	SD	Mean/Prop.	SD
Young adulthood										
Earnings (log)	9.13	2.45	8.74	2.85	9.20	2.37	9.11	2.49	9.17	2.39
Earnings	23,343	21,883	20,772	20,760	23,810	22,053	23,419	22,390	23,224	21,087
Mental health (K6)	5.04	3.15	5.81	3.68	4.89	3.03	5.15	3.24	4.86	3.00
Controls										
Mother education	13.09	2.15	12.94	2.08	13.11	2.16	13.16	2.16	12.97	2.13
Sex (male)	0.49		0.66		0.47		0.52		0.47	
Age	24.05	2.53	24.06	2.51	24.05	2.53	24.00	2.56	24.14	2.48
Birth weight	7.27	1.45	7.29	1.55	7.26	1.43	7.28	1.48	7.25	1.41
Household income	79,745	88,375	71,676	71,982	81,221	90,990	82,220	89,065	75,920	87,199
Household income (log)	10.98	0.79	10.87	0.79	11.00	0.79	11.02	0.77	10.91	0.89
Education	13.47	1.94	12.76	1.80	13.60	1.94	13.47	1.94	13.47	1.93
N	2942		455		2487		1786		1156	

Notes: Outcome variables in young adulthood and controls for decomposition analyses described by presence of child health conditions. All dollar values are adjusted to 2017 values. Birth weight is measured in pounds (lbs.). Education and age are measured in years. Descriptive statistics are unweighted. Prop. = proportion.

Table 2
Parametric and non-parametric tests.

Child Health	Outcome	T-test			KS			MW			ES		
		Stat.	p-value	Sig.	Stat.	p-value	sig.	Stat.	p-value	sig.	Stat.	p-value	sig.
Mental/dev. Health	Earnings	3.635	0.000	***	0.093	0.003	***	3.371	0.001	***	12.613	0.013	**
	Mental Health	−5.728	0.000	***	0.135	0.000	***	−4.902	0.000	***	37.794	0.000	***
Physical Health	Earnings	0.605	0.546		0.027	0.693		0.411	0.681		6.539	0.162	
	Mental Health	−2.482	0.013	*	0.058	0.017	*	−1.947	0.052		7.553	0.109	

p-value: * <0.05; ** <0.01; *** <0.001.
Notes: KS: Kolmogrov-Smirnov test; MW: Mann-Whitney test; ES: Epp-Singleton test. Statistics (from left to right): t-statistic, combined difference, z-statistic, W2 *t*-test.

physical health condition in childhood is only significantly associated with poorer mental health scores in young adulthood for the Kolmogorov-Smirnov test.

4.2. Relative distributions

In the following figures, the deciles of the reference group (i.e., individuals without a report of a chronic health condition in childhood) are indicated on the lower x-axis, the size of the relative density on the y-axis and logged earnings or mental health scores on the upper x-axis. A mean additive shift is used to quantify the location and shape decompositions and the scale is the interquartile range (IQR) as it is less sensitive to outliers. We used the RD framework default bandwidth measure based on the RD generalized cross-validation method. The method assumes common support: for pairs of groups compared, there are corresponding observations in earnings and mental health scores. The common support assumption ensures that the non-parametric comparisons are consistent and avoids comparisons where no observations exist. For each ensemble of graphs below, the first graph represents the overall distributional difference, the second graph represents the location decomposition, and the third graph represents the shape decomposition. The entropy scores are presented above each graph.

Graph A-1 of Fig. 1 shows that the earnings of young adults who reported at least one mental/developmental disorder in childhood are more concentrated in the lower deciles of the relative earnings distribution compared to those who did not (>1.0). The earnings of young adults who did not report a mental/developmental disorder in childhood are more concentrated in the upper deciles (<1.0) of earnings in young adulthood, though not dramatically as there is equality (1.0) in the ninth decile. The effects of the location decomposition are not negligeable (graph A-2). Acting on its own, the lower mean earnings of individuals reporting at least one mental/developmental condition in childhood leads to their greater concentration in the bottom deciles of the relative earnings distribution (bottom three deciles) in young adulthood. In addition to the impact of this location shift (lower mean earnings), there is evidence of dispersion due to the shape. In graph A-3 of Fig. 1, even without the lower mean earnings in adulthood for the individuals reporting at least one mental/developmental disorder in childhood, the dispersion of earnings for this group implies relatively more individuals with earnings in the bottom earnings decile in early adulthood. This implies that operating on its own, the dispersion would have increased the proportion of earnings in the upper decile (higher earnings) for the young adults with a report of at least one mental/developmental condition in childhood. In sum, the lower earnings observed for young adults with an indicator of at least one chronic mental/developmental disorder in childhood are produced by both a lower mean as well as dispersion of earnings concentrated in the lower earnings deciles, but the latter to a lesser extent. The more dramatic effect of the difference in mean earnings in adulthood is also confirmed by its measures of entropy, which is well over 50% of the value of the overall entropy score. Graph B-1 of Fig. 1 shows the distributional differences in earnings between individuals who report at least one chronic physical health condition in childhood compared to those who do not. Differences are relatively flat across the distribution, and the shape and location decompositions show little effect.

Fig. 2 presents the distributional differences in mental health scores in young adulthood. Here, a higher score represents poorer mental health, while a lower score represents better mental health. These graphs are therefore reversed in comparison to the earnings graphs presented in Fig. 1. In graph A-1 of Fig. 2, individuals with an indicator of at least one chronic mental/developmental disorder in childhood report poorer mental health (higher score) relative to those who do not in early adulthood. Examining the mean (location) decomposition in graph A-2 in Fig. 2, we see that the concentration of poor mental health scores for individuals with a report of at least one chronic mental/developmental health condition in childhood are still concentrated in the top deciles (i.e., worse mental health outcomes) of mental health scores in young adulthood, but that they are more spread out across the

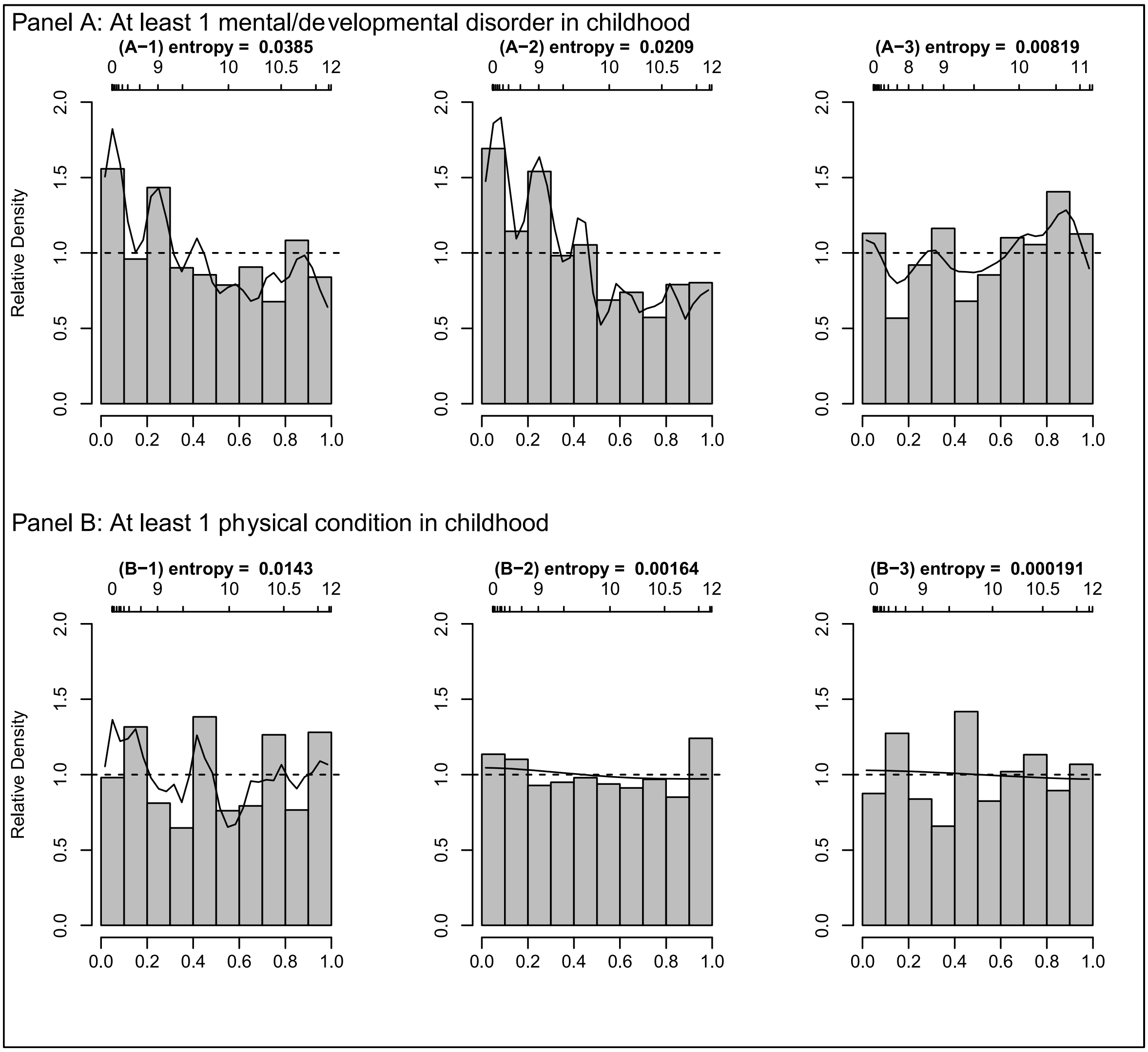

Fig. 1. Distributional differences in earnings (18–28 years old), mental/developmental disorder and physical health
Notes: The lower x-axis represents the deciles of the reference group (i.e., individuals without a report of a chronic health condition in childhood). The y-axis represents the size of the relative density between the two groups. The upper x-axis represents logged earnings.

top deciles. When examining the shape decomposition in graph A-3 of Fig. 2, the proportion of poor mental health scores in the top decile decreases for individuals with a report of at least one mental/developmental disorder in childhood. The measures of entropy indicate that most of the overall distributional difference is due to dispersion (shape decomposition): operating on its own, the dispersion of the distribution would have led to more spread of the mental health scores of individuals with a report of at least one mental/developmental disorder in childhood towards the bottom decile (i.e., tending towards better mental health scores in young adulthood).

In graph B-1 of Fig. 2, individuals with a report of at least one physical health condition in childhood are concentrated in the top deciles of the mental health score distribution (i.e., poorer mental health). Turning to the location and shape decompositions, the graphs and the entropy scores indicate that much of the overall distributional differences are due to dispersion in the shape of distributions of mental health scores. Said otherwise, while the means of mental health scores in young adulthood between those who did and did not experience a physical chronic condition in childhood were not different, some individuals experienced mental health scores in adulthood that tended towards better mental health (i.e., towards the bottom deciles), while others experienced mental health scores in adulthood that tended towards poorer mental health (i.e., towards the upper deciles).

4.3. Covariate decompositions

The decompositions for the distributional differences in earnings using educational attainment are presented below. For brevity we only present results for earnings. Decomposition analyses were also conducted for mental health scores in adulthood; however, educational attainment was not found to be a salient pathway linking childhood health conditions to mental health scores in young adulthood. Said otherwise, had the two groups had the same educational attainment, the observed distributional differences in mental health scores would be unchanged. Decomposition results for mental health scores are available upon request.

In Fig. 3, graph A-1 shows the same results as graph A-1 in Fig. 1. Graph A-2 of Fig. 3 reveals that the difference in educational compositions between the groups was modest as the relative distribution is relatively flat, though there are some differences at the very bottom and at the very top of the distribution. The residual effect analysis presented in graph A-3 of Fig. 3 adjusts for the differences in educational composition. Here, the educational attainment of the comparison group (individuals with a report of a mental/developmental disorder in

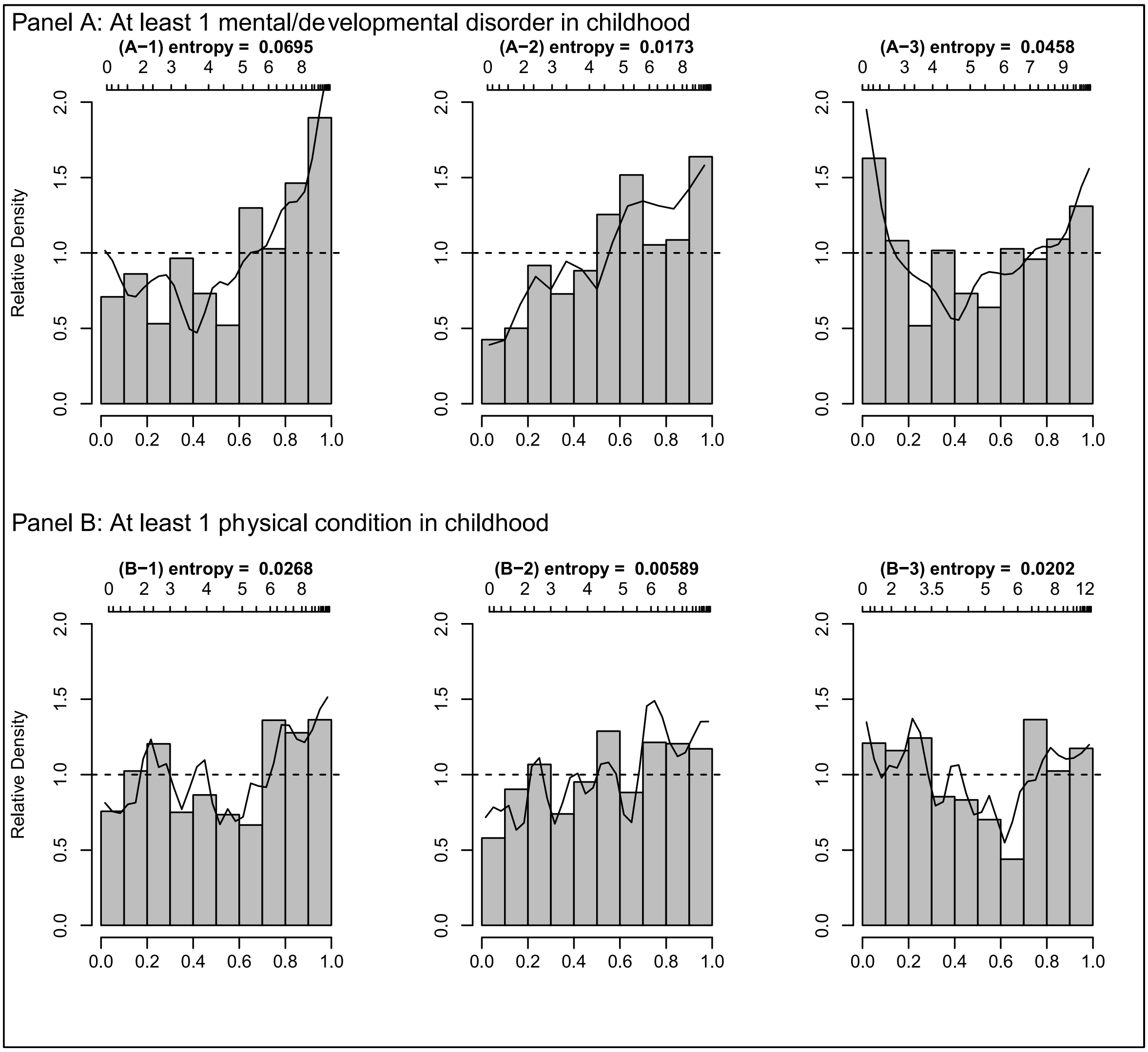

Fig. 2. Distributional differences in mental health scores (18–28 years old), mental/developmental disorder and physical health
Notes: The lower x-axis represents the deciles of the reference group (i.e., individuals without a report of a chronic health condition in childhood). The y-axis represents the size of the relative density between the two groups. The upper x-axis represents the mental health scores.

childhood) is matched to the educational attainment of the reference group (individuals without a report of a mental/developmental disorder in childhood). Results show that educational attainment does matter in the lower deciles as it reduces the proportion of individuals who experienced at least one mental/developmental disorder in childhood that are found in the bottom of the earnings distribution in adulthood. Said otherwise, had the comparison group (those with an illness) had the same educational composition as the reference group (those without an illness), their earnings distribution would have been shifted to the right, towards the higher deciles of earnings in adulthood. This suggests that educational attainment matters for earnings and that a health condition in childhood may inhibit educational attainment.

Panel B of Fig. 3 reports the decomposition results for an indicator of at least one physical health condition. There are stark differences from the previous panel: years of education do not act as a mediator (pathway) between physical health in childhood and earnings later in life. Graph B-1 of Fig. 3 reproduces graph B-1 of Fig. 1, which reveals that the differences in educational attainment were not important to explain the differences in adulthood between the groups since the relative distribution of having a physical condition is flat. The residual analysis in graph B-3 of Fig. 3 indicates a graphical display very similar to that shown in graph B-1 of Fig. 3.

4.4. Sensitivity analyses

A series of sensitivity analyses were conducted to assess the robustness of the reported results. All are available upon request. First, two alternative measures of income were investigated: total income (earnings, assets, federal assistant programs) and residualized earnings. Results were similar to those produced for the measure of earnings used in the main analyses. The second set of robustness checks involved conducting the relative distributions exercise for additional childhood health conditions separately (e.g., ADHD, asthma, diabetes, epilepsy), an indicator of a limiting condition and two indicators of service use (e.g., two or more hospitalizations in childhood excluding birth). Interestingly, having had any one of the above listed chronic conditions in childhood yields similar patterns to those observed for those having reported a chronic physical health condition in childhood, while results for having a limiting condition in childhood are similar to the reported results for mental/developmental disorders. Similarly, much of the overall distributional difference is driven by the lower mean (location decomposition).

Finally, covariate decompositions were conducted for birth weight, household permanent income in childhood and maternal education. Only household permanent income in childhood showed a significant

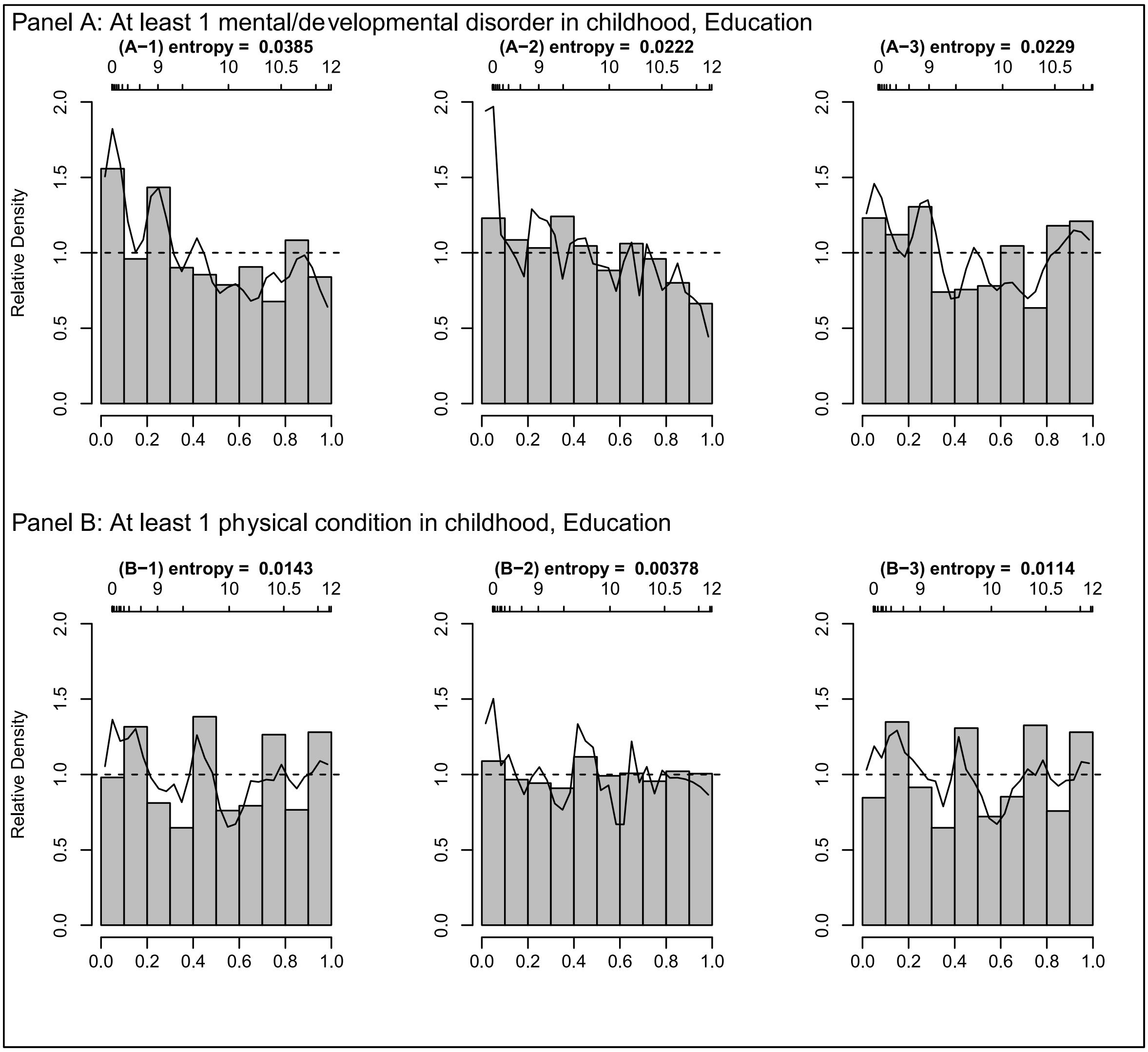

Fig. 3. Educational decomposition for earnings, mental/developmental disorder and physical condition
Notes: The lower x-axis represents the deciles of the reference group (i.e., individuals without a report of a chronic health condition in childhood). The y-axis represents the size of the relative density between the two groups. The upper x-axis represents logged earnings.

decomposition effect for having a mental/developmental disorder in childhood. In other words, had the two groups of individuals had the same household permanent income in childhood, there would be fewer individuals with a report of a mental/developmental disorder in childhood in the bottom decile of the relative earnings distribution in early adulthood. This suggests that household income in childhood moderates the effect of a child mental/developmental health condition on future outcomes.

5. Discussion

The results show that young adults with a report of a health condition in childhood (physical, mental/developmental) fare worse in terms of both earnings and mental health scores in young adulthood compared to those who did not. This is particularly salient for individuals with a report of a mental/developmental disorder in childhood. The earnings of individuals who experienced a mental/developmental disorder in childhood are overwhelmingly represented in the bottom deciles of the relative earnings distribution and the top deciles for mental health scores (i.e., worse mental health) distribution in adulthood. An examination of which parts of the relative distributions are driving the overall difference was conducted with location and shape decompositions. There is greater evidence that the location (mean) drives the overall difference for the relative earnings distribution in adulthood between the groups, whereas there is more dispersion at play in the case of the mental health scores observed in adulthood. Finally, covariate decompositions suggest that chronic conditions in childhood may indirectly affect later outcomes through educational attainment.

The finding that distributional differences are more salient for individuals with mental/developmental disorders in childhood builds on the previous literature. Mental/developmental health conditions in childhood consistently demonstrate negative and persistent effects on numerous outcomes, such as early and later education, health and earnings (Andersen & Gunes, 2018; Case et al., 2005; Contoyannis & Dooley, 2010). The differential effects between mental/developmental and physical health conditions are of particular interest and these findings resonate with the extant literature that also examined child health conditions comparatively (Andersen & Gunes, 2018; Case et al., 2005; Currie et al., 2010).

These differing results may occur for several reasons. First, mental/developmental health conditions may be more difficult to detect by parents and guardians because the symptoms for particular conditions are not always externalizing. Externalizing conditions include externally-focused behavioural symptoms including aggression, conduct problems, hyperactivity, and attention problems, whereas internalizing conditions relate to internally-focused symptoms including anxiety, fear, sadness/depression, and somatic complaints (Achenbach et al., 2016). The manifestation of certain developmental conditions may also vary based on child sex. For example, evidence suggests that ADHD manifests itself earlier and as hyperactivity in males, while it manifests itself later and as inattention in females (Loyer Carbonneau et al., 2021). Relatedly, the interpretation of symptoms and selected treatment for these conditions may also vary by guardians, parents and teachers (Coplan et al., 2011; Johnston & Burke, 2020). These characteristics can make detection challenging for parents, guardians and teachers.

In addition, many health services are not publicly insured in the US, even under remedial programs (e.g., Medicaid, Children's Health Insurance Program [CHIP]). Health services for these conditions are covered through out-of-pocket payments or employment-based insurance schemes, thus leading to potential inequities in access to care and treatment plans. By extension, this may lead to increased use of emergency department visits, and other suboptimal forms of care. Finally, health services for mental/developmental health conditions may also extend beyond the health care system into school and/or social work services, thus implying costs in terms of time and resources for parents and caregivers to navigate the broader care system (Ronis et al., 2017). These barriers may contribute to a lack of early detection and adequate care supports.

Location and shape decompositions shed light on the drivers of the overall distributional differences. For earnings, decompositions indicate that there is little dispersion towards the upper deciles of the earnings distribution for individuals with a report of a mental health/developmental condition in childhood. These results indicate that the earnings potential for the aforementioned group plateaus around the mean. The plateauing suggests that policy efforts should focus on ensuring that individuals who report a mental/developmental condition in childhood can reach their full educational and/or earnings potential in young adulthood. The location and shape decompositions for the mental health scores in adulthood show a different story. Rather than the distributional differences being largely driven by the differences in the mean, it is driven by the shape. The dispersion in the distribution of mental health scores in young adulthood suggests that individuals with a report of a health condition in childhood may see either an improvement or worsening in their mental health in young adulthood.

Covariate decompositions support the examination of potential pathway effects. The residual analyses in the covariate decompositions show that had the two groups had the same educational composition as the reference group (individuals without a chronic health condition in childhood), the proportion of individuals with a report of a mental health/developmental condition in childhood in the lower decile of the earnings distribution would be reduced by about 20 percentage points and spread across the distribution in the lower deciles. This suggests that educational attainment matters for earnings (leads to an improvement in earnings) and that illnesses in childhood may inhibit educational potential. This finding builds on the literature which has emphasized education as an important pathway for future socioeconomic outcomes as cognitive skills are developed and professional credentials are acquired, all of which influence employment and earnings in later life (Hou & Myles, 2008; Hout, 2012). In addition, the literature finds that childhood conditions do impact early as well as later educational attainment, thus suggesting that childhood conditions might indirectly impact future outcomes by imposing a limit on educational attainment (Case et al., 2005; Contoyannis & Dooley, 2010).

Although not presented, our supplementary analyses find that educational attainment does not represent a salient pathway between child health conditions and mental health in adulthood. This somewhat contrasts previous literature, but may be explained by a few reasons. First, the measure of health in adulthood we examined may not adequately capture mental health in adulthood. Relatedly, educational attainment may be operating on another domain of health, such as physical health or health behaviors (Lundborg, 2013). In addition, cognitive and non-cognitive scores developed in educational settings may represent a more valid pathway to consider rather than the measure of attainment (Arpin et al., 2023). Future research may consider other measures of health in adulthood as well as measures of skills in adolescence.

This study contributes to the empirical literature that seeks to examine distributional differences (Basu et al., 2015; Siddiqi et al., 2018). Until recently, distributional methods had been used predominantly in the income inequalities literature to complement the commonly used Lorenz curves and Gini coefficient but offering greater flexibility and imposing weaker assumptions (Handcock & Morris, 1998, 2006; Hao & Naiman, 2010). Through the application of the relative distributions framework, this study also makes a conceptual contribution to what Siddiqi and colleagues call "distributional inequalities" (Siddiqi et al., 2018). Siddiqi and colleagues suggest that it is necessary to move beyond dichotomous conceptualizations and modeling techniques when considering health inequalities; it is rather necessary to consider a continuum of risk factors or social determinants of health that influence population health and social inequalities (Rose, 2001; Siddiqi et al., 2018).

Finally, this study is not without limitations. The CDS-TAS's rich, longitudinal data provide several advantages for our study. For instance, detailed information on diagnosed child health conditions reduces concerns regarding measurement error. In a similar vein, questions are also asked during childhood, rendering data that are age specific. This is an improvement on previous studies which have primarily relied on retrospective accounts of health before the age of 16 (Andersen & Gunes, 2018; Case et al., 2005; Smith, 2009). However, the CDS-TAS lacks information on certain key variables such as immigration status, leading to some concerns around omitted variable bias in our analyses. This information would be useful to provide a better understanding of care seeking behaviors, for example (Akresh, 2009; Garcés et al., 2006). Although there have been significant efforts to include immigrants in the PSID and its supplements since 1997, the representativeness of the immigrant population in the data only occurred after our study period of interest (Johnson et al., 2018). Scholars analyzing the new PSID supplements should include these data in future research.

The generalizability of the results due to attrition may raise some concerns. This is warranted as attrition analyses show that healthier and wealthier children tend to remain in the CDS-TAS for a longer period of time (McGonagle et al., 2012; Sastry et al., 2021). This form of survivorship bias can imply a downward bias in our results, meaning underreporting of the true effect from health conditions developed in childhood: health resilience and wealth effects reduce the probability of poor health in childhood, while also positively influencing income and mental health in young adulthood. As such the negative effect of a child health condition that we observe may in fact be an attenuated effect due to this omitted variable bias. Although the CDS weights adjust for the attrition, further investigations and corrections for this attenuation may remove this downward bias.

Methodologically, non-parametric methods have a superior performance with larger samples relative to the size of the analytical sample of the CDS-TAS. The small sample size also limited the ability to run age-specific sub-analyses for individuals with a report of a physical and/or mental/developmental health condition in childhood (e.g., <100). Finally, RD analyses are descriptive and non-causal. Nevertheless, the important insight into distributional differences rendered by this study highlight hypotheses that merit further investigation in parametric analyses.

6. Conclusion

This study examined differences in earnings and mental health scores in young adulthood between individuals who reported a physical or mental/developmental health condition in childhood compared to those who did not. Non-parametric relative distribution methods were applied to assess distributional differences across the two groups. The results suggest that differences in health in early life carry persistent effects into early adulthood. Results reaffirm some findings in the existing literature but offer more detail in terms of the extent of these differences across distributions. These descriptive, non-parametric results are useful to inform policy to mitigate the legacy effects of health conditions in childhood and to generate hypotheses for subsequent parametric analyses.

Financial disclosure statement

EA acknowledges the financial support for a doctoral fellowship from the Social Sciences and Humanities Research Council (SSHRC). AS is supported by the Canada Research Chair in Population Health Equity.

Ethics approval/Statement EA not required

This study uses publicly available, de-identified micro-data from the Panel Study of Income Dynamics (PSID), collected by the Institute for Social Research, University of Michigan. The use of the publicly available data does not require ethics approval from the ISR nor the host institution of the researchers (University of Toronto). Confirmation from the University of Toronto is available upon request.

Authors' statement

Thank you for the opportunity to revise our manuscript (SSMPH-D-22-00346). All authors have revised the manuscript. We have edited the manuscript in accordance with the reviewers' feedback and suggestions. We thank the reviewers for their feedback and believe the manuscript is now presented in a much clearer manner.

Declaration of competing interest

None.

Data availability

Readers may examine the PSID data center website (https://simba.isr.umich.edu/).

Acknowledgements

We are grateful for the methodological guidance from Kate Choi, David Rudoler and Katherine Zagrodney, as well as the thoughtful feedback from Youngmin Yi and the Population Association of America 2021 conference participants (session: "Inequality in the Transition to Adulthood"). Finally, we are grateful for feedback on PSID data from Paula Fomby and Noura Insolera during the 2021 PSID Data Workshop. EA acknowledges the financial support for a doctoral fellowship from the Social Sciences and Humanities Research Council (SSHRC). AS is supported by the Canada Research Chair in Population Health Equity.

References

Achenbach, T. M., Ivanova, M. Y., Rescorla, L. A., Turner, L. V., & Althoff, R. R. (2016). Internalizing/externalizing problems: Review and recommendations for clinical and research applications. *Journal of the American Academy of Child & Adolescent Psychiatry, 55*(8), 647–656. https://doi.org/10.1016/j.jaac.2016.05.012

Akresh, I. R. (2009). Health service utilization among immigrants to the United States. *Population Research and Policy Review, 28*(6), 795–815. https://doi.org/10.1007/s11113-009-9129-6

Almond, D., & Currie, J. (2011). Killing me softly: The fetal origins hypothesis. *The Journal of Economic Perspectives, 25*(3), 153–172. https://doi.org/10.1257/jep.25.3.153

Almond, D., Currie, J., & Duque, V. (2018). Childhood circumstances and adult outcomes: Act II. *Journal of Economic Literature, 56*(4), 1360–1446. https://doi.org/10.1257/jel.20171164

Andersen, D. C., & Gunes, P. M. (2018). The role of adolescent health in adult SES outcomes. *The B.E. Journal of Economic Analysis & Policy, 18*(2). https://doi.org/10.1515/bejeap-2017-0169

Arpin, E., de Oliveira, C., Siddiqi, A., & Laporte, A. (2023). The "long-arm" of chronic conditions in childhood: Evidence from Canada using linked survey-administrative data. *Economics and Human Biology*. , Article 101257. https://doi.org/10.1016/j.ehb.2023.101257

Barker, D. J. (1990). The fetal and infant origins of adult disease. *BMJ British Medical Journal, 301*(6761), 1111.

Basu, S., Hong, A., & Siddiqi, A. (2015). Using decomposition analysis to identify modifiable racial disparities in the distribution of blood pressure in the United States. *American Journal of Epidemiology, 182*(4), 345–353. https://doi.org/10.1093/aje/kwv079

Bernhardt, A., Morris, M., & Handcock, M. S. (1995). Women's gains or men's losses? A closer look at the shrinking gender gap in earnings. *American Journal of Sociology, 101*(2), 302–328. https://doi.org/10.1086/230726

Case, A., Fertig, A., & Paxson, C. (2005). The lasting impact of childhood health and circumstance. *Journal of Health Economics, 24*(2), 365–389. https://doi.org/10.1016/j.jhealeco.2004.09.008

Case, A., Lubotsky, D., & Paxson, C. (2002). Economic status and health in childhood: The origins of the gradient. *The American Economic Review, 92*(5), 1308–1334.

Centres for Disease Control. (2021). Managing chronic health conditions in schools | healthy schools | CDC. https://www.cdc.gov/healthyschools/chronicconditions.htm.

Chetty, R., Hendren, N., Kline, P., Saez, E., & Turner, N. (2014). Is the United States still a land of opportunity? Recent trends in intergenerational mobility. *The American Economic Review, 104*(5), 141–147. https://doi.org/10.1257/aer.104.5.141

Contoyannis, P., & Dooley, M. (2010). The role of child health and economic status in educational, health, and labour market outcomes in young adulthood. *Canadian Journal of Economics/Revue Canadienne d'économique, 43*(1), 323–346. https://doi.org/10.1111/j.1540-5982.2009.01574.x

Contoyannis, P., & Li, J. (2011). The evolution of health outcomes from childhood to adolescence. *Journal of Health Economics, 30*(1), 11–32. https://doi.org/10.1016/j.jhealeco.2010.10.007

Contoyannis, P., & Wildman, J. (2007). Using relative distributions to investigate the body mass index in England and Canada. *Health Economics, 16*(9), 929–944. https://doi.org/10.1002/hec.1240

Coplan, R., Hughes, K., Bosacki, S., & Rose-Krasnor, L. (2011). Is silence golden? Elementary school teachers' strategies and beliefs regarding hypothetical shy/quiet and exuberant/talkative children. *Journal of Educational Psychology, 103*, 939–951. https://doi.org/10.1037/a0024551

Cunha, F., & Heckman, J. (2007). The technology of skill formation. *The American Economic Review, 97*(2), 31–47. https://doi.org/10.1257/aer.97.2.31

Cunha, F., & Heckman, J. J. (2008). Formulating, identifying and estimating the technology of cognitive and noncognitive skill formation. *Journal of Human Resources, 43*(4), 738–782. https://doi.org/10.2307/40057370

Currie, J., & Stabile, M. (2003). Socioeconomic status and child health: Why is the relationship stronger for older children? *The American Economic Review, 93*(5), 1813–1823.

Currie, J., & Stabile, M. (2006). Child mental health and human capital accumulation: The case of ADHD. *Journal of Health Economics, 25*(6), 1094–1118.

Currie, J., Stabile, M., Manivong, P., & Roos, L. L. (2010). Child health and young adult outcomes. *Journal of Human Resources, 45*(3), 517–548. https://doi.org/10.3368/jhr.45.3.517

Dahl, G., & Lochner, L. (2008). *The Impact of family Income on child achievement: Evidence from the earned income tax credit (working paper No. 14599)*. National Bureau of Economic Research. https://doi.org/10.3386/w14599

Dooley, M., Lipman, E., & Stewart, J. (2005). Exploring the good mother hypothesis: Do child outcomes vary with the mother's share of income? *Canadian Public Policy, 31*(2), 123–143 (ecn).

DuPaul, G. J., Weyandt, L. L., & Janusis, G. M. (2011). ADHD in the classroom: Effective intervention strategies. *Theory Into Practice, 50*(1), 35–42. https://doi.org/10.1080/00405841.2011.534935

Fletcher, J. M. (2014). The effects of childhood adhd on adult labor market outcomes. *Health Economics, 23*(2), 159–181. https://doi.org/10.1002/hec.2907

Garcés, I. C., Scarinci, I. C., & Harrison, L. (2006). An examination of sociocultural factors associated with health and health care seeking among latina immigrants. *Journal of Immigrant and Minority Health, 8*(4), 377–385. https://doi.org/10.1007/s10903-006-9008-8

Haas, S. A. (2006). Health selection and the process of social stratification: The effect of childhood health on socioeconomic attainment. *Journal of Health and Social Behavior, 47*(4), 339–354. https://doi.org/10.1177/002214650604700403

Haas, S. (2008). Trajectories of functional health: The 'long arm' of childhood health and socioeconomic factors. *Social Science & Medicine, 66*(4), 849–861. https://doi.org/10.1016/j.socscimed.2007.11.004

Haider, S., & Solon, G. (2006). Life-cycle variation in the association between current and lifetime earnings. *The American Economic Review, 96*(4), 1308–1320. https://doi.org/10.1257/aer.96.4.1308

Handcock, M. S., & Morris, M. (1998). Relative distribution methods. *Sociological Methodology, 28*(1), 53–97. https://doi.org/10.1111/0081-1750.00042

Handcock, M. S., & Morris, M. (2006). *Relative distribution methods in the social Sciences*. Springer Science & Business Media.

Hao, L., & Naiman, D. (2010). *Assessing inequality*. SAGE Publications, Inc. https://doi.org/10.4135/9781412993890

Hermeto, A., & Rangel, R. (2009). *Cohort trends in the relative wage distribution by gender in Brazil*. Detroit, Michigan: Population Association of America.

Hertzman, C., & Power, C. (2003). Health and human development: Understandings from life-course research. *Developmental Neuropsychology, 24*(2–3), 719–744. https://doi.org/10.1080/87565641.2003.9651917

Hou, F., & Myles, J. (2008). The changing role of education in the marriage market: Assortative marriage in Canada and the United States since the 1970s. *The Canadian Journal of Sociology/Cahiers Canadiens de Sociologie, 33*(2), 337–366.

Hout, M. (2012). Social and economic returns to college education in the United States. *Annual Review of Sociology, 38*(1), 379–400. https://doi.org/10.1146/annurev.soc.012809.102503

Hsin, A. (2012). Is biology destiny? Birth weight and differential parental treatment. *Demography, 49*(4), 1385–1405. https://doi.org/10.1007/s13524-012-0123-y

Johnson, D. S., McGonagle, K. A., Freedman, V. A., & Sastry, N. (2018). Fifty years of the panel study of income dynamics: Past, present, and future. *The Annals of the American Academy of Political and Social Science, 680*(1), 9–28. https://doi.org/10.1177/0002716218809363

Johnston, O. G., & Burke, J. D. (2020). Parental problem recognition and help-seeking for disruptive behavior disorders. *The Journal of Behavioral Health Services & Research, 47*(1), 146–163. https://doi.org/10.1007/s11414-018-09648-y

Jones, C. P. (1997). Living beyond our "means": New methods for comparing distributions. *American Journal of Epidemiology, 146*(12), 1056–1066. https://doi.org/10.1093/oxfordjournals.aje.a009234

Kabudula, C. W., Houle, B., Collinson, M. A., Kahn, K., Tollman, S., & Clark, S. (2017). Assessing changes in household socioeconomic status in rural South Africa, 2001–2013: A distributional analysis using household asset indicators. *Social Indicators Research, 133*(3), 1047–1073. https://doi.org/10.1007/s11205-016-1397-z

Kessler, R. C., Andrews, G., Colpe, L. J., Hiripi, E., Mroczek, D. K., Normand, S.-L. T., Walters, E. E., & Zaslavsky, A. M. (2002). Short screening scales to monitor population prevalences and trends in non-specific psychological distress. *Psychological Medicine, 32*(6), 959–976. https://doi.org/10.1017/S0033291702006074

Kessler, R. C., Barker, P. R., Colpe, L. J., Epstein, J. F., Gfroerer, J. C., Hiripi, E., Howes, M. J., Normand, S.-L. T., Manderscheid, R. W., Walters, E. E., & Zaslavsky, A. M. (2003). Screening for serious mental illness in the general population. *Archives of General Psychiatry, 60*(2), 184–189. https://doi.org/10.1001/archpsyc.60.2.184

Kuh, D., Ben-Shlomo, Y., Lynch, J., Hallqvist, J., & Power, C. (2003). Life course epidemiology. *Journal of Epidemiology & Community Health, 57*(10), 778–783. https://doi.org/10.1136/jech.57.10.778

van der Lee, J. H., Mokkink, L. B., Grootenhuis, M. A., Heymans, H. S., & Offringa, M. (2007). Definitions and measurement of chronic health conditions in ChildhoodA systematic review. *JAMA, 297*(24), 2741–2751. https://doi.org/10.1001/jama.297.24.2741

Loyer Carbonneau, M., Demers, M., Bigras, M., & Guay, M.-C. (2021). Meta-analysis of sex differences in ADHD symptoms and associated cognitive deficits. *Journal of Attention Disorders, 25*(12), 1640–1656. https://doi.org/10.1177/1087054720923736

Lundborg, P. (2013). The health returns to schooling—what can we learn from twins? *Journal of Population Economics, 26*(2), 673–701. https://doi.org/10.1007/s00148-012-0429-5

McGonagle, K. A., Schoeni, R. F., Sastry, N., & Freedman, V. A. (2012). The panel study of income dynamics: Overview, recent innovations, and potential for life course research. *Longitudinal and Life Course Studies, 3*(2). https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3591471/.

Oreopoulos, P., Stabile, M., Walld, R., & Roos, L. L. (2008). Short-, medium-, and long-term consequences of poor infant health an analysis using siblings and twins. *Journal of Human Resources, 43*(1), 88–138. https://doi.org/10.3368/jhr.43.1.88

Ronis, S. T., Slaunwhite, A. K., & Malcom, K. E. (2017). Comparing strategies for providing child and youth mental health care services in Canada, the United States, and The Netherlands. *Administration and Policy in Mental Health and Mental Health Services Research, 44*(6), 955–966. https://doi.org/10.1007/s10488-017-0808-z

Rose, G. (2001). Sick individuals and sick populations. *International Journal of Epidemiology, 30*(3), 427–432. https://doi.org/10.1093/ije/30.3.427

Ross, C. E., & Wu, C. (1995). The links between education and health. *American Sociological Review, 60*(5), 719–745. https://doi.org/10.2307/2096319

Rudoler, D., Laporte, A., Barnsley, J., Glazier, R. H., & Deber, R. B. (2015). Paying for primary care: A cross-sectional analysis of cost and morbidity distributions across primary care payment models in ontario Canada. *Social Science & Medicine, 124*, 18–28. https://doi.org/10.1016/j.socscimed.2014.11.001

Sastry, N., Fomby, P., & McGonagle, K. A. (2021). Effects on panel attrition and fieldwork outcomes from selection for a supplemental study: Evidence from the panel study of income dynamics. In P. Lynn (Ed.), *Wiley series in probability and statistics* (1st ed., pp. 74–99). Wiley. https://doi.org/10.1002/9781119376965.ch4.

Sibley, M. H., Olson, S., Morley, C., Campez, M., & Pelham, W. E., Jr. (2016). A school consultation intervention for adolescents with ADHD: Barriers and implementation strategies. *Child and Adolescent Mental Health, 21*(4), 183–191. https://doi.org/10.1111/camh.12159

Siddiqi, A., Shahidi, F. V., Hildebrand, V., Hong, A., & Basu, S. (2018). Illustrating a "consequential" shift in the study of health inequalities: A decomposition of racial differences in the distribution of body mass. *Annals of Epidemiology, 28*(4), 236–241. e4. https://doi.org/10.1016/j.annepidem.2018.02.003

Smith, J. P. (2009). The impact of childhood health on adult labor market outcomes. *The Review of Economics and Statistics, 91*(3), 478–489. https://doi.org/10.1162/rest.91.3.478

Zajacova, A., & Lawrence, E. M. (2018). The relationship between education and health: Reducing disparities through a contextual approach. *Annual Review of Public Health, 39*(1), 273–289. https://doi.org/10.1146/annurev-publhealth-031816-044628

Zajacova, A., Walsemann, K. M., & Dowd, J. B. (2015). The long arm of adolescent health among men and women: Does attained status explain its association with mid-adulthood health? *Population Research and Policy Review, 34*(1), 19–48. https://doi.org/10.1007/s11113-014-9327-8