THREE ESSAYS ON THE ECONOMICS OF CHILD WELL-BEING

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Abstract

This thesis consists of three major essays that respectively investigate three factors that might influence child well-being: family income, family structure, and time spent in child care. Using the Canadian National Longitudinal Survey of Children and Youth (NLSCY), the first essay finds that income-based gaps in child health are statistically significant, quantitatively meaningful, and more pronounced as children age. Contrary to previous U.S. evidence, the observed income gradient in child health cannot be attributed to the protective effects of income on the incidence and severity of children's health problems at birth and chronic conditions. This contrast may reflect the effects of universal health insurance in Canada. An instrumental variable estimator predicts a stronger causal effect of income on child health than does OLS. Also using the NLSCY, the second essay indicates that children persistently living in single-parent families have poorer health and educational outcomes compared to children persistently living in intact families. In addition, children whose parents separate during a given period exhibit worse health and educational outcomes compared to children whose parents remain together. Using a sibling fixed-effect approach substantially reduces the associations between children's outcomes and parental separation predicted by OLS, but several gaps, especially in mental health, remain statistically significant and quantitatively meaningful. Using time-use data taken from the General Social Survey (GSS), the third essay finds that parental time spent in child care continuously and dramatically increased in Canada between 1986 and 2010. The increase in average time spent in child care applied to all gender and education groups but was associated with a growing dispersion in child care time. While more highly educated

parents are more likely to spend time in child care, the education-based gaps in child care time are found to decline.

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Declaration of Academic Achievement

The first essay is co-authored with Professor David Feeny and was published in *Social Science & Medicine*, Volume 226, 2019, Pages 182-189. I am the sole author for the other two essays. I participated in all stages of the research and wrote the manuscripts.

Introduction

The fact that individuals with higher socio-economic status (SES) are on average heathier is referred to as social gradient in health. Such a gradient has been persistently observed in many countries and extends throughout the range of social status (Hurley, 2010). A great deal of research has shown that the social gradient in health has its origins in childhood by indicating that children from families with lower SES are associated with poorer health status (Case et al., 2002; Currie and Stabile, 2003). Poor child health could result in poor SES in adulthood either by directly limiting employment opportunities or by impeding children from accumulating human capital (Case and Paxson, 2006). Therefore, for policy makers who are interested in reducing the social gradient in health, one appealing strategy is to enact policies that improve child health through compensating for parental SES disadvantages.

To develop effective policies, it is important to understand how and to what extent parental SES might affect child well-being. Economic theories provide insights into these questions. Taking child health as an example, Currie (2009) presents a standard health production model that explains the potential mechanisms through which parental SES might affect child health. First, children from high-income families benefit from less binding budget constraints so that wealthier parents are able to purchase more and/or better material health inputs (e.g. medical care, nutrition intake, neighborhood quality). Second, parental productivity in producing child health may vary by SES. One plausible hypothesis is that more highly educated parents are more productive in producing child health. Another possibility is that low-SES parents are associated with poorer health so that they are less productive and have less time available in producing child health. Third, low-SES parents may be more likely to have children born in poor health status, which implies that the children are more likely to receive adverse health shocks in the future. This idea is known as “the fetal origins hypothesis.” Fourth, from a perspective of dynamic capacity formation, parental capabilities in child care produced at one stage of the life augment the capabilities attained at a later stage and consequently raise the productivity of investment at subsequent stages. These mechanisms, known as “self-productivity” and “dynamic complementarities”, might produce multiplier effects that contribute to the emergence of socio-economic differentials in child health (Heckman, 2007). Fifth, parents with different SES might have different experience with the health care system, different health beliefs, and different rates of time preference, all of which might affect how parents combine inputs to produce child health (Currie, 2009).

This thesis consists of three major essays that provide Canadian evidence for the relationship between parental SES, parental investments in children, and child well-being. Each essay focuses on one factor that might affect child well-being.

The first essay focuses on the relationship between family income and child health. An influential study investigating U.S. children (Case et al., 2002) indicates that a strong income-health gradient applies to children and that the magnitude of the gradient increases as children age. Using the Canadian National Longitudinal Survey of Children and Youth (NLSCY), we first follow the approach of Case et al. (2002) to determine whether a strong and increasing income gradient in child health can be found in a Canadian context. In addition to the conventional ordinal self-rated health, we use the Health Utilities Mark 3 as an alternative measure of child health to check the robustness of the income gradient in child health. Regarding the potential causes of the income gradient in child health, Case et al. (2002) attribute a part of gradient to the protective effects of income on the incidence and severity of children's health problems at birth and chronic conditions. Using the same approach, we examine whether child health at birth and chronic conditions are potential mechanisms through which family income affects child health in Canada. Lastly, we use local unemployment rates as instrumental variables (IV) for income to examine the causality between income and child health. As the validity of the IV is the pivot in identification, we use the bound estimation method proposed in Conley et al. (2012) to document the cases when the IV is not perfectly valid.

The second essay focuses on the relationship between family structure and child well-being. In the existing literature, various approaches such as cross-sectional comparison, before-after comparison, sibling fixed effects, and quasi-experiments have been used to document the effects of family structure on child well-being. However, the evidence is not consistent either across or within approaches. This is partially due to different definitions of family structures and different variables used to measure child well-being. This essay examines how children's outcomes vary across family structure using multiple approaches, different dimensions of family structure, and a wide range of children's outcomes including mental health, general health, and educational attainment. Using the NLSCY, it first compares the differences in outcomes between children persistently living in two-parent families and children persistently living in single-parent families and examines whether the differences in outcomes could be accounted for by the differences in household income and parenting quality. Then, following children initially living in biological-two-parent families, it compares the differences between children whose parents separate later and children whose parents remain together and examines whether the differences withstand adjustments for pre-existing conditions. Lastly, using a sibling fixed-effect model, it investigates whether children living in the same household but with different experience of family structure in the past exhibit significantly different outcomes.

The third essay investigates the relationship between parental education and child care time and trends in Canadians' time allocation. Traditional economic models such as that of Becker (1965) suggest that parental time spent in child care increases with parents' wages. As wages and education are strongly and positively correlated, child care time is also expected to increase with parents' educational attainment. In the long run, with an increase in real wage and educational attainment, time spent in child care is expected to increase. This essay aims to examine these hypotheses using five cycles of time-use data taken from the General Social Survey (GSS) between 1986 and 2010. First, it describes changes in average time spent in four primary categories including child care, market work, domestic work, and leisure, controlling for demographic composition. Second, it examines whether the inequality in child care time has increased over time. Third, it investigates whether more highly educated parents spend more time in child care and how the education-based gaps in child care have changed over time.

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Chapter 1 The dynamics of the gradient between child's health and family income: evidence from Canada

1.1 Introduction

Wealthy/high-income people are more likely to be healthy. This phenomenon is called the health-income gradient. Although the health-income gradient is one of the most well-documented findings in social science, the causes and the mechanisms underlying the gradient are not well understood. A number of empirical studies find that the health-income gradient observed in adulthood has its origins in childhood: children's health is positively correlated with family income, and this relationship becomes more pronounced as children age (Case et al., 2002; Currie and Stabile, 2003). This income-related health inequality in childhood is not only unfavorable from an equity perspective but can contribute to income inequality in adulthood through two channels. First, poor health impedes children from low-income families from accumulating human capital, which in turn affects their future employment opportunities and wages (Case and Paxson, 2006). Second, poor health by itself limits employment opportunities and wages, which implies that low-income children who arrive at the doorstep of adulthood with poorer health will have lower income in adulthood than high-income children even when other factors are equal (Case and Paxson, 2006).

To effectively and efficiently reduce the income-related health inequality in childhood, it is necessary to study its size and importance at different ages and to identify the causes and the mechanisms that contribute to the childhood health-income gradient. Using the Canadian National Longitudinal Survey of Children and Youth (NLSCY), we first study the statistical significance, the size and the dynamics of the income gradient in children's health with different health measures, including the conventional ordinal self-rated health (SRH) on a scale of 1-5 and the Health Utilities Index Mark 3 (HUI3), which has much finer gradations than the conventional SRH scale and has been shown to be reliable and valid in a large number of clinical studies of children and adults (Furlong et al., 2001). Then we investigate whether parental health and children's health at birth can account for an important part of the observed income gradient. We also examine whether chronic conditions are a possible mechanism through which income affects children's health. Our approach follows that of an influential study that provides U.S. evidence (Case et al., 2002), and our results reveal both similarities and distinct differences between the Canadian and the U.S. evidence. Finally, we study whether income has a causal effect on children's health and what its magnitude could be, by using local unemployment rates as instrumental variables for family income. This approach is similar to that of a previous study that provides U.K. evidence (Kuehnle, 2014) and reveals comparable results. These results provide insights into a key policy question: can governments substantially improve children's health by increasing cash or in-kind transfers to low-income families?

This study makes several contributions to the literature. First, in addition to the conventional SRH scales, we use HUI3 as an alternative health measure and demonstrate a strong income gradient in child health that is robust using many econometric models (OLS regression, ordered probit, and interval regression). Second, children in our study have been followed for a longer period than in other major studies that investigate the relationship between child health and income, providing a better description of the dynamics of the health-income gradient. Third, we show that two potential causes of the steepening gradient indicated in previous U.S. evidence (poor birth health and chronic conditions) are not the main factors accounting for the steepening gradient in Canada. This contrast may be related to universal health insurance in Canada. Fourth, we develop the IV approach of Kuehnle (2014) using the bound estimation method proposed in Conley et al. (2012), documenting the cases when the IV is not perfectly valid.

1.2 Background and literature review

Parental income can affect children's health through multiple mechanisms. First, children living in high-income families can benefit from more and/or better health inputs (e.g. health care, neighborhood, etc.), but may also receive less time input from their parents, who have higher time opportunity cost. Second, parental education affects parents' cognitive and health behaviors, which in turn affects parental productivity in regard to children's health (Cutler and Lleras-Muney, 2010). Third, low-income parents are associated with poorer health, and the parents in poor health are more likely to have low productivity and less time available to produce children's health. Fourth, children who are born with low health endowment, such as low birth weight, are more likely to have poorer general health status in childhood (Black et al., 2007).

Various empirical studies offer insights into the relationship between parental income and children's health. Using U.S. data and an ordered probit model, Case et al. (2002) observe an income gradient in children's health, which is statistically significant and becomes more pronounced as children age. In addition, they find that family income is negatively correlated with the incidence and the adverse effects of chronic conditions, suggesting that chronic conditions are a possible pathway through which family income affects children's general health. The Case et al. (2002) approach has been widely applied in other countries, and the steepening income gradient in children's health has been found even in the countries with universal health insurance, such as Canada and the U.K (Currie and Stabile, 2003; Case et al., 2008). Using a panel of Canadian children, Currie and Stabile (2003) also observe such a steepening gradient, but their panel method suggests that family income does not buffer the adverse effect of chronic conditions. Instead, low-SES children have poorer health partially because they acquire chronic conditions more frequently. Controlling for children's health status in the last period, Murasko (2008) finds that the gradient remains statistically significant but the steepening shape disappears by using a longitudinal data in the U.S. Applying the same approach on a sample of Australian children, Khanam (2009) finds that the income gradient in children's health is no longer statistically significant or steepening when controls for parental health are included.

Although a strong correlation between parental income and children's health is well-documented, very few studies conclude that parental income has a causal effect on children's health. The first challenge in identifying a causal relationship is reverse causality. Notwithstanding the assumption that children's health does not produce an important impact on parental income seems reasonable, especially in developed countries with universal health insurance, it remains impossible to rule out the possibility that a severe health shocks such as disability or cancer in children will change parental employment patterns. Another identification difficulty stems from unobserved factors that affect both parental SES and children's health. One solution is to use instrumental variables (IV). The instruments that have been used for parental SES in the relevant literature include grandparental SES (Dolye et al., 2007) and local labor market characteristics (Kuehnle, 2014). The validity of these potential instrumental variables is the key in identification, and the main challenge is that the instruments that correlate with parental SES are also likely to have a direct effect on children's health and therefore should be considered as variables to be entered into the structural model.

1.3 Data and descriptive statistics

We use the data from the National Longitudinal Survey of Children and Youth (NLSCY), a nationally representative longitudinal dataset that contains detailed information on Canadian children's health and family socioeconomic status. Among 22,831 children ages 0-11 surveyed in Cycle 1 (1994/95), 16,903 of them were included in the longitudinal group and were followed up with every two years thereafter. In Cycle 8 (2008/09), 62% of the children in the original longitudinal group remained in the survey; they were ages 14-25 years old at that time.

Children's health is reported on a scale of 1-5 (1: excellent; 2: very good; 3: good; 4: fair; 5: poor). Only the children ages 0-15, whose health status is reported by the person the most knowledgeable (the PMK), are included throughout our analyses. To apply linear probability model and binary probit model, we follow Currie and Stabile (2003), which generate a dummy variable indicating whether a child is in poor health. The poor health dummy equals one if children's health is reported to be 3 (good), 4 (fair), or 5 (poor).

The NLSCY provides self-reported household annual income. In cases where the household income is not reported, the NLSCY imputes household income from individual income sources or from other demographic information (Currie and Stabile, 2003). In this study, we measure family income by the average of annual household real income across cycles because, first, taking the average of family income across different periods reduces the inaccuracy of the self-reported income. Second, average family income can be considered as a proxy of family's permanent income, which might have a greater impact on children's health than current family income (Curtis et al., 2001). Third, reverse causality problem is moderated given that a children's health status shock is expected to produce a smaller impact on family permanent income than on current family income (Curtis et al., 2001).

Table 1.1 provides summary statistics for our core sample, which consists of 8,019 children ages 0-7 in Cycle 1 who were surveyed in each of the first five cycles. In Cycle 1, the average age of the children was 3.1 years old. The average household real income was about $55,300 (in 2002 Canadian dollars). The average mother's age was 28 years old, and average father's age was 30.8 years old. 93% of the PMK were female, and 92% of the PMK were the biological mothers of the children. 88% of the children lived in a two-parent household. About 40% of mothers had a college degree. From Cycle 1 to Cycle 5, the fraction of children reported to be in poor health status (health = 3, 4, or 5) remained stable, while the incidence of asthma rose from 9% to 19%. However, general practitioner (GP) visits and hospitalization likelihood decreased with children's age.

1.4 Empirical analysis

1.4.1 The dynamics of the income gradient in children's health

1.4.1.1 Using self-reported health status on a scale of 1-5 as the measure of children's health

To study the magnitude of the income gradient in children's health and its evolution as children age, we begin by replicating the ordered probit model used by Case et al. (2002) and then add the parental self-reported health status as a control variable into the baseline regression. Our sample consists of children ages 0-7 in Cycle 1 who were surveyed in each of the first five cycles (the children ages 8-15 in Cycle 5). To see whether the gradient increases with children's age, the ordered probit model is estimated at four separate age ranges: 0-3, 4-7, 8-11 and 12-15. Children's health is measured by the PMK-reported health status on a scale of 1-5, with 1 being excellent and 5 being poor. Family income, the explanatory variable of interest, is measured by the log of the average of estimated household income over the five cycles. The log form is used to reduce the skewness in the distribution of income and capture the potentially non-linear relationship between income and children's health. Parental health is derived from the health status reported by the PMK and the spouse of the PMK at the same time as child health. Only children from two-parent families whose parental health is not missing are included in the analyses.

The estimates of the income gradient are shown in Table 1.2. Without controlling for parental health, the estimated coefficient on the log of family income is negative and statistically significant across all age ranges. The point estimate increases as children age and reaches the highest level when the children are ages 12-15. Controlling for parental health reduces the magnitude of the estimated coefficients on income by 29-49%. However, except for the age group 0-3, the estimated coefficient on family income remains statistically significant for all age groups and increases across the first three age ranges. In addition, children's health is strongly associated with parental health, especially with mother's health.

The ordered probit coefficients in Table 1.2 reveal the qualitative effect of explanatory variables. To examine whether the association between children's health and family income is quantitatively important, we predict the average marginal effect (AME) with a binary probit model in which the dependent variable is whether the child is or is not in poor health. The results shown in Table 1.3 provide quantitative interpretations. For instance, for a child between 8 and 11 years old, a doubling of average family income is associated with a 0.03 decrease in the probability that the child is in poor health, while having a mother whose health is excellent or very good is associated with a 0.14 decrease in the probability.

1.4.1.2 Using the Health Utilities Index Mark 3 as an alternative measure of children's health

Although five-category SRH has been widely used to measure a child's general health, its limitations cannot be overlooked. First, children with the same general health status are likely reported as having different health status, merely because their parents have a different definition of what good health is. This is formally referred to state dependent reporting errors (Kerkhofs and Lindeboom, 1995). Second, considering the stigma of being perceived as having poorly taken care of children, parents with children in poor health might be unwilling to report the true health status of their children. Third, given that there are only five categories, SRH is a coarse measure of child's health.

Compared to five-category SRH, the HUI3 provides a more comprehensive and more objective description of children's general health in that it is based on eight major attributes of health-related quality of life: vision, hearing, speech, ambulation, dexterity, emotion, cognition and pain. Each attribute has five or six levels of ability/disability. By using multi-attribute utility functions derived from community preferences for health states, the levels within attributes are then converted into an overall utility score, which ranges from -0.36 (worst health state) through 0.00 (dead) to 1.00 (full health) (Horsman et al., 2003; Feng et al., 2009). The HUI3 has been used in many major population health survey in Canada since 1989 and a large number of clinical studies support the strong validity of the HUI3 (Furlong et al., 2001).

An alternative to using the overall utility scores is grouping them into four disability categories for overall health: 1. No disability (1.00); 2. Mild disability (0.89-0.99); 3. Moderate disability (0.70-0.88); 4. Severe disability (less than 0.70) (Feng et al., 2009). This approach has been applied in various empirical studies and has several practical advantages over the overall scores. First, the four ordered categories are more understandable than the continuous scores ranging from -0.36 to 1.00. Second, the overall continuous scores are typically highly skewed (the skew is expected to be greater among children than adults), which compromises the conventional assumption that the error term in linear regression is normally distributed (Feng et al., 2009).

Past research suggests that interval regressions in which the HUI3 scores are mapped onto SRH scales are more efficient than OLS regressions and ordered probit models (Doorslaer and Jones, 2003). To determine the boundaries of intervals, we follow Lecluyse and Cleemput (2006) and divide the HUI3 into five intervals according to the cumulative frequency of the five-level SRH. The boundaries are: -0.36, 0.45, 0.75, 0.93, 0.98, 1.00.

The NLSCY reports the HUI3 for all children above 3 years old in Cycle 1 and Cycle 2. We use this sample to check whether the observed income gradient in children's health is robust when the HUI3 is used as an alternative measurement of children's general health. The results are shown in Table 1.4. Panel A reports the OLS estimates of income coefficients where the dependent variable is the log of the HUI3 scores. Without controlling for parental health, the estimated coefficient on income is small but statistically significant for all age ranges and reaches the highest level for the age range 7-9. For children in this age range, the OLS estimate predicts that HUI3 scores increase by 0.012% if family income increases by 1%. Panel B uses ordered probit model in which the dependent variable is a disability category based on the HUI3 scores. The estimated coefficient on income is statistically significant and increases with children's age for children ages 4-9; controlling for parental health has no effect on this. Panel C reports the estimates from an interval regression in which the HUI3 scores are mapped onto SRH scales. Controlling for parental health or not, the income coefficients are statistically significant for all age ranges. The youngest age group exhibits the lowest health-income gradient. For children ages 4-6 and 7-9, controlling for parental health, a doubling of family income is associated with an increase in the HUI3 by 0.003 and 0.007 units, respectively. Overall, the results based on the HUI3 are consistent with the results derived from the ordered probit model which uses conventional five-category SRH as the dependent variable (see Panel D).

1.4.2 Children's health at birth

The observed health-income gradient in childhood might be accounted for by omitted variables; children's health at birth is an example. Health at birth can contribute to income gradient in children's health through two main channels. First, children born to low-income families may initially have more and severer health problems than high-income children so, physically, they need a longer period to recover from illnesses and they have higher risk to acquire health problems in later life. Second, given the same severity and the same incidence of health problems at birth, the real adverse effect could be smaller for high-income children, who receive more health care, better parental care and have better living environments to cushion poor birth health. Consequently, high-income children recover faster from poor birth health.

Case et al. (2002) examine these possibilities and find that, first, additional control for children's health at birth has little impact on health-income gradient. Second, poor birth health has larger adverse effects on children at low-income levels. Third, recovery from poor birth health is slower for low-income children. We follow their approach to examine whether these findings can be confirmed for Canadian children, who benefit from access to universal health insurance.

The NLSCY collected the information on birth health such as birth weight for the children ages 0-3 in Cycle 1. We create a binary variable "poor birth heath" that equals one if the child's birth weight is less than 2.5 kilograms, and then follow the children over the next five cycles. Table 1.5 presents the estimation results of ordered probit model. Column (1) presents the estimates from the baseline regression. Overall, low-income children have worse health. Column (2) adds to the baseline regression an indicator variable for poor birth health and also an interaction of poor birth health and age. The estimated coefficient on the indicator variable for poor birth health is positive and statistically significant, suggesting that children born with poorer health are more likely to have worse health in their later life. The coefficient estimate on the interaction of poor birth health and age is negative but not statistically significant, suggesting that the adverse effect of health at birth might not diminish as children age. Column (3) includes the interaction of poor birth health and income, the coefficient estimate of which is positive and not statistically significant, indicating that children from low-income families do not suffer from poor birth health any more than high-income children. This result differs from Case et al. (2002). Column (4) examines the hypothesis that the adverse effects of poor birth health dissipates faster with age for high income children, by including an interaction of poor birth health, age and income. The coefficient estimate of this interaction term is surprisingly positive and statistically significant, suggesting that low-income children recover even more quickly from poor birth health than do high-income children. This finding also contrasts sharply with Case et al. (2002). The last column includes poor birth health and all interactions of poor birth health. Adding the complete set of interactions does not alter the basic finding that children from lower income families are associated with poorer health. Again, little evidence suggests that low-income children suffer from poor birth health more than high-income children or that recovery from poor birth health is slower for low-income children.

1.4.3 The role of chronic conditions

Case et al. (2002) propose a theoretical framework in which income affects children's health through, what they call, "prevalence effect" and "severity effect" of chronic conditions. "Prevalence effect" means that low-income children have chronic conditions more frequently than high-income children; "severity effect" refers to the idea that, for a given health shock, the associated adverse effect is smaller for high-income children, who have more resources to buffer the impact of health shock. Case et al. (2002) find that family income not only decreases the "prevalence effect", but also reduces the "severity effect" of a chronic condition. Nevertheless, by using the first two cycles in the NLSCY and exploiting its panel nature, Currie and Stabile (2003) conclude that family income protects children's health probably because income reduces the likelihood of having chronic conditions, but not because it buffers the adverse effect of chronic conditions. In this section, we turn back to the approach presented in Case et al. (2002) to examine whether our results based on more cycles in the NLSCY are consistent with Currie and Stabile (2003). The sample of estimation is the core sample used to study the dynamics of the health-income gradient (see Section 1.4.1). We use the same regression equations as presented in Case et al. (2002):

$$C = \alpha_0 + \alpha_1 \ln y + X\delta^C + \varepsilon^C$$

$$H = \beta_0 + \beta_1(\ln y - \overline{\ln y}\ ) + \beta_2 C + \ \beta_3(\ln y - \overline{\ln y})C \ + X\delta^H + \varepsilon^H$$

where C is a dummy for chronic conditions (e.g. C=1 if the child has been diagnosed to have a chronic condition such as asthma). H is a dummy for children being in poor health. $\ln y$ is the log of a family's average income across five cycles; $\overline{\ln y}$ is the average of $\ln y$ in the sample. X includes a set of other control variables. α_1 is expected to be negative, indicating that the incidence of chronic condition is negatively associated with family's income. β_1 measures the correlation between family income and health status for children who have not been diagnosed to have a chronic condition. β_2 indicates to what extent the probability of reporting poor health is associated with different chronic conditions. A negative β_3 suggests that income buffers the adverse effects of chronic conditions on children's health.

The OLS estimates are shown in Table 1.6. Except for bronchitis, none of the estimates of α_1 are statistically significant, indicating that the incidences of chronic conditions are not significantly associated with income. This finding contrasts sharply with Case et al. (2002) in which all estimates of α_1 are statistically significant. All estimates of β_1 are negative and statistically significant, indicating that the probability of being in poor health decreases with family income for children who have not been diagnosed with a chronic condition. All estimates of β_2 are positive and statistically significant, suggesting that poor health is strongly related to chronic conditions. Specifically, diagnosed asthma is associated with a 0.17 increase in the probability of reporting poor health. Epilepsy exhibits the strongest relation with poor health among all conditions. These findings are consistent with Case et al. (2002). The estimate of β_3 is negative and statistically significant only for asthma, suggesting that family income buffers the adverse effect of chronic conditions only for asthma. This finding also contrasts sharply with Case et al. (2002) in which the estimated β_3 is negative and statistically significant for almost all chronic conditions.

1.4.4 Causality between family income and children's health

We investigate whether income produces causal effects on children's health, by following the instrumental variable approach used by Kuehnle (2014), who uses local unemployment rate as an instrument for income. Local unemployment rate might be a valid instrument because, first, family income is very likely correlated with the local unemployment rate. Second, as the children under 15 years of age are not in the labor market, local unemployment does not directly affect children's health. Given that children's health is strongly associated with parental health, which has been shown in a number of studies to be correlated with unemployment, we control for parental health in the regression to address the indirect effect that unemployment affects children's health via parental health.

The sample used for estimation consists of children from the NLSCY living in a census metropolitan area (CMA) or a census agglomeration area (CA) in 1996 (i.e. Cycle 2). CMA and CA are large urban areas that on the previous census have an urban core population of at least 100,000 and 10,000, respectively. Local unemployment rates for 136 CMA and CA are derived from the 1996 Census of Canada. Income is measured by the average household income over the first two cycles.

Table 1.7 presents the OLS and the 2SLS estimates. With the control for parental health, the OLS estimate predicts that a doubling of family income decreases the probability of a child being in poor health by 3.3% (Column 1). Using local unemployment rate as the instrument for income, the 2SLS estimate of income coefficient is statistically significant and almost five times as large as the OLS estimate: the probability being reported in poor health decreases by 15.8% when the family income doubles (Column 2). The third column shows the 2SLS estimates where the instrument is the local unemployment rate among individuals younger than 25 years old, and the last column presents the 2SLS estimates obtained by using both local unemployment rate and local unemployment rate among young individuals as instruments for income. Across the different instruments used, the size of the 2SLS estimates of income coefficient are rather close, and all of them are greater than the OLS estimates. Although the standard errors of the 2SLS estimates are much greater than the OLS estimate, the 2SLS estimates of income coefficient remain statistically significant in column 2 and column 4. All instruments used strongly correlate with income, passing the first-stage test. The model that uses two instruments passes the over-identifying restriction (OIR) test. We also apply the IV to an ordered probit model in which the dependent variable is SRH, which generates results (not reported in the paper) that are comparable with the results shown in Table 1.7.

These results are consistent with previous studies that adopt the IV approach (Kuehnle, 2014; Doyle et al., 2007) in that, although less precise, the IV estimate of the effect of income on children's health is statistically significant and greater in magnitude than the OLS estimate, suggesting that the OLS estimate understates the true effect of income on children's health. Nonetheless, it should be noted that the OLS estimate captures average marginal effects, while the IV estimate captures local average treatment effects (LATE) which is the average causal effect of income on health for compliers, whose income varies by local unemployment rates. As indicated in Kuehnle (2014), families with volatile or low-quality employment are most likely to be the group of compliers. In addition, as our sample excludes individuals not living in CMA/CA, the results may not be valid for individuals living in small urban areas or rural areas that are not included in CMA/CA.

The validity of using the local unemployment rate as IV for income is not impeccable if there exist channels through which local unemployment affects children's health other than via family income. For instance, high local unemployment rates might adversely affect the quality of the neighborhood environment (domestic violence, smoking, excessive consumption of alcohol), which in turn can be harmful for children's health. Unemployment might also change parental time allocation in that unemployed parents could have more time to take care of their children. If either of these was the case, the assumption of exclusion restriction would no longer hold, and the 2SLS estimates would be inconsistent.

Conley et al. (2012) propose a sensitivity analysis approach to the question of validity of IV, which slightly relaxes the exclusion restriction. Consider a regression equation $y = X\beta + Z\gamma + \varepsilon$, where X includes both exogenous and endogenous variables. Z is a set of instrumental variables, and ε satisfies the conventional assumption about error term. The standard IV estimation assumes that the instrumental variables Z could be excluded from the structure equation, which corresponds to $\gamma = 0$. Conley et al. (2012) relaxes this assumption by assuming that the true value of γ is γ_0, which could be slightly different from zero, suggesting that the IVs have a slight direct effect on the outcome variable. If the γ_0 is known, then the unbiased 2SLS estimate can be obtained by estimating the regression equation $y - Z\gamma_0 = X\beta + \varepsilon$. Although γ_0 is unknown, it can be assumed to be around zero. Thus, for each potential value, there is an associated point 2SLS estimate and a confidence interval (CI), and the union of the confidence intervals (UCI) constitutes a new confidence interval for β: $\mathrm{CI}(1\text{-}\alpha) = \cup_{\gamma_0 \in \Gamma} \mathrm{CI}\left(1\text{-}\alpha,\gamma_0\right)$, where α is the significance level and Γ is the union of potential values of γ_0 (also called the support of γ_0).

We apply this method to check whether the 2SLS estimate of income coefficient remains negative and statistically significant when the local unemployment rate has a slightly independent effect on children's health. Table 1.8 describes the results in three cases. First, assuming that using the local unemployment rate as the IV for family income is perfectly valid (i.e. $\gamma_0 = 0$), the 2SLS estimate of income coefficient is negative and statistically significant because $\beta = 0$ is above the 95% CI. Second, if local unemployment has a very small negative impact on children's health ($\gamma_0 \in [0, 0.005]$), the estimated effect of income on children's health is no longer statistically significant at 5% as $\beta = 0$ is included in the 95% CI. Third, if local unemployment has a tiny positive effect on children's health ($\gamma_0 \in [-0.005, 0]$), income has a protective effect on children's health which is statistically significant. Compared to the first case, the lower bound of the 2SLS estimate decreases, suggesting that the true protective effect of income on children's health might be greater than the point 2SLS estimate.

1.5 Discussion and conclusion

Using a longitudinal sample of Canadian children, we observe a strong and steepening income gradient in child's health which is robust to different health measures (conventional SRH status and the Health Utilities Index Mark 3) and which withstands several third-factor explanations such as parental health and child's health at birth. These findings are consistent with the previous U.S. evidence based on the same approach. Regarding the causes of the steepening health-income gradient in childhood, we investigate two possible pathways. First, a steepening gradient could appear if low-income children, who are more likely to be born with poorer health status, suffer more from poor birth health or recover more slowly from poor birth health. We find no evidence that supports this hypothesis in the Canadian context. Second, a steepening gradient could also appear if low-income children more readily acquire chronic conditions and the adverse effect of chronic conditions is associated with income. For most chronic conditions that we have studied, our results do not support this hypothesis either. The exception is asthma. In general, these findings contrast with the previous U.S. evidence. The contrast between the two countries may reflect the effects of a more generous safety net in Canada, universal health insurance, in particular. Universal coverage is expected to benefit children from low-income families in that they have access to the same necessary health care as children from high-income families and, consequently, are cushioned from the adverse effects of poor health at birth and of chronic conditions. Nonetheless, income can affect child health through many mechanisms, such as nutrition intake and neighborhood quality, which are not mediated by universal health insurance. These factors may help explain why a strong and steepening income gradient in child health is still observed in Canada.

Our results based on the IV approach suggest that family income has a causal on children's health, the size of which is bigger than the OLS estimate and is economically meaningful. However, this conclusion is sensitive to the validity of using local unemployment rate as an IV for income. If local unemployment has itself a slightly negative impact on children's health, income may produce no effect on children's health. In contrast, if local unemployment produces a small positive impact on children's health, the causal effect of income on children's health is more likely to exist and the size of it can be considerable.

From a policy perspective, if the relationship between parental income and children's health is causal, the policies that attempt to improve children's health by enhancing parental income are expected to be effective. However, cost should also be taken into consideration. Cash transfers that give money to low-income families could be effective in improving children's health but not necessarily cost-effective. Alternatively, amending the policies that address the factors most relevant to children's health and family income could also be effective (e.g. in-kind transfers policies, such as the U.S. Special Supplemental Nutrition Program for Women, Infants, and Children). In addition, parental income could substantially affect children's health via unobserved socially partitioned environments: children raised in high-income and low-income families may have systematic differences in life experience which alter biological processes that influence health over the life course (Hertzman and Boyce, 2010). If this is the case, then policy-makers may need to consider comprehensive programs that support early childhood development such as early childhood education. Such programs could provide an environment for children to have universal access to opportunities for development (e.g. the Sure Start program in the U.K. and Ontario Early Years Child and Family Centres in Canada).

In conclusion, the income gradient in children's health, or income-related health inequality among children, is generally considered unfavorable, and it is more worrying that the income-related health inequality appears to widen as children age. Thus, it is rather important for policy makers to develop policies that can effectively and efficiently reduce the gradient. To achieve this goal at low cost, it is important to identify the causes and the mechanisms underlying the income gradient in children's health. However, as one mechanism is unlikely to account for the entire observed childhood health-income gradient, a single policy that addresses one factor might not substantially reduce the income-related health inequality among children.

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Table 1.1 Summary statistics

	Cycle 1	Cycle 2	Cycle 3	Cycle 4	Cycle 5
Ages range	0-7	2-9	4-11	6-13	8-15
Number of observations	8,019	8,019	8,019	8,019	8,019
Age	3.05	5.03	6.97	9.00	11.01
	(2.31)	(2.31)	(2.31)	(2.30)	(2.29)
Health	1.52	1.55	1.61	1.62	1.59
	(0.73)	(0.75)	(0.75)	(0.76)	(0.74)
Poor health	0.11	0.12	0.13	0.13	0.12
	(0.32)	(0.32)	(0.34)	(0.34)	(0.33)
Household income (in 2002 dollar)	55,277	55,909	63,031	67,727	70,984
	(36,000)	(38,027)	(42,025)	(48,352)	(49,013)
PMK is female	0.93	0.94	0.94	0.93	0.92
	(0.25)	(0.29)	(0.24)	(0.26)	(0.27)
PMK is not the biological mother	0.08	0.09	0.08	0.09	0.10
	(0.27)	(0.29)	(0.27)	(0.29)	(0.30)
Two-parent household	0.88	0.86	0.85	0.84	0.83
	(0.32)	(0.34)	(0.36)	(0.37)	(0.38)
Mother has a college degree	0.39	0.42	0.43	0.41	0.43
	(0.49)	(0.49)	(0.50)	(0.49)	(0.50)
Household size	4.08	4.18	4.28	4.29	4.24
	(1.11)	(1.09)	(1.09)	(1.09)	(1.09)
Mother's age at birth of child	28.04	28.04	28.04	27.57	27.57
	(4.86)	(4.88)	(4.89)	(4.89)	(4.89)
Father's age at birth of child	30.79	30.75	30.72	30.24	30.24
	(5.17)	(5.20)	(5.24)	(5.24)	(5.25)
Asthma	0.09	0.13	0.15	0.17	0.19
	(0.29)	(0.34)	(0.36)	(0.37)	(0.39)
GP visits in past year	4.28	3.31	2.86	2.61	1.84
	(5.19)	(4.42)	(4.09)	(2.82)	(3.28)
Overnight patient	0.08	0.05	0.04	0.03	0.03
	(0.27)	(0.22)	(0.19)	(0.17)	(0.16)

Note: Standard deviations are in parentheses.

Table 1.2 Income gradient in children's health

	Ordered probit model Children's health status (1=excellent, 5=poor)			
	(1)	(2)	(3)	(4)
Ages	0-3	4-7	8-11	12-15
Number of observations	6,349	11,875	10,550	3,770
	Control 1: without parental health			
ln(Average family income)	-0.199***	-0.314***	-0.389***	-0.403***
	(-3.34)	(-6.44)	(-7.38)	(-5.04)
	Control 2: with parental health			
ln(Average family income)	-0.102	-0.198***	-0.277***	-0.216***
	(-1.72)	(-4.18)	(-5.26)	(-2.81)
Mother's health is excellent or very good	-0.579***	-0.546***	-0.550***	-0.656***
	(-10.21)	(-12.67)	(-12.55)	(-10.04)
Father's health is excellent or very good	-0.265***	-0.349***	-0.278***	-0.358***
	(-4.42)	(-8.20)	(-6.39)	(-5.16)

Notes: *t* statistics in parentheses; * p<0.05, ** p<0.01, *** p<0.001. Standard errors are clustered at individual level. Estimates are weighted using funnel weights provided by the NLSCY. The funnel weights are longitudinal weights that have been assigned to children who have responded at every cycle. The other regressors include a dummy for child's gender, a dummy for PMK's gender, a dummy indicating child's mother has a college degree, a complete set of dummies for children's age, the log of family size, a dummy indicating that PMK is not the biological mother of child, mother's age at the birth of child, a set of dummies for birth year and a set of year dummies.

Table 1.3 Predicted average marginal effects (AME)

	Binary probit model Poor health = 1			
	(1)	(2)	(3)	(4)
Ages	0-3	4-7	8-11	12-15
Number of observations	6,349	11,875	10,550	3,770
	Control 1: without parental health			
ln(Average family income)	-0.025	-0.047	-0.055	-0.074
	(0.038)	(0.000)	(0.000)	(0.000)
	Control 2: with parental health			
ln(Average family income)	-0.004	-0.024	-0.034	-0.034
	(0.750)	(0.016)	(0.001)	(0.018)
Mother's health is excellent or very good (1 vs.0)	-0.134 (0.000)	-0.136 (0.000)	-0.144 (0.000)	-0.176 (0.000)
Father's health is excellent or very good (1 vs.0)	-0.067 (0.000)	-0.087 (0.000)	-0.060 (0.000)	-0.101 (0.000)

Notes: *p*-values in parentheses (H_0: average marginal effect is zero). Standard errors are clustered at individual level. Estimates are weighted using funnel weights provided by the NLSCY. The indicator variable for poor health equals 1 if child's health is reported good, fair, or poor. The other regressors are the same as in Table 1.2.

Table 1.4 Income gradient in children's health, by HUI3

	(1)	(2)	(3)	(4)
Ages	4-6	7-9	10-13	Overall
Number of observations	6,038	5,215	5,274	16,527
Panel A	OLS ln(HUI3 scores)			
	Control 1: without parental health			
ln(Average family income)	0.005*	0.012***	0.011*	0.010***
	(2.55)	(3.46)	(2.47)	(3.68)
	Control 2: with parental health			
ln(Average family income)	0.004	0.011**	0.008	0.008**
	(1.93)	(2.95)	(1.90)	(2.88)
Mother's health is excellent or very good	0.008**	0.005	0.012**	0.008***
	(2.94)	(1.19)	(3.21)	(3.55)
Father's health is excellent or very good	0.003	0.010*	0.004	0.006**
	(1.05)	(2.54)	(1.14)	(3.11)
Panel B	Ordered probit model HUI3 disability categories (1: no disability, 4: severe disability)			
	Control 1: without parental health			
ln(Average family income)	-0.195***	-0.279***	-0.130	-0.196***
	(-3.31)	(-4.61)	(-1.96)	(-4.68)
	Control 2: with parental health			
ln(Average family income)	-0.157**	-0.256***	-0.094	-0.162***
	(-2.66)	(-4.09)	(-1.37)	(-3.78)
Mother's health is excellent or very good	-0.222***	-0.057	-0.193**	-0.158***
	(-3.39)	(-0.87)	(-3.15)	(-3.89)
Father's health is excellent or very good	-0.068	-0.163**	-0.105	-0.118**
	(-0.99)	(-2.64)	(-1.68)	(-3.15)
Panel C	Interval regression HUI3 scores (thresholds: -0.36, 0.45, 0.75, 0.93, 0.98, 1.00)			
	Control 1: without parental health			
ln(Average family income)	0.003**	0.008***	0.007**	0.006***
	(2.65)	(4.31)	(2.89)	(4.60)
	Control 2: with parental health			
ln(Average family income)	0.003*	0.007***	0.006*	0.005***
	(2.01)	(3.73)	(2.31)	(3.69)
Mother's health is excellent or very good	0.005***	0.003	0.007**	0.005***
	(3.31)	(1.61)	(3.23)	(4.09)
Father's health is excellent or very good	0.001	0.005*	0.003	0.003**
	(0.92)	(2.42)	(1.14)	(2.77)
Panel D	Ordered probit model Children's health status (1=excellent, 5=poor)			
	Control 1: without parental health			
ln(Average family income)	-0.270***	-0.322***	-0.241***	-0.277***
	(-5.39)	(-5.64)	(-3.94)	(-7.98)
	Control 2: with parental health			
ln(Average family income)	-0.167**	-0.213***	-0.127*	-0.168***
	(-3.23)	(-3.65)	(-2.07)	(-4.75)
Mother's health is excellent or very good	-0.525***	-0.539***	-0.527***	-0.534***
	(-6.79)	(-8.78)	(-9.11)	(-13.48)
Father's health is excellent or very good	-0.322***	-0.350***	-0.408***	-0.359***
	(-5.67)	(-5.97)	(-7.00)	(-10.56)

Notes: *t* statistics in parentheses; * p<0.05, ** p<0.01, *** p<0.001. Standard errors are clustered at individual level. Estimates are weighted using longitudinal weight provided by the NLSCY. The other regressors are the same as in Table 1.2.

Table 1.5 Health at birth and income gradient in children's health

	Ordered probit model Children's health status (1=excellent, 5=poor)				
	(1)	(2)	(3)	(4)	(5)
Number of observations	24,207	24,207	24,207	24,207	24,207
Variables					
ln *y*	-0.156*	-0.144*	-0.165**	-0.142*	-0.157*
	(-2.49)	(-2.30)	(-2.70)	(-2.28)	(-2.54)
Age	0.256*	0.265*	0.271*	0.306**	0.285*
	(2.34)	(2.42)	(2.47)	(2.68)	(2.54)
ln *y* × age	-0.019*	-0.020**	-0.020**	-0.023**	-0.021**
	(-2.57)	(-2.62)	(-2.67)	(-2.89)	(-2.77)
Indicator: Poor birth health		0.373*	−3.362	0.367*	-2.102
		(2.01)	(-1.56)	(1.96)	(-0.50)
(Poor birth health) × age		-0.016	-0.015	-0.487**	-0.201
		(-0.74)	(-0.66)	(-2.63)	(-0.55)
(Poor birth health) × ln *y*			0.344		0.228
			(1.82)		(0.60)
(Poor birth health) × ln *y* × age				0.044*	0.017
				(2.48)	(0.52)
Chi-squared statistics in Wald test					
H_0: Poor birth health and all its interactions are jointly zero.		14.89 [0.0006]	27.86 [0.0000]	27.76 [0.0000]	28.50 [0.0000]
H_0: All interactions of poor birth health are jointly zero.			4.35 [0.1134]	5.08 [0.0787]	5.27 [0.1530]

Notes: *y* stands for average family income. *t* statistics in parentheses; *p*-values in brackets; * p<0.05, ** p<0.01, *** p<0.001. Standard errors are clustered at individual level. Estimates are weighted using funnel weights provided by the NLSCY. "Poor birth health" is an indicator variable equal to 1 if birth weight is less than 2.5 kilograms. The other regressors include a dummy for child's gender, a dummy for PMK's gender, a dummy indicating child's mother has a college degree, a complete set of dummies for children's age, the log of family size, a dummy indicating whether child is living in a two-parent household, a dummy indicating that PMK is not the biological mother of child, mother's age at the birth of child, a set of dummies for birth year and a set of year dummies.

Table 1.6 Chronic conditions, income and poor health

Condition (C)	(1) C = 1 (Fraction)	(2) α_1	(3) β_1	(4) β_2	(5) β_3	(6) β_3 0-7	(7) β_3 8-15
Asthma	0.1783	-0.0033	-0.045***	0.170***	-0.116***	-0.149***	-0.081*
[38,373]		(-0.27)	(-5.74)	(13.42)	(-4.36)	(-4.90)	(-2.26)
Allergies	0.2212	0.0061	-0.063***	0.108***	-0.012	0.021	0.003
[38,362]		(0.44)	(-7.58)	(9.76)	(-0.54)	(0.77)	(0.10)
Bronchitis	0.0556	-0.0157*	-0.057***	0.158***	-0.053	0.005	-0.118
[38,362]		(-2.38)	(-6.91)	(5.81)	(-0.92)	(0.07)	(-1.58)
Cerebral palsy	0.0030	-0.0021	-0.061***	0.187*	0.026	0.027	0.078
[38,362]		(-0.43)	(-7.10)	(2.43)	(0.32)	(0.25)	(0.89)
Epilepsy	0.0046	-0.0022	-0.060***	0.271**	-0.169	0.004	-0.184
[38,362]		(-1.48)	(-7.06)	(3.25)	(-1.09)	(0.02)	(-1.03)
Heart conditions	0.0177	-0.0019	-0.061***	0.074*	0.033	0.045	0.030
[38,362]		(-0.52)	(-7.15)	(1.99)	(0.37)	(0.53)	(0.24)
Kidney disease	0.0076	-0.0011	-0.061***	0.239***	-0.008	0.081	-0.162
[38,362]		(-0.86)	(-7.13)	(3.83)	(-0.07)	(0.46)	(-0.87)
Mental handicap	0.0058	0.0006	-0.062***	0.308***	0.320**	0.504**	0.217
[38,362]		(0.40)	(-7.30)	(4.44)	(2.89)	(2.85)	(1.71)

Notes: Number of observations in brackets; *t* statistics in parentheses; * p<0.05, ** p<0.01, *** p<0.001. Standard errors are clustered at individual level. Estimates are weighted using funnel weights provided by the NLSCY. The other regressors include a dummy for child's gender, a dummy for PMK's gender, a dummy indicating child's mother has a college degree, a complete set of dummies for children's age, the log of family size, a dummy indicating whether child is living in a two-parent household, a dummy indicating that PMK is not the biological mother of child, mother's age at the birth of child, a set of dummies for birth year and a set of year dummies.

Table 1.7 The effect of family income on children's health

	Linear probability model Poor health = 1			
	(1)	(2)	(3)	(4)
	OLS	IV1	IV2	IV3
Number of observations	7,280	7,280	7,280	7,280
	Control 1: without parental health			
ln(Average family income)	-0.061***	-0.163*	-0.122	-0.182*
	(-7.78)	(-2.04)	(-0.92)	(-2.48)
First-stage test: *F* statistics		73.07	23.37	45.27
OIR test: *p*-value				0.61
	Control 2: with parental health			
ln(Average family income)	-0.033*	-0.158*	-0.178	-0.149*
	(-4.31)	(-2.00)	(-1.44)	(-2.01)
Mother's health is excellent or very good	-0.139***	-0.122***	-0.119***	-0.123***
	(-13.05)	(-8.17)	(-6.02)	(-8.52)
Father's health is excellent or very good	-0.069***	-0.056***	-0.053**	-0.057***
	(-6.97)	(-4.29)	(-3.24)	(-4.47)
First-stage test: F statistics		73.24	26.74	43.30
OIR test: *p*-value				0.77

Notes: *t* statistics in parentheses; * p<0.05, ** p<0.01, *** p<0.001. Robust standard errors are used. The other regressors include a dummy for child's gender, a dummy for PMK's gender, a dummy indicating child's mother has a college degree, a complete set of dummies for children's age, the log of family size, a dummy indicating that PMK is not the biological mother of child, mother's age at the birth of child, a set of dummies for birth year, a set of year dummies, and a set of dummies for provinces.

Table 1.8 Union of confidence intervals

		Estimated β_{2sls}	
		Lower bound	Upper bound
$\gamma_0 = 0$	95% CI	-0.312	-0.003
$\gamma_0 \in [0, 0.005]$	95% UCI	-0.312	0.217
$\gamma_0 \in [-0.005, 0]$	95% UCI	-0.554	-0.003

Chapter 2 The variation in children's outcomes across family structures: evidence based on Canadian longitudinal data

2.1 Introduction

Over the past five decades, one of the most significant changes in demography in industrialized countries is the substantial decline in the share of children living in two-parent families. As an example, in 1961, 6.4% of Canadian children aged 24 and under lived in single-parent families. In 2011, this proportion was 21.2 % (Bohnert et al., 2014). Triggered by the tremendous change in family structures, a large and growing number of studies in social sciences have studied the potential effects of changes in family structure on children's outcomes from theoretical and/or empirical perspectives.

Social scientists from different disciplines provide various theories to explain why children living in single-parent families may be disadvantaged compared to children living in two-parent families. Traditional economic models consider that parents derive utilities from children's well-being, which is produced by the resources that parents spend on a child, such as money and time (e.g. Becker, 1991). When a family disruption occurs, tighter budget and time constraints make it more difficult for a lone parent to produce a child's welfare. In addition, the associated decline in a child's welfare might be proportionally greater than the decline in the resources for several reasons. First, when parents live apart, they forgo economies of scale created by sharing market capital, such as housing and food costs (McLanahan and Sandefur, 1994). Consequently, it is more costly for a lone parent to produce a given amount of a child's welfare. Second, split parents also lose economies of scale derived from specialization. Given that two parents may have different paid wages and different productivities in parenting, two parents respectively have comparative advantages in labor market and child care; thus, a within-household specialization, which increases child's well-being, is expected (Browning et al., 2014). Finally, other potential economic disadvantages associated with a family disruption include the loss of income-risk pooling, reduction in the child's access to social capital community connections, and decline in the child's expectations and motivations (Browning et al., 2014; McLanahan and Sandefur, 1994).

Sociological theories such as control theories and learning theories emphasize the structural advantages of two-parent families in forming a child's personality and socialization. Control theory suggests that an important unfavourable consequence of family disruption is a decline in parental control (the ability of parents to monitor children). In addition, because two parents not only monitor children but also monitor each other to maintain appropriate parenting, a parental split may make parenting less consistent, overly permissive, or punitive (Biblarz and Raftery, 1999). Learning theory considers that family is a primary site for children to acquire social skills. Without a father and a mother, children may lack a male or a female model and lose some degree of opportunity to learn social skills before reaching adulthood (Biblarz and Raftery, 1999).

Although various theories conceptually predict the disadvantages of children living in single-parent families, it cannot rule out the possibility that the negative effects of single-parent families stem from a selection effect. Because many pre-existing socioeconomic disadvantages, such as lower income, family dysfunctions, and marital conflicts, may trigger a family disruption and negatively impact children's outcomes, a part of the disadvantages of children living in single-parent families may be attributable to pre-existing parental disadvantages.

Most empirical studies across different disciplines have found that children living in a family structure other than a two-parent family are associated with worse outcomes in health, education, and performance in the labor market. However, there is less consensus regarding whether the disadvantages are caused by family structure per se. The most conventional approach in evaluating the effect of family structure on children's outcomes relies on cross-sectional data and OLS estimates of a regression that treat children's outcomes as a function of family structure and a set of control variables that describe a child's family background (McLanahan et al., 2013). The most significant disadvantage of this approach is that such a regression omits unobserved factors that affect both family structure and a child's outcomes.

Several more innovative approaches have been used to address the endogeneity problem. One example is a before-after comparison that compares a child's outcomes before and after parental separation. An influential example is Cherlin et al. (1991), which shows that the effect of parental separation on children's behaviour problems and test scores was significantly reduced by controlling for children's pre-existing behavior problems, test scores, and family difficulties. Conversely, Painter and Levine (2000) find that the pre-divorce characteristics of youth or family are not strongly related to divorce, and they conclude that the correlation between changes in family structure and youth outcomes is largely causal.

Another strategy for controlling selection bias may be the family/sibling fixed effect (FE) model. Using such an FE model, Ermisch and Francesconi (2001) find that living in a single-parent family is associated with negative outcomes, such as lower educational attainment, higher risks of early child bearing. However, Björklund et al. (2007) find that the negative relationship between a non-intact family and a child's outcomes becomes no longer significant when sibling FE is applied, and their findings are remarkably similar in both Sweden and the U.S.

There are also a few studies using a quasi-experiment approach. For example, parental death and changes in divorce laws have been used as exogenous treatments of family structures. Lang and Zagorsky (2001) show that, overall, having a mother or father die has little impact on a child's economic well-being in adulthood. In contrast, using changes in divorce laws as an exogenous treatment, Gruber (2004) finds that unilateral divorce has a significantly negative effect on children's education attainment.

In conclusion, the evidence of the effects of family structure on child's well-being is not consistent either across or within approaches. Aside from the differences in methods, various factors could lead to the mixed conclusions on the effects of family structure, including different definitions of family structures, different choices of sample and control variables, and different variables used as proxy for children's well-being.

This study includes a wide range of children's outcomes including mental health, general health, and educational attainment. Using Canadian longitudinal data and multiple approaches presented in the literature, this study documents the relationship between family structure and children's outcomes in three ways. First, it compares the differences in outcomes between children persistently living in two-parent families and children persistently living in single-parent families and examines whether the differences in outcomes could be attributable to the differences in household permanent income and parenting quality. Second, by following children initially living in biological-two-parent families, it compares the differences between children whose parents separate later and children whose parent remain together and examines whether the differences withstand adjustment for pre-existing conditions. Third, using a sibling fixed-effect model, it investigates whether children currently living in the same household but with different experience of family structure in the past exhibit significant differences in well-being. In addition, this study tests the hypothesis of stress relief, which suggests that a parental separation improves children's mental health for children living in families with high levels of family dysfunction (Strohschein, 2005). Furthermore, it looks into whether the relationship between parental separation and family structure varies by children's gender. However, this paper makes no attempt to estimate the structural relationship between family structure and children's outcomes; the empirical results are viewed as association rather than causality.

In the remainder of the article, Section 2.2 describes data and methods, Section 2.3 reports results, and Section 2.4 summarizes the findings, discusses policy implications, and provides several potential areas for future research.

2.2 Data and methods

The data come from the first four cycles of the National Longitudinal Survey of Children and Youth (NLSCY) from 1994 to 2000. The NLSCY is a Canadian national longitudinal dataset that contains detailed information on children's development and family socioeconomic status. Starting from 1994/95 (Cycle 1), an original cohort that consisted of 22,831 children ages 0-11 years old were surveyed biennially until 2008/09 (Cycle 8). A child's outcomes and family background are typically reported by the person most knowledgeable (the PMK), and in most cases (approximately 92% in every cycle), the PMK is the biological mother of the child. Main samples for analysis are taken from the first four cycles for several reasons. First, persistently living in non-intact families for an interval of six years (1994/95-2000/01) may have a decisive influence on children's development. Second, control variables such as family income and parenting quality, which may be associated with family structure and affect child's outcomes, may not be cross-sectionally accurate. Using longitudinal data and taking the averages across four cycles improves the accuracy of such control variables. Third, children's outcomes are reported for specific age ranges in the NLSCY. For example, child mental health was assessed similarly in each cycle only for children between the ages of 4 and 11 (Strohschein, 2005). Child general health was assessed by the PMK for children ages 15 years or younger, and child educational attainment was reported for children ages 4 to 15. In Cycle 4 (2000/01), children from the original cohort were ages 6 to 17. To avoid excluding a large number of observations due to unreported outcomes, the cycles after Cycle 4 are not included in this study.

2.2.1 Methods and samples

In comparing the differences in outcomes between children growing up in different family structures, the sample is restricted to children continuously living in intact families (i.e. children living with married or common-law couples) and children continuously living in single-parent families from Cycle 1 (1994) to Cycle 4 (2000). Although step family is an important category in family structures, the number of children persistently living in step families across Cycles 1-4 is too small to be included for estimation. The differences in children's outcomes are estimated by the following regression:

$$y_i^{2000} = \beta_0 + \beta_1 \textit{ persistently single-parent}_i + \lambda \mathbf{X}_i + u_i \tag{1a}$$

where y_i^{2000} represents the outcomes of child i in Cycle 4 (2000). **X** includes child's basic demographic characteristics and parental background, such as child's age and gender, mother's highest education level, and household size. In the regression, the reference group is children persistently living in intact families. The estimated coefficient on "persistently single-parent" indicates the estimated differences in children's outcomes between the two groups conditional on children's demographic and parental background.

In testing whether family income and parenting quality account for a part of the differences, I re-estimate Eq. (1a) by adding a set of explanatory variables **Z** into the baseline regression:

$$y_i^{2000} = \beta_0 + \beta_1 \textit{ persistently single-parent}_i + \lambda \mathbf{X}_i + \gamma \mathbf{Z}_i + u_i \tag{1b}$$

where **Z** includes the average of annual household real income across the first four cycles as well as three scores that respectively measure the effectiveness, the consistency, and the punitiveness of parenting. The three scores are provided by the NLSCY. More details on measurements will be described later. If the differences in children's outcomes between the two groups are strongly associated with the differences in family income and parenting quality, the magnitude of β_1 in Eq. (1b) is expected to be substantially lower than that in Eq. (1a).

To document the association between parental separation and children's future outcomes, I restrict the sample to the NLSCY children who lived in intact families in Cycle

1 (1994), and then follow the children until Cycle 4 when they are split into two groups: children who experienced at least one change in family structure and children whose parents remained together. The following equation is estimated to capture the differences in children's outcomes between the two groups:

$$y_i^{2000} = \alpha_0 + \alpha_1 \, parental\ separation_i + \lambda \mathbf{X}_i + u_i \qquad (2a)$$

where y_i^{2000} and **X** are the same notations as in Eq. (1a).

To test whether the differences can be attributable to the pre-existing disadvantages of parents who separated later compared to parents who remained together, I add into Eq. (2a) a set of variables $\mathbf{p}_i^{1994}$ controlling for household's SES index, parental depression, and family dysfunction in Cycle 1 (1994):

$$y_i^{2000} = \alpha_0 + \alpha_1 \, parental\ separation_i + \lambda \mathbf{X}_i + \delta \mathbf{p}_i^{1994} + u_i \qquad (2b)$$

To test the stress relief hypothesis, which suggests that, for children living in families with severe parental conflicts, a parental separation improves children's mental health, I re-estimate Eq. (2b) adding the interactions between parental separation and $\mathbf{p}_i^{1994}$:

$$y_i^{2000} = \alpha_0 + \alpha_1 \, parental\ separation_i + \lambda \mathbf{X}_i + \delta \mathbf{p}_i^{1994} \qquad (2c)$$

$$+ \, \phi \, parental\ separation_i \times \mathbf{p}_i^{1994} + u_i$$

The magnitude and the sign of ϕ would indicate whether a parental separation substantially reduces the negative effects of the pre-existing parental depression and family dysfunction on children's later outcomes.

Finally, using the sample that consists of households having multiple children in Cycle 1, I apply a sibling fixed-effect approach to document the effect of parental separation on children's later outcomes. In Cycle 1, the NLSCY surveyed at most 4 children from the same household and collected the custody history of each child including whether the parents of the child had broken up and stopped living together. Given that, for children living in a same household in 1994, a child might have had a difference experience in the family structure from another prior to 1994, a sibling FE model such as Eq. (3) can be applied.

$$y_{ij} = \gamma_0 + \gamma_1\, parental\ separation_{ij} + \lambda \mathbf{Z}_{ij} + A_j + u_{ij} \tag{3}$$

where y_{ij} represents the outcomes of child i from household j. **Z** is a vector that includes child i's basic characteristics excluding the variables that are common to children living in the same household. A_j refers to the unobserved heterogeneity of household j. By assuming that A_j is constant within each household and u_{ij} is *i.i.d.* with zero mean, the fixed-effect estimator of γ_1 identifies the differences in outcomes between children living in the same household but with different experience of family structure in the past. Whether this identification assumption is satisfied will be discussed in the last section.

2.2.2 Measures

Outcome variables

Children's outcomes are measured in three dimensions: mental health, general health, and educational attainment. Specifically, mental health is measured by five scores on hyperactivity, emotional disorder, physical aggression, indirect aggression, and property offense. Each score was derived using the PMK's responses to a specific set of questions. For instance, to derive the hyperactivity score, the PMK of a child ages 4-11 was asked to answer eight questions, such as whether the child is inattentive. The responses to the questions could be never, sometimes/somewhat or often/very true, and the responses were scaled as 0, 1, and 2 respectively. The sum of the scaled responses is the score for hyperactivity, with high score indicating increasing levels of hyperactivity. The questions used by the NLSCY to derive all mental health scores are described in Table A2.1 in the appendix. General health measures include whether the child is in poor health and the number of GP visits in the past 12 months. For children ages 15 and younger, the PMKs were asked to report the child's general health on a scale of 1-5 (1: excellent; 2: very good; 3: good; 4: fair; 5: poor). A child is considered in poor health if the child's reported health status is in the three bottom categories on the scale (Currie and Stabile, 2006, 2009). Children's educational attainments include whether the child has repeated a grade including kindergarten across Cycles 1-4 and the child's standardized math scores.

Control variables

In Eq. (1b), family income is measured by the average of annual household real income across Cycles 1-4 (in 2002 dollars), while parenting quality is measured by the averages of ineffective parenting scores, consistent parenting scores, and punitive parenting scores across Cycles 1-4. Similar to mental health scores, the three scores measuring parenting quality were provided in the NLSCY and were the sum of the scaled responses to three sets of questions (see Table A2.2 in the appendix for the survey questions).

$\mathbf{p}_i^{1994}$ in Eq. (2b), which captures parents' pre-existing conditions, includes three control variables: SES index in 1994, the PMK depression level in 1994, and family dysfunction score in 1994. All three variables were directly provided in the NLSCY. SES index was based on parental education, occupation, and household income.[1] The PMK depression and family dysfunction scores are the sum of scaled responses to relevant questions. Higher scores indicate higher levels of parental depression and family dysfunction. All questions and scaled responses used to derive the scores measuring pre-existing conditions are shown in Table A2.3 in the appendix.

2.2.3 Descriptive statistics

Table 2.1 presents descriptive statistics for children living in two family structures: persistently two-parent (PTP) families and persistently single-parent (PSP) families. Children persistently living in PTP families across Cycles 1-4, on average, exhibit more favourable outcomes than children from PSP families for all measures: mental health, general health, and educational attainment. The most significant differences appear in the probability of being in poor health and grade repetition: children from PSP families are approximately twice more likely to be in poor health and to repeat a grade since Cycle 1. There are also substantial differences in household characteristics that may affect children’s outcomes. Children from PTP families tend to have more educated mothers and receive better parenting care (more effective, more consistent, and less punitive). The most striking difference in household background by family structures appears in the average household income across Cycles 1-4: the average household income of PTP families is 2.5 times as high as that of PSP families. As a result, it is possible that the differences in household characteristics by family structure account for a part of the differences in children’s outcomes.

[1] I also used household income in 1994 as a control variable instead of SES index in 1994. However, SES index is found to have stronger correlation with child’s outcomes and is associated with a better goodness of fit.

Based on children who lived with two biological parents in Cycle 1, Table 2.2 provides summary statistics for children who remained living with two biological parents in Cycle 4 and children who lived in another family structure in Cycle 4. On average, children whose parents remain together are associated with noticeably better outcomes in health and education which include lower scores in mental health indicators, lower likelihood of poor health, fewer GP visits, lower chance of grade repetition, and higher math scores. In terms of household background, children whose parents separate are more likely to have a less-educated mother, lower maternal age at birth, and fewer siblings. In addition, parents who separate later initially report lower SES index and income, greater family dysfunction, and higher depression levels than parents who remain together.

2.3 Results

2.3.1 Comparison of children persistently living in two-parent families and single-parent families

Table 2.3 presents the differences in mental health between children persistently living in two-parent families and children persistently living in single-parent families. According to the baseline regression (Model 1), children from PSP families exhibit worse mental health status except for emotional disorders and indirect aggression. To facilitate interpretation, all the scores to measure mental problems have been transformed into z-scores, and the unit of the coefficient on PSP families is standard deviation. For example, a child persistently living in a single-parent family is, on average, likely to earn a higher hyperactivity score by 0.27 standard deviations, compared to a child persistently living in a two-parent family.

Controlling for the quality of parenting (efficiency, consistency, and punitiveness) substantially reduces the estimated gaps in mental health between the two groups (Model 2), and only the gap in offense scores between the two groups remains statistically significant. The ineffectiveness of parenting is positively and significantly correlated to all five mental problems, while consistent parenting is negatively associated with almost all mental problems. Punitive parenting appears to have little correlation with a child's mental problems except for offense. When household income is controlled for, all the estimated coefficients on persistently single-parent families become statistically insignificant (Model 3). Household income is strongly and negatively correlated with all mental problems. Finally, compared to the baseline regression, controlling for both parenting and household income drastically reduces the magnitude of the estimated coefficients on persistently single-parent families (by 75%-85%), with no estimated coefficient remaining statistically significant (Model 4). This suggests that the gaps in mental health between children growing up in single-parent families and children growing up in two-parent families might be largely attributable to the differences in parenting quality and household income between the two family structures.[2]

Table 2.4 compares general health and educational attainment between children from PSP families and children from PTP families. Among the dependent variables shown in the table, poor health and grade repetition are binary variables; the number of GP visits and math scores are in z-scores. Model 1 indicates that, on average, children from PSP

[2] However, it should be noticed that the differences in parenting quality between family structures may stem from sources other than family structure. For example, parents who have more poorly behaved children are more likely to report lower scores on parenting quality. Given the fact that children from PSP families exhibit more mental problems, it is questionable whether the differences in parenting quality cause the gaps in children’s outcomes across family structures.

families are more likely to be in poor health and to visit a GP more frequently and are more likely to repeat a grade and earn lower math scores. All the gaps between the two groups are statistically significant. In contrast to mental health, for general health and educational attainment, controlling for parenting quality only slightly reduces the magnitude of the estimated coefficients on PSP families, and all the estimated coefficients remain statistically significant (Model 2). When household income is controlled for, the estimated coefficients on PSP families are no longer statistically significant for educational attainment (Model 3). Household income is associated with better general health and better educational attainment.

In the end, controlling for both parenting quality and household income decreases the estimated coefficients on PSP families by 28%-124% compared to Model 1. The gap in general health remains statistically significant and quantitatively meaningful: on average, a child from a PSP family is 8.9% more likely to be in poor health and to visit a GP more frequently by 0.23 standard deviations (which correspond to 0.43 visits) than a child from a PTP family. In conclusion, for a child's educational attainment, it is the difference in household income rather than the difference in parenting quality that accounts for the majority of the gaps between the two family structures, while for a child's general health, some of the gaps between family structures seem to be independent of the differences in parenting quality and household income.

2.3.2 Parental separation and children's future outcomes

Table 2.5 and Table 2.6 present the association between parental separation and children's future outcomes based on Eq. (2). As shown in Table 2.5, without controlling for households' initial characteristics, children with parental separation exhibit more severe mental problems. The gaps are statistically significant except for indirect aggression, ranging from 0.17 standard deviations (emotional disorder) to 0.23 standard deviations (hyperactivity). The gaps also withstand the additional controls for pre-existing conditions such as SES index, parental depression scores, and family dysfunction reported in Cycle 1 (Model 2). Among the pre-existing conditions, parental depression levels prior to parental separation show the strongest association with children's future mental health. By adding interactions between parental separation and the pre-existing characteristics, Model 3 examines whether a parental separation mitigates the negative effects of pre-existing family dysfunction and parental depression on children's future mental health. Almost all coefficients on the interactions are very small and not statistically significant except that a parental separation is associated with a slight strengthening of the marginal effect of pre-existing family dysfunction on children's offense scores by 0.03 standard deviations.

Table 2.6 shows that children whose parents separate are slightly more likely to be in poor health and visit GPs more frequently. When the pre-existing conditions are controlled for, the probability of being in poor health is found to have no statistically significant association with parental separation. Children's general health and educational attainment have stronger associations with the initial SES index compared to initial parental depression or initial family dysfunction. All the estimated coefficients on the interactions between parental separation and pre-existing conditions are quantitatively trivial, suggesting that a parental separation does not alleviate the negative effects of pre-existing family dysfunction and parental depression on children's later general health and educational attainment.

Table 2.7 and Table 2.8 illustrate how the association between parental separation and children's later outcomes varies with a child's gender. For boys, controlling for pre-existing conditions, the estimated coefficients on parental separation are positive, statistically significant, and quantitatively meaningful for all five mental problems. For girls, only hyperactivity is predicted to have a statistically significant association with parental separation. The results suggest that, in terms of the selected measures of mental health, boys are more sensitive than girls to a parental separation. In contrast, in terms of general health, Table 2.8 shows that when controlling for pre-existing conditions, girls with parental separation experience are more likely to be in poor health (by 5%) and to visit a GP more frequently (by 0.23 standard deviations, which correspond to 0.43 visits) than their counterparts whose parents have not separated, while boys with parental separation experience do not exhibit disadvantages compared to boys whose parents have remained together. For both boys and girls, the probability of repeating a grade and math scores do not vary by parental separation whether controlling for pre-existing conditions or not. Regarding the interactions between parental separation and pre-existing conditions, almost none of the estimated coefficients on the interaction items are statistically significant for both boys and girls. The only exceptions are that a parental separation reduces the negative effect of pre-existing family dysfunction on boys' probability of being in poor health by 1% and decreases the adverse effect of pre-existing parental depression on girls' offense scores by 0.04 standard deviations. In general, for both boys and girls, very little evidence is found to suggest that a parental separation alleviates the negative effects of the pre-existing disadvantages on children's future outcomes.

2.3.3 Parental separation and children's outcomes: OLS estimates vs. sibling fixed-effect

Table 2.9 presents the sibling fixed-effect estimates of the association between parental separation and children's outcomes as well as the corresponding OLS estimates by using the sample that consists of households having multiple children in Cycle 1. For all unfavourable outcomes, OLS estimates on parental separation are positive and statistically significant. In the models using sibling fixed-effect, the effects of parental separation are lower but remain statistically significant for hyperactivity, emotional disorder, indirect aggression, and grade repetition. For both OLS estimates and sibling FE estimates, mental health shows stronger association with parental separation, compared to general health and educational attainment.

2.4 Discussion and conclusion

This study shows that children growing up in two-parent families exhibit advantages over children growing up in single-parent families in the areas of mental health, general health, and educational attainment. Most of the gaps in mental health and educational attainment are associated with the differences in permanent household income and parenting quality between the family structures.

Next, by following children who initially live with two biological parents for six years, this study finds that, compared to the children whose parents remain together, the children with parental separation experience during the period exhibit worse subsequent outcomes. A number of the gaps withstand additional controls for pre-existing family disadvantages in social-economic status, parental depression, and family dysfunction. In addition, little evidence is found to suggest that a parental separation mitigates the adverse effects of pre-existing family dysfunction and parental depression on children's future outcomes. Furthermore, using a sibling fixed-effect approach substantially reduces the associations between children's outcomes and parental separation predicted by the OLS estimates, but several gaps, especially in mental health, still remain statistically significant and quantitatively meaningful.

Limitations

The gaps in outcomes between children growing up in two-parent families and children growing up in single-parent families as well as the gaps in well-being between children with parental separation experience and children without are interpreted as association rather than causation. This is because neither Eq. (1b) nor Eq. (2b) fully controls the variables that affect both family structure/parental separation and children's outcomes, such as parental competence and how parents value a child. As for the sibling fixed-effect approach, which makes weaker assumptions than the OLS estimates, it still requires the assumption that parental separation is uncorrelated with children's "idiosyncratic endowments", which include inherent differences between siblings, such as disability at birth (Ermisch and Francesconi, 2001). Unfortunately, this assumption may not accord with reality. For example, marital conflicts could trigger a parental separation and have detrimental effects on children’s development. An elder sibling who experienced a parental separation may also spent a big part of his childhood with parents having marital conflicts. As a result, he may suffer more from the detrimental effects of parents’ marital conflicts compared to the younger sibling who did not experience a parental separation.

There needs to be cautious when generalizing the observed association between children's outcomes and family structures. First, children persistently living in single-parent families could have different life experience (e.g. persistently living with a single mother may differ from persistently living with a single father). Due to the small sample size for single fathers, this study does not distinguish between different types of persistent single-parent families. Second, the association between children's future outcomes and parental separation is likely to vary by parental socio-economic status. The negative effect of a parental separation might be smaller for children who have high-income parents.

Boys are found more sensitive than girls to a parental separation in terms of the selected mental health measures, but it remains unknown whether mental health issues could arise in other ways for girls, such as eating disorders and suicidal thoughts.

Policy implications

Although the findings are interpreted as associations, they provide some insight into possible policy implications. First, as children's outcomes are shown to be strongly associated with household characteristics such as household permanent income and parenting quality, policies that prevent family disruption may have a limited effect on children's outcomes unless low income and poor parenting quality are caused by family disruption. As parents who later separate initially have lower household income and greater family dysfunction than parents who do not separate (shown in Table 2.2), it is very likely that unfavourable household characteristics are not only the consequence of family disruption but also one of the causes.

Second, both lack of income and lack of parental involvement can contribute to the disadvantages of children living in non-intact families. From a policy perspective, if the lack of income dominates, then a policy such as an income transfer could be effective but expensive. If the lack of parental involvement dominates, then policies promoting parental involvement might be more cost-effective (Painter and Levine, 2004). This study suggests that both household income and parenting quality matter, but that household income is more important than parenting quality in accounting for the gaps in children's well-being.

Third, although the results offer little evidence to suggest that a parental separation mitigates the adverse effects of pre-existing family dysfunction and parental depression, it is important to be cautious when concluding that a parental separation has no protective effect on children because the counterfactual outcomes of children whose parents separate are impossible to observe.

Fourth, policy makers may need to take into account the fact that the potential effects of family structure are not constant across children's outcomes and vary with children's gender. This study finds that, in general, mental health is more strongly associated with family structure, compared to general health and educational attainment. One possibility is that general health problems may be more readily detected than mental health problems and that the healthcare system, schools, and other services may more readily compensate for deficiencies in general health than in mental health. In addition, in terms of the selected mental health problems, the results seem to imply that boys are more sensitive than girls to a parental separation.

Areas for future research

More evidence is required to understand the mechanisms through which family structure affects children's well-being. Other than investigating the association/causality between family structure and children's well-being, studying how parental investment in child care (e.g. resources, behaviours, and time) vary by family structures may shed more lights (e.g. Case and Paxson, 2001).

It might be of importance to study how the association between family structure and children's outcomes changes over time. As Biblarz and Raftery (1999) state, from an economic perspective, it is expected that the negative effects might be reduced over time for several reasons. First, more separations may give single parents more chances to find another partner, which would reduce the duration of the single-parent period experienced by children. Second, as the number of children per parent decreases (due to decrease in birth rates), the negative effects of loss of resources become smaller for each child.

Moreover, it is interesting to compare the associations between family structure and children's outcomes across countries. The effects of family structure are expected to be smaller in countries with social norms that de-emphasize the importance of marriage and that have an extensive social safety net (Björklund et al., 2007). Such a comparison might also provide clarity to the question of whether public policy could alleviate the disadvantages of children living in non-intact families.

Conclusion

By using multiple approaches and considering different dimensions of family structure (persistent family structure and changes in family structure) and a wide range of children's well-being, the evidence based on Canadian longitudinal data suggests that children's outcomes vary across family structures. Although the gaps in children's outcomes may not be caused by family structures per se, family non-intactness such as persistently living in single-parent families and experiencing a parental separation is found to be a strong predictor of less favourable child outcomes. Given the significant and continuous decline in the share of children living in intact families over the past decades, it is important for policy makers to consider how to prevent disadvantages for children living in non-intact families. Policies that focus on family structure through tax or marriage/divorce law may have a limited effect if it is primarily the variables other than family structure that affect children's outcomes. This study suggests that policies that raise household income or improve parental involvement for non-intact families might be more effective in reducing the gaps in child's well-being between family structures.

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Table 2.1 Differences between children persistently living in two-parent and single-parent families

Summary statistics

	Age coverage in Cycle 4	(1) Whole sample	(2) Persistently two-parent family	(3) Persistently single-parent family	(4) Difference
Outcomes in Cycle 4					
Hyperactivity	6-11	3.61	3.55	4.42	0.87***
Emotional disorder	6-11	2.32	2.30	2.63	0.33
Physical aggression	6-11	1.23	1.22	1.30	0.08
Indirect aggression	6-11	1.05	1.05	1.15	0.10
Offense	8-11	0.64	0.62	0.94	0.32***
Poor health	6-15	0.13	0.12	0.23	0.11***
GP visits	6-15	1.48	1.42	2.02	0.60***
Grade repetition since Cycle 1	6-15	0.05	0.04	0.09	0.05**
Math scores	7-15	456.84	458.72	437.77	-20.95***
Control variables					
Child is female	6-17	0.48	0.48	0.48	0.00
Child's age	6-17	11.52	11.44	12.25	0.81***
PMK is female	6-17	0.93	0.93	0.92	-0.01
PMK is not the biological mother	6-17	0.08	0.08	0.10	0.02
Mother has a college degree	6-17	0.41	0.43	0.30	-0.13***
Household size	6-17	4.42	4.58	3.09	-1.49***
Number of siblings	6-17	1.43	1.50	0.89	-0.61***
Mother's age at birth	6-17	28.52	28.64	27.43	-1.24***
Living in a rural area	6-17	0.14	0.15	0.07	-0.08***
Average household income (in 2002 dollars)	6-17	71,023	75,825	30,329	-45,496***
Average ineffective parenting score	8-17	8.93	8.88	9.36	0.48***
Average consistency parenting score	8-17	15.04	15.13	14.21	-0.92**
Average punitive parenting score	8-17	8.79	8.78	8.86	0.08

Notes: Means are weighted using funnel weights provided by the NLSCY. The funnel weights are longitudinal weights that have been assigned to children who have responded at every cycle. "Whole sample" includes both persistently two-parent families and persistently single-parent families. Difference = "Persistently single-parent family" minus "Persistently two-parent family". * p<0.10, ** p<0.05, *** p<0.01.

Table 2.2 Parental separation and children's later outcomes

Summary statistics

	Age coverage in Cycle 4	(1) Whole sample	(2) Parents remain together	(3) Parents separate	(4) Difference
Outcomes in Cycle 4					
Hyperactivity	6-11	3.67	3.54	4.38	0.84***
Emotional disorder	6-11	2.36	2.29	2.71	0.42***
Physical aggression	6-11	1.26	1.22	1.52	0.30***
Indirect aggression	6-11	1.07	1.04	1.15	0.11
Offense	8-11	0.66	0.62	0.93	0.31***
Poor health	6-15	0.13	0.12	0.15	0.03*
GP visits	6-15	1.46	1.42	1.69	0.27***
Grade repetition since Cycle 1	6-15	0.04	0.04	0.05	0.01
Math scores	7-15	454.74	458.61	429.93	-28.68***
Control variables					
Child is female	6-17	0.49	0.49	0.49	0.00
Child's age	6-17	11.34	11.43	10.85	-0.58***
PMK is female	6-17	0.92	0.93	0.84	-0.09***
PMK is not the biological mother	6-17	0.09	0.08	0.21	0.13***
Mother has a college degree	6-17	0.41	0.42	0.38	-0.04*
Household size	6-17	4.46	4.59	3.75	-0.84***
Number of siblings	6-17	1.47	1.51	1.28	-0.23***
Mother's age at birth	6-17	28.44	28.63	27.26	-1.37***
SES index in Cycle 1	6-17	0.07	0.10	-0.09	-0.19***
Household income in Cycle 1 (in 2002 dollar)	6-17	66,727	67,686	60,831	-6,855***
PMK depression score in Cycle 1	6-17	8.93	8.88	9.36	0.48***
Family dysfunction score in Cycle 1	6-17	7.74	7.53	8.97	1.44***

Notes: Means are weighted using funnel weights provided by the NLSCY. "Whole sample" includes both children whose parent separate between Cycle 1 and Cycle 4 and children whose parents remain together. Difference = "Parents separate" minus "Parents remain together". * p<0.10, ** p<0.05, *** p<0.01.

Table 2.3 Differences between children persistently living in two-parent and single-parent families

Mental health

	(1) Hyperactivity	(2) Emotional disorder	(3) Physical aggression	(4) Indirect aggression	(5) Offense
Number of observations	5,338	5,343	5,331	5,060	3,055
Model 1					
Persistently single-parent	0.273**	0.173	0.212**	0.242	0.396***
	(2.38)	(1.00)	(1.99)	(1.61)	(2.96)
R-squared	0.075	0.029	0.045	0.056	0.061
Model 2					
Persistently single-parent	0.160	0.114	0.136	0.146	0.248*
	(1.64)	(0.75)	(1.42)	(1.16)	(1.89)
Ineffective parenting	0.122***	0.102***	0.133***	0.109***	0.091***
	(11.44)	(8.49)	(12.16)	(8.34)	(7.21)
Consistent parenting	-0.024***	-0.005	0.008	-0.031***	-0.015
	(-2.75)	(-0.49)	(1.18)	(-2.83)	(-1.45)
Punitive parenting	0.002	-0.023	0.006	-0.0268	0.070***
	(0.11)	(-1.12)	(0.36)	(-1.16)	(2.90)
R-squared	0.212	0.102	0.191	0.147	0.187
Model 3					
Persistently single-parent	0.137	0.101	0.128	0.129	0.179
	(1.16)	(0.56)	(1.11)	(0.79)	(1.26)
ln(average income)	-0.140***	-0.076	-0.089*	-0.119*	-0.257***
	(-2.72)	(-1.38)	(-1.90)	(-1.89)	(-3.99)
R-squared	0.079	0.030	0.046	0.058	0.072
Model 4					
Persistently single-parent	0.040	0.0431	0.051	0.050	0.071
	(0.40)	(0.27)	(0.49)	(0.36)	(0.51)
Ineffective parenting	0.124***	0.103***	0.135***	0.111***	0.094***
	(11.61)	(8.67)	(12.34)	(8.47)	(7.29)
Consistent parenting	-0.022**	-0.004	0.010	-0.030***	-0.011
	(-2.47)	(-0.35)	(1.42)	(-2.69)	(-1.07)

Punitive parenting	-0.002	-0.026	0.003	-0.030	0.063***
	(-0.12)	(-1.25)	(0.18)	(-1.30)	(2.63)
ln(average income)	-0.127**	-0.077	-0.093**	-0.102*	-0.191***
	(-2.53)	(-1.43)	(-2.14)	(-1.77)	(-3.64)
R-squared	0.215	0.103	0.193	0.149	0.194

Notes: All the dependant variables have been transformed into z-scores. *t* statistics in parentheses; * $p<0.10$, ** $p<0.05$, *** $p<0.01$. Robust standard errors are used. Estimates are weighted using funnel weights provided by the NLSCY. The other regressors in the Models 1-4 include a dummy for child's gender, a dummy for PMK's gender, a dummy indicating child's mother has a college degree, number of siblings, a dummy indicating whether the household lives in rural area, a complete set of dummies for children's age, the log of family size, a dummy indicating that PMK is not the biological mother of child, and mother's age at the birth of child.

Table 2.4 Differences between children persistently living in two-parent and single-parent families

General health and educational attainment

	(1) Poor health	(2) GP visits	(3) Grade repetition	(4) Math score
Number of observations	8,001	7,992	7,896	5,439
Model 1				
Persistently single-parent	0.134***	0.311**	0.037**	-0.140**
	(2.83)	(2.61)	(2.15)	(-2.38)
R-squared	0.023	0.045	0.044	0.717
Model 2				
Persistently single-parent	0.126***	0.307**	0.030*	-0.113**
	(2.69)	(2.65)	(1.72)	(-1.97)
Ineffective parenting	0.000	-0.001	0.001	-0.009
	(0.14)	(-0.16)	(0.55)	(-1.57)
Consistent parenting	-0.005**	0.000	-0.005***	0.022***
	(-2.29)	(0.02)	(-3.36)	(4.63)
Punitive parenting	0.002	0.0127	0.000	0.016*
	(0.40)	(0.82)	(0.15)	(1.68)
R-squared	0.025	0.045	0.048	0.720
Model 3				
Persistently single-parent	0.093**	0.225*	0.007	0.017
	(1.96)	(1.88)	(0.34)	(0.26)
ln(average income)	-0.045***	-0.095**	-0.034***	0.181***
	(-3.02)	(-2.50)	(-4.73)	(6.39)
R-squared	0.026	0.047	0.049	0.723
Model 4				
Persistently single-parent	0.089*	0.225*	0.003	0.033
	(1.88)	(1.91)	(0.15)	(0.51)
Ineffective parenting	0.001	-0.000	0.001	-0.010*
	(0.29)	(-0.04)	(0.79)	(-1.76)
Consistent parenting	-0.004*	0.002	-0.004***	0.019***
	(-2.00)	(0.24)	(-3.01)	(4.02)
Punitive parenting	0.001	0.011	-0.000	0.021**
	(0.21)	(0.70)	(-0.12)	(2.14)
ln(average income)	-0.042***	-0.094**	-0.031***	0.173***

	(-2.82)	(-2.45)	(-4.49)	(6.08)
R-squared	0.028	0.047	0.052	0.726

Notes: GP visits and math score have been transformed into z-scores. Poor health and grade repetition are binary variables. *t* statistics in parentheses; * p<0.10, ** p<0.05, *** p<0.01. Robust standard errors are used. Estimates are weighted using funnel weights provided by the NLSCY. The other regressors in Models 1-4 are the same as in Table 2.3.

Table 2.5 Parental separation and children's later outcomes

Mental health

	(1) Hyperactivity	(2) Emotional disorder	(3) Physical aggression	(4) Indirect aggression	(5) Offense
Number of observations	5,662	5,665	5,654	5,368	3,201
Model 1					
Parental separation	0.231***	0.172**	0.181***	0.053	0.227***
	(3.47)	(2.28)	(2.92)	(0.78)	(2.59)
R-squared	0.081	0.022	0.038	0.046	0.058
Model 2					
Parental separation	0.195***	0.147*	0.162**	0.018	0.202**
	(2.97)	(1.96)	(2.63)	(0.27)	(2.30)
SES index in 1994	-0.114***	-0.011	-0.032	-0.049	-0.105**
	(-3.47)	(-0.29)	(-0.90)	(-1.26)	(-2.37)
Parental depression 1994	0.023***	0.019***	0.015***	0.010	0.017**
	(4.30)	(3.00)	(3.11)	(1.53)	(2.52)
Family dysfunction 1994	0.006	0.008	0.004	0.014**	0.008
	(1.37)	(1.58)	(1.02)	(2.59)	(1.38)
R-squared	0.102	0.034	0.046	0.056	0.075
Model 3					
Parental separation	0.186	0.103	0.048	0.004	0.025
	(1.61)	(0.71)	(0.46)	(0.03)	(0.14)
SES index in 1994	-0.102***	-0.010	-0.025	-0.050	-0.122***
	(-2.94)	(-0.27)	(-0.67)	(-1.23)	(-2.66)
Parental depression in 1994	0.022***	0.016**	0.014***	0.008	0.022***
	(3.66)	(2.09)	(2.76)	(1.04)	(2.86)
Family dysfunction in 1994	0.006	0.010	0.002	0.015**	0.002
	(1.36)	(1.59)	(0.40)	(2.38)	(0.25)
Parental separation × family dysfunction in 1994	-0.003	-0.005	0.012	-0.004	0.034**
	(-0.29)	(-0.43)	(1.09)	(-0.30)	(2.15)
Parental separation × parental depression in 1994	0.005	0.017	0.002	0.010	-0.021
	(0.34)	(1.38)	(0.16)	(0.75)	(-1.35)
Parental separation × SES index in 1994	-0.092	0.001	-0.057	0.013	0.103
	(-1.01)	(0.01)	(-0.61)	(0.14)	(0.88)

R-squared	0.102	0.035	0.047	0.057	0.080

Notes: All the dependant variables have been transformed into z-scores. *t* statistics in parentheses; * p<0.10, ** p<0.05, *** p<0.01. Robust standard errors are used. Estimates are weighted using funnel weights provided by the NLSCY. The other regressors in the Models 1-3 include a dummy for child's gender, a dummy for PMK's gender, a dummy indicating child's biological mother has a college degree, a complete set of dummies for children's age, the log of family size, a dummy indicating that PMK is not the biological mother of child, and mother's age at the birth of child.

Table 2.6 Parental separation and children's later outcomes

General health and educational attainment

	(1) Poor health	(2) GP visits	(3) Grade repetition	(4) Math score
Number of observations	8,307	8,298	8,215	5,610
Model 1				
Parental separation	0.032*	0.141***	0.009	-0.066
	(1.85)	(2.95)	(0.94)	(-1.43)
R-squared	0.012	0.033	0.035	0.716
Model 2				
Parental separation	0.020	0.141***	0.005	-0.051
	(1.16)	(2.92)	(0.54)	(-1.10)
SES index in 1994	-0.048***	-0.045*	-0.039***	0.175***
	(-5.26)	(-1.95)	(-6.44)	(7.98)
Parental depression 1994	0.006***	0.010***	0.002***	-0.004
	(4.00)	(3.12)	(2.71)	(-1.46)
Family dysfunction 1994	0.002*	-0.006**	-0.001	0.001
	(1.92)	(-2.10)	(-1.24)	(0.50)
R-squared	0.030	0.036	0.050	0.726
Model 3				
Parental separation	0.063*	0.154	0.003	-0.057
	(1.79)	(1.56)	(0.18)	(-0.67)
SES index in 1994	-0.047***	-0.044*	-0.039***	0.178***
	(-4.88)	(-1.84)	(-6.11)	(7.82)
Parental depression in 1994	0.005***	0.009***	0.002**	-0.005*
	(3.38)	(2.59)	(2.55)	(-1.66)
Family dysfunction in 1994	0.003***	-0.006*	-0.001	0.002
	(2.70)	(-1.67)	(-1.24)	(0.63)
Parental separation × family dysfunction in 1994	-0.006**	-0.005	0.000	-0.002
	(-2.05)	(-0.60)	(0.21)	(-0.28)
Parental separation × parental depression in 1994	0.002	0.007	-0.000	0.005
	(0.53)	(0.72)	(-0.08)	(0.68)
Parental separation × SES index in 1994	-0.010	-0.007	0.001	-0.022
	(-0.40)	(-0.10)	(0.08)	(-0.33)
R-squared	0.031	0.036	0.050	0.726

Notes: GP visits and math score have been transformed into z-scores. Poor health and grade repetition are binary variables. *t* statistics in parentheses; * $p<0.10$, ** $p<0.05$, *** $p<0.01$. Robust standard errors are used. Estimates are weighted using funnel weights provided by the NLSCY. The other regressors in the Models 1-3 are the same as in Table 2.5.

Table 2.7 Parental separation and children's later outcomes (gender differences)

Mental health

	(1) Hyperactivity		(2) Emotional disorder		(3) Physical aggression		(4) Indirect aggression		(5) Offense	
	Boys	Girls	Boys	Girls	Boys	Girls	Boys	Girls	Boys	Girls
Number of observations	2,869	2,793	2,870	2,795	2,862	2,792	2,716	2,652	1,637	1,564
Model 1										
Parental separation	0.226***	0.225**	0.288***	0.065	0.314***	0.055	0.153**	-0.029	0.288**	0.193*
	(2.62)	(2.30)	(3.11)	(0.57)	(3.46)	(0.67)	(2.03)	(-0.27)	(2.23)	(1.67)
R-squared	0.044	0.069	0.029	0.026	0.038	0.038	0.035	0.042	0.044	0.072
Model 2										
Parental separation	0.198**	0.173*	0.274***	0.0141	0.306***	0.015	0.147*	-0.113	0.282**	0.142
	(2.33)	(1.83)	(2.91)	(0.13)	(3.40)	(0.18)	(1.94)	(-1.10)	(2.13)	(1.32)
SES index in 1994	-0.154***	-0.074*	0.012	-0.048	-0.058	-0.012	0.018	-0.127*	-0.161***	-0.057
	(-3.34)	(-1.67)	(0.26)	(-0.90)	(-1.18)	(-0.25)	(0.46)	(-1.86)	(-2.65)	(-0.93)
Parental depression 1994	0.019***	0.030***	0.010	0.029***	0.008	0.023***	0.003	0.021**	0.003	0.034***
	(2.65)	(3.77)	(1.34)	(3.18)	(1.22)	(4.01)	(0.42)	(2.20)	(0.36)	(4.07)
Family dysfunction 1994	0.001	0.011*	0.007	0.011	-0.002	0.011**	0.005	0.023***	0.002	0.016*
	(0.19)	(1.87)	(1.04)	(1.40)	(-0.33)	(2.17)	(0.78)	(2.85)	(0.26)	(1.86)
R-squared	0.062	0.101	0.034	0.051	0.041	0.060	0.036	0.070	0.054	0.117
Model 3										
Parental separation	0.147	0.242	0.231	-0.047	0.120	-0.047	0.128	-0.156	0.075	0.064
	(1.08)	(1.39)	(1.34)	(-0.22)	(0.84)	(-0.35)	(1.00)	(-0.73)	(0.27)	(0.32)
SES index in 1994	-0.134***	-0.071	0.008	-0.040	-0.050	-0.004	0.000	-0.102	-0.169***	-0.076
	(-2.72)	(-1.53)	(0.16)	(-0.70)	(-0.92)	(-0.07)	(0.01)	(-1.41)	(-2.64)	(-1.22)
Parental depression in 1994	0.016**	0.032***	0.005	0.028**	0.009	0.022***	0.003	0.0169	0.006	0.041***
	(2.03)	(3.54)	(0.59)	(2.52)	(1.24)	(3.78)	(0.48)	(1.47)	(0.62)	(4.63)
Family dysfunction in 1994	0.002	0.011*	0.009	0.011	-0.007	0.010*	0.004	0.026***	-0.004	0.008
	(0.30)	(1.72)	(1.32)	(1.15)	(-1.06)	(1.76)	(0.56)	(2.71)	(-0.42)	(0.97)
Parental separation × family	-0.005	-0.003	-0.013	0.003	0.026	0.004	0.005	-0.008	0.033	0.032*
dysfunction in 1994	(-0.33)	(-0.24)	(-0.73)	(0.16)	(1.48)	(0.29)	(0.34)	(-0.45)	(1.38)	(1.67)
Parental separation × parental	0.016	-0.009	0.030*	0.006	-0.006	0.004	-0.003	0.016	-0.013	-0.035**
depression in 1994	(0.88)	(-0.48)	(1.84)	(0.30)	(-0.32)	(0.23)	(-0.19)	(0.87)	(-0.50)	(-2.11)
Parental separation × SES	-0.147	-0.024	0.043	-0.071	-0.074	-0.070	0.140	-0.202	0.036	0.145
index in 1994	(-1.21)	(-0.18)	(0.37)	(-0.55)	(-0.59)	(-0.48)	(1.12)	(-1.40)	(0.24)	(0.81)
R-squared	0.064	0.101	0.036	0.051	0.044	0.060	0.038	0.072	0.057	0.127

Notes: All the dependant variables have been transformed into z-scores. *t* statistics in parentheses; * $p<0.10$, ** $p<0.05$, *** $p<0.01$. Robust standard errors are used. Estimates are weighted using funnel weights provided by the NLSCY. The other regressors in the Models 1-3 are the same as in Table 2.5.

Table 2.8 Parental separation and children's later outcomes (gender differences)

General health and educational attainment

	(1) Poor health		(2) GP visits		(3) Grade repetition		(4) Math score	
	Boys	Girls	Boys	Girls	Boys	Girls	Boys	Girls
Number of observations	4,217	4,090	4,212	4,086	4,169	4,046	2,800	2,810
Model 1								
Parental separation	0.006	0.057**	0.038	0.230***	0.004	0.010	-0.078	-0.062
	(0.25)	(2.26)	(0.63)	(3.15)	(0.26)	(0.97)	(-1.17)	(-1.02)
R-squared	0.012	0.028	0.035	0.043	0.039	0.028	0.715	0.724
Model 2								
Parental separation	-0.006	0.046*	0.036	0.232***	-0.000	0.008	-0.0611	-0.050
	(-0.27)	(1.78)	(0.60)	(3.10)	(-0.00)	(0.74)	(-0.92)	(-0.82)
SES index in 1994	-0.067***	-0.034***	-0.047	-0.039	-0.045***	-0.031***	0.176***	0.172***
	(-4.52)	(-2.99)	(-1.47)	(-1.15)	(-4.53)	(-4.64)	(6.50)	(5.21)
Parental depression 1994	0.004**	0.007***	0.007	0.014***	0.003**	0.001	-0.002	-0.004
	(2.31)	(3.36)	(1.64)	(3.07)	(2.10)	(1.56)	(-0.69)	(-1.11)
Family dysfunction 1994	0.003**	0.001	-0.004	-0.008*	-0.001	-0.001	-0.001	0.004
	(2.13)	(0.64)	(-1.02)	(-1.75)	(-0.50)	(-1.47)	(-0.41)	(1.03)
R-squared	0.037	0.042	0.037	0.048	0.057	0.040	0.726	0.733
Model 3								
Parental separation	0.048	0.079	0.110	0.187	0.005	0.002	-0.007	-0.160
	(1.08)	(1.47)	(1.14)	(1.06)	(0.20)	(0.12)	(-0.08)	(-1.32)
SES index in 1994	-0.061***	-0.034***	-0.039	-0.045	-0.045***	-0.030***	0.182***	0.171***
	(-4.13)	(-2.91)	(-1.16)	(-1.36)	(-4.30)	(-4.32)	(6.41)	(4.91)
Parental depression in 1994	0.004*	0.007***	0.008	0.011**	0.003*	0.001	-0.004	-0.004
	(1.66)	(3.18)	(1.65)	(2.34)	(1.93)	(1.61)	(-1.19)	(-1.02)
Family dysfunction in 1994	0.005***	0.002	-0.003	-0.008	-0.000	-0.001	0.001	0.002
	(2.92)	(0.91)	(-0.64)	(-1.58)	(-0.33)	(-1.59)	(0.25)	(0.49)
Parental separation × family	-0.010**	-0.003	-0.006	-0.003	-0.001	0.001	-0.013	0.012
dysfunction in 1994	(-2.44)	(-0.65)	(-0.61)	(-0.21)	(-0.31)	(0.45)	(-1.28)	(1.15)
Parental separation × parental	0.006	-0.002	-0.006	0.015	0.001	-0.001	0.012	0.001
depression in 1994	(1.29)	(-0.32)	(-0.52)	(1.18)	(0.17)	(-0.38)	(1.04)	(0.12)
Parental separation × SES	-0.013	-0.004	-0.068	0.052	0.007	-0.007	-0.032	0.011
index in 1994	(-0.46)	(-0.12)	(-0.86)	(0.49)	(0.30)	(-0.48)	(-0.41)	(0.12)
R-squared	0.040	0.043	0.037	0.049	0.057	0.041	0.726	0.734

Notes: GP visits and math score have been transformed into z-scores. Poor health and grade repetition are binary variables. *t* statistics in parentheses; * p<0.10, ** p<0.05, *** p<0.01. Robust standard errors are used. Estimates are weighted using funnel weights provided by the NLSCY. The other regressors in the Models 1-3 are the same as in Table 2.5.

Table 2.9 Effects of parental separation on children's outcomes: OLS vs. Fixed-effect

	Outcomes	OLS estimates	Fixed-effect estimates
(1)	Hyperactivity	0.384***	0.242*
		(7.87)	(1.78)
	R-squared	0.084	0.083
	Number of observations	9,588	9,864
(2)	Emotional disorder	0.358***	0.255**
		(6.40)	(2.02)
	R-squared	0.054	0.095
	Number of observations	9,595	9,871
(3)	Physical aggression	0.316***	0.009
		(4.83)	(0.07)
	R-squared	0.049	0.044
	Number of observations	9,572	9,848
(4)	Indirect aggression	0.279***	0.212*
		(3.75)	(1.73)
	R-squared	0.036	0.026
	Number of observations	9,294	9,558
(5)	Property offense	0.411***	0.102
		(6.64)	(0.62)
	R-squared	0.073	0.073
	Number of observations	9,606	9,881
(6)	Poor health	0.047***	-0.008
		(2.98)	(-0.32)
	R-squared	0.007	0.004
	Number of observations	14,837	15,163
(7)	GP visits	0.082**	0.005
		(2.04)	(0.08)
	R-squared	0.045	0.038
	Number of observations	14,828	15,153
(8)	Grade repetition	0.066***	0.138**
		(3.40)	(2.16)
	R-squared	0.045	0.013
	Number of observations	6,738	6,527
(9)	Math scores	-0.007	-0.049
		(-0.11)	(-0.13)
	R-squared	0.588	0.713
	Number of observations	2,647	2,729

Notes: Poor health and grade repetition are binary variables. The other dependant variables have been transformed into z-scores. *t* statistics in parentheses; * $p<0.10$, ** $p<0.05$, *** $p<0.01$. For the OLS estimates, robust standard errors are used. Estimates are weighted using cross-sectional weights provided by the NLSCY. The other regressors include child's age, a dummy for child's gender, a dummy indicating child's mother has a college degree, number of siblings, the log of family size, and mother's age at the birth of child. For the sibling FE estimates, the other regressors include child's age and a dummy for child's gender.

Appendix

Table A2.1 Survey instruments for mental health (NLSCY, Cycle 4)

Variables	Coverage	Survey questions	Scaled answers
Hyperactivity - inattention	children ages 4-11	1. How often would you say that -- Can't sit still, is restless or hyperactive? 2. How often would you say that -- Is distractible, has trouble sticking to an activity? 3. How often would you say that -- Fidgets? 4. How often would you say that -- Can’t concentrate, can’t pay attention for long? 5. How often would you say that -- Is impulsive, acts without thinking? 6. How often would you say that -- Has difficulty awaiting turn in games or groups? 7. How often would you say that -- Cannot settle to anything for more than a few moments? 8. How often would you say that -- Is inattentive?	0 - never 1 - sometimes/somewhat 2 – often/very true
Emotional health - anxiety scores	children ages 4-11	1. How often would you say that -- Seems to be unhappy, sad or depressed? 2. How often would you say that -- Is not as happy as other children? 3. How often would you say that -- Is too fearful or anxious? 4. How often would you say that -- Is worried? 5. How often would you say that -- Cries a lot? 6. How often would you say that -- Is nervous, high strung or tense? 7. How often would you say that -- Has trouble enjoying him/herself?	0 - never 1 - sometimes/somewhat 2 – often/very true
Physical aggression - conduct disorder	children ages 4-11	1. How often would you say that -- Gets into many fights? 2. How often would you say that -- When another child accidentally hurts him/her (such as by bumping into him/her), assumes that the other child meant to do it, and then reacts with anger and fighting? 3. How often would you say that -- Physically attacks people? 4. How often would you say that -- Threatens people? 5. How often would you say that -- Is cruel, bullies or is mean to others? 6. How often would you say that -- Kicks, bites, hits other children?	0 - never 1 - sometimes/somewhat 2 – often/very true
Indirect aggression	children ages 4-11	1. How often would you say that -- When mad at someone, tries to get others to dislike that person? 2. How often would you say that -- When mad at someone, becomes friends with another as revenge?	0 - never 1 - sometimes/somewhat 2 – often/very true

		3. How often would you say that -- When mad at someone, says bad things behind the other's back? 4. How often would you say that -- When mad at someone, says to others: let's not be with him/her? 5. How often would you say that -- When mad at someone, tells the other one's secrets to a third person?	
Property offense	children ages 8-11	1. How often would you say that -- Destroys his/her own things? 2. How often would you say that -- Steals at home? 3. How often would you say that -- Destroys things belonging to his/her family, or other children? 4. How often would you say that -- Tells lies or cheats? 5. How often would you say that -- Vandalizes? 6. How often would you say that -- Steals outside the home?	0 - never 1 - sometimes/somewhat 2 – often/very true

Table A2.2 Survey instruments for parenting quality (NLSCY, Cycles 1-4)

Variables	Coverage	Survey questions	Scaled answers
Ineffective/hostile parenting	children ages 2-11	1. How often do you get annoyed with your child for saying or doing something he/she is not supposed to? 2. Of all the times you talk to your child about his/her behaviour, what proportion is praise? 3. Of all the times you talk to your child about his/her behaviour, what proportion is disapproval? 4. How often do you get angry when you punish your child? 5. How often do you think the kind of punishment you give your child depends on your mood? 6. How often do you feel you have problems managing your child in general? 7. How often do you have to discipline your child repeatedly for the same thing?	0 - never 1 - about once a week or less/ less than half the time 2 - a few times a week/ about half the time 3 - one or two times a day/ more than half the time 4 - many times each day/ all the time
Consistent parenting	children ages 2-11	1. When you give him/her a command or order to do something, what proportion of the time do you make sure that he/she does it? 2. If you tell him/her he/she will get punished if he/she doesn't stop doing something, and he/she keeps doing it, how often will you punish him/her? 3. How often does he/she get away with things that you feel should have been punished? 4. How often is he/she able to get out of a punishment when he/she really sets his/her mind to it? 5. How often when you discipline him/ her, does he/she ignore the punishment?	0 - never 1 - about once a week or less/ less than half the time 2 - a few times a week/ about half the time 3 - one or two times a day/ more than half the time 4 - many times each day/ all the time
Punitive/aversive parenting	children ages 2-11	1. When -- breaks the rules or does things that he/she is not supposed to, how often do you: Raise your voice, scold or yell at him /her? 2. When -- breaks the rules or does things that he/she is not supposed to, how often do you: Calmly discuss the problem? 3. When -- breaks the rules or does things that he/she is not supposed to, how often do you: Use physical punishment? 4. When -- breaks the rules or does things that he/she is not supposed to, how often do you: Describe alternative ways of behaving that are acceptable?	0 - never 1 - rarely 2 - sometimes 3 - often 4 - always

Table A2.3 Survey instruments for pre-existing conditions (NLSCY, Cycle 1)

Variables	Coverage	Survey questions	Scaled answers
The PMK depression	children ages 0-11	1. How often have you felt this way during the past week: I did not feel like eating, my appetite was poor? 2. How often have you felt this way during the past week: I felt like I could not shake off the blues even with help from family or friends? 3. How often have you felt this way during the past week: I had trouble keeping my mind on what I was doing? 4. How often have you felt this way during the past week: I felt depressed? 5. How often have you felt this way during the past week: I felt that everything I did was an effort? 6. How often have you felt this way during the past week: I felt hopeful about the future? 7. How often have you felt this way during the past week: My sleep was restless? 8. How often have you felt this way during the past week: I was happy? 9. How often have you felt this way during the past week: I felt lonely? 10. How often have you felt this way during the past week: I enjoyed life? 11. How often have you felt this way during the past week: I had crying spells? 12. How often have you felt this way during the past week: I felt that people disliked me?	0 - Rarely or none of the time (less than 1 day) 1 - Some or a little of the time (1-2 days) 2 - Occasionally or a moderate amount of the time (3-4 days) 3 - Most or all of the time (5-7 days) *Notes*: the order of the categories was reversed for questions 6, 8, 10.
Family dysfunction	children ages 0-11	1. Planning family activities is difficult because we misunderstand each other. 2. In times of crisis we can turn to each other for support. 3. We cannot talk to each other about sadness we feel. 4. Individuals (in the family) are accepted for what they are. 5. We avoid discussing our fears or concerns. 6. We express feelings to each other. 7. There are lots of bad feelings in our family. 8. We feel accepted for what we are. 9. Making decisions is a problem for our family. 10. We are able to make decisions about how to solve problems. 11. We don't get along well together. 12. We confide in each other	0 - Strongly agree 1 - agree 2 - disagree 3 - Strongly disagree *Notes*: the order of the categories was reversed for questions 1, 3, 5, 7, 9, 11

Chapter 3 Trends in parental time allocated to child care: evidence from Canada, 1986-2010

3.1 Introduction

The positive relationship between parental time spent with children and children's development has been extensively documented in the literature (Fiorini and Keane, 2014; Milkie et al., 2015; Fomby and Musick, 2018). This study first investigates whether time spent in child care has increased in Canada from 1986 to 2010 by using cross-sectional data sets on time use. In addition, it examines whether the dispersion of child care time has grown during the period. Lastly, it analyzes whether more highly educated parents spend more time in child care, how large the differences in child care time between education groups may be, and whether the education-based gaps in child care time have increased over time.

The most remarkable finding in the trends of Canadians' time allocation between 1986 and 2010 is a dramatic increase in time spent in reported child care across gender and education groups. During the period, child care increased by 0.81 hours per day for women and 0.48 hours per day for men. Women increased time spent in market work by 0.60 hours per day and decreased time spent in domestic work by 0.37 hours per day. Conversely, men decreased market work by 0.34 hours per day and increased domestic work by 0.49 hours per day. Moreover, women and men reduced leisure time by 0.87 hours per day and 0.46 hours per day, respectively. Given the fact that child care accounts for a much smaller proportion of total time compared to work and leisure, the changes in child care time are much larger in terms of percentages compared to the changes in work and leisure.

The increase in average time spent in child care is also associated with a growing inequality in child care time. Specifically, the difference between the 10th and the 90th percentiles of the cross-sectional child care time distribution increased by 1.45 hours between 1986 and 2010. The results of Blinder-Oaxaca decomposition and John-Murphy-Pierce decomposition show that changes in time allocation among demographic groups are much more important than demographic changes in accounting for the increase in the mean time spent in child care and the growing inequality in child care time.

Time spent in child care is found to be strongly and positively correlated with parental education. Compared to women and men with a high school degree or less, women and men with a university degree or more spend up to 71% and 85% more time in child care, respectively. The strong education-based gaps in child care time are explained primarily by the fact that more educated parents are more likely to spend time in child care. In addition, the inequality in child care time has increased within education groups but has not increased between education groups.

The remainder of the paper is organized as follows: Section 3.2 presents a conceptual framework to understand time allocation and summarizes related empirical literature; Section 3.3 describes data sets; Section 3.4 reports on the trends in time allocation in Canada; Section 3.5 reports the findings on the relationship between time spent in child care and parental education; further discussion and conclusions appear in Section 3.6.

3.2 Conceptual framework and empirical literature

Traditional economic models such as that of Becker (1965) provide explanations for how individuals make decision about time allocation. The Beckerian model considers that individuals' utilities derive from a range of final goods, such as home-produced goods, leisure, and child care. Each final good is produced through a combination of time and market goods. Total expenditure on market goods is constrained by earnings in the labor market and other income. Total time spent in producing the final goods is constrained by total time excluding labor market hours. Subject to budget constraints, time constraints, and the production functions for final goods, individuals maximize their utilities by choosing the amount of time and market goods for producing each final good. The theoretical framework of a standard Beckerian model is presented in the appendix. The model suggests that, in addition to the difference in preferences, the opportunity cost of time (i.e. wage) and the productivity of time affect individuals' time allocation. A higher wage will lead to substitution effect, which reduces time spent in the final goods but increases market work hours. A higher wage will also bring an income effect, which increases the demand for all final goods and consequently raises time spent on producing the final goods. Higher non-market productivity induces individuals to spend more time producing the final goods, but it also reduces time required to produce a given amount of the final goods.

This conceptual framework implies that individuals with higher wages spend more time on child care. First, it is not easy to substitute market goods for time spent in child care so that the substitution effect of a higher wage might be weak with respect to child care time. Second, as shown in a number of empirical studies, parents consider time spent with children more enjoyable than other standard domestic work (Juster and Stafford, 1985; Robinson and Godbey, 1999). It is possible that parents consider child care as a luxury good, which is associated with a higher income elasticity of demand. As a result, the income effect of a higher wage on child care time could be strong. Overall, if the income effect dominates the substitution effect, child care time will increase with wages. Given the strong and positive correlation between education and wages, it is also expected that child care time increases with educational attainment. In the long run, with an increase in real wage and educational attainment, time spent in child care is expected to increase over time.

A great deal of empirical research shows that more highly educated parents spend more time with their children. For instance, using 2003-2006 waves of the American Time Use Survey, Guryan et al. (2008) find that mothers with a college education or more spend roughly 4.5 hours more per week in child care than mothers with a high school degree or less. In addition, using a sample of 14 countries, the authors find that in countries with higher GDP per capita on average more time is spent in child care and that the positive education gradient in child care time holds within each country. Moreover, several studies show that more highly educated parents spend more time on the activities that favour children's cognitive development (Bianchi and Robinson, 1997; Fiorini and Keane, 2014; Hofferth and Sandberg; 2001). However, less is known about whether the difference in child care time between education groups has increased over time.

To describe the trends in time allocation in Canada between 1986 and 2010, this study follows the work of Aguiar and Hurst (2007), which describes the trends in time use adjusted for changing demographics in the U.S. between 1965 and 2003. Aguiar and Hurst (2007) find a dramatic increase in leisure time that is robust to various definitions of leisure.

In addition, the inequality in leisure time between and within education groups has grown over time. According to their decomposition results, changes in demographic composition explain little of the increase in average time spent in leisure and the growth in leisure inequality.

3.3 Data

The data used in this study are taken from the General Social Survey (GSS) for five years of information collected on Canadians' time use: 1986 (Cycle 2), 1992 (Cycle7), 1998 (Cycle12), 2005 (Cycle 19), and 2010 (Cycle 24).[3] The GSS is nationally representative, and its target population includes persons ages 15 and older living in Canada's ten provinces. The GSS collected information on time allocation using time diaries, in which respondents were asked to report how much time they spent in various activities over a given 24-hour period. The period is called the Designated Day, which could be either a weekday or a weekend. The interviews were conducted throughout the year so that every month and every day could be equally represented in the survey (Rapoport and Le Bourdais, 2008). In addition to time allocation, the GSS provides information on individuals' demographic and socio-economic characteristics including age, gender, and educational attainment.

The sample used in this study consists of individuals between the ages of 25 and 64 with at least one child under age 19 in the household. The age restriction on respondents is

[3] This study includes all cycles of the GSS that collected information on time allocation except the 2015 GSS, in which the classification of activities and children's age coverage in measuring child care hours are not consistent with the previous five cycles.

meant to exclude full-time students and retired individuals. The GSS asked respondents to indicate their time use for a wide range of activities and consistently classified the activities into ten categories. For analytical purposes, I collapse the activities into five primary categories: child care, market work, domestic work, leisure, and sleep. The details of the classification of activities are shown in Table A3.1 in the appendix.

3.4 Trends in time allocation

3.4.1 Mean changes in time allocation

To document the trends in time allocation between 1986 and 2010, I first investigate the changes in average hours per day spent in major activities during the period. As changes in Canadian demographics might affect time trends, I use the approach of fixed demographic weights, which has been used in Katz and Murphy (1992) and Aguiar and Hurst (2007), to keep the demographic composition constant. Specifically, the full sample is divided into 48 demographic cells according to the interactions of the following characteristics: four age categories (25-34, 35-44, 50-54, 55-64); three educational categories based on individuals' highest education level (high school degree or less; beyond high school degree but no university degree; university degree and more); two gender categories; and whether or not there is any child aged under 5 years old in the household. For any demographic cell j, mean time spent in a specific activity in year t is equal to $\sum_i h_{ijt} w_{ijt} / \sum_i w_{ijt}$, where h refers to the hours that individual i spends in the activity, and w is the GSS sample weight. All cell-means for activity k constitute a 48×1 vector, denoted by Y_{kt}. Fixed demographic weights are defined as the percentages of individuals in each demographic cell (adjusted by the GSS sample weights) after pooling together all cross-sectional data sets, which constitute a 48×1 vector, denoted by *W*. The demographically adjusted average time spent in activity *k* in year *t* is $W'Y_{kt}$.

Table 3.1 presents the evolution of average hours per day spent in five time-use categories (child care, market work, domestic work, leisure, and sleep) from 1986 to 2010. Panels 1-5 in the table respectively report the time-use trends for five samples: full sample, women, men, weekdays, and weekends.

Trends in child care

Table 3.1 shows that, between 1986 and 2010, average time spent in child care exhibited a continuous and substantial increase. The increase was observed in all five samples.[4] Overall, average hours per day spent in child care increased by 0.65 hours (from 0.94 hours per day in 1986 to 1.58 hours per day in 2010). While women exhibited a greater increase in average time spent in child care than men (0.81 hours for women and 0.48 hours for men), the increase is greater in terms of percentage for men (83%) than for women (63%). The increase in child care time on weekdays is greater than that on weekends in terms of magnitude and percentage.

Table 3.2 shows the trends in child care hours for three sub-categories: primary child care, educational child care, and recreational child care. Educational child care hours include time spent reading, talking, and in conversation with children as well as helping, teaching, and reprimanding children. Recreational child care is defined as hours playing

[4] During the period Quebec introduced a universal child care program, which could affect parental allocated to child care in Quebec. To check the robustness of the increase in child care time, I used a sample excluding households from Quebec and obtained very similar results.

with children. Child care time excluding educational and recreational child care is defined as primary child care, which primarily consists of basic care (e.g. babysitting), medical care, and travel hours for child care. Panels 1-5 in Table 3.2 indicate that the significant rise in overall total care was driven by increases in primary child care and recreational child care. Both of these increased nearly continuously for all five samples while there was no substantial variation in educational care.

Trends in market work

As shown in the Panel 1 of Table 3.1, for the full sample, average hours per day spent in market work increased slightly between 1986 and 2010, but changes in market work hours differed by gender. For women, average market work hours per day increased by 0.67 hours (Panel 2), while for men, average market work hours per day dropped by 0.34 hours (Panel 3).

Table 3.3 defines market work time as the sum of core market work and other market work time which includes all idle time at work and travel time to and from work. Panels 2-3 show that the increase in market work for females was driven by an increase in core market work, while the decline in market work for males primarily resulted from a decline in other market work.

Trends in domestic work

Table 3.1 shows that average domestic work hours per day were around three hours between 1986 and 2010 (Panel 1). However, women and men exhibited opposite trends in domestic work. Women decreased domestic work hours by 0.37 hours per day (Panel 2) while men increased domestic work by 0.43 hours per day (Panel 3).

Table 3.3 splits domestic work time into two sub-categories, core domestic work and shopping activities. Core domestic work includes activities such as meal preparation, clean-up, doing laundry, mending, gardening, and pet care. Shopping activities include everyday shopping, purchasing durable goods, and obtaining government and financial services. Panel 2 in Table 3.3 shows that the decline in domestic work for women was associated with decreases in both core domestic work and shopping activities. Panel 3 in Table 3.3 indicates that the increase in domestic work for men was associated with an increase in core domestic work.

Trends in leisure

As seen in Table 3.1, Panels 1-3, leisure is the largest category of time allocation except sleep. Overall, average leisure time per day decreased by 0.67 hours between 1986 and 2010, and the decline in leisure occurred for all five samples. Women experienced a greater decline in leisure compared to men (Panels 2-3), and weekdays exhibited a more important reduction in leisure compared to weekends (Panels 4-5).

Dividing total leisure time into five sub-categories – personal care, organizational activities, entertainment, sports, and media & communication –Table 3.4 shows that the sub-components of leisure exhibited different trends. The fall in overall leisure time was associated with decreases in time spent in personal care and media communication. Time spent in organizational activities and entertainment remained stable during the period. On average, men substantially increased time spent on sports while women did not.

3.4.2 Changes in the dispersion of time allocation

In addition to changes in the average time allocated to each activity, another important trend in time allocation is the change in dispersion. Table 3.5 presents the 30th, 45th, 60th, 75th, and 90th percentiles of child care, market work, domestic work, and leisure from 1986 to 2010. Child care hours not only increased at each key percentile point but also exhibited greater increase at higher percentile points: child care at the 45th, 60th, 75th, and 90th percentile points increased by 0.50 hours, 0.75 hours, 1.03 hour, and 1.45 hours, respectively. There was no change in child care time at (or below) the 30th percentile point, which remained zero from 1986 to 2010. Figure 3.1 depicts changes in child care hours at each percentile point between 1986 and 2010, showing that the increase in child care hours increased linearly with the initial level of child care hours. In conclusion, Table 3.5 and Figure 3.1 provide evidence of a growing dispersion in child care time. However, such a pattern is not found in market work, domestic work, or leisure.[5]

3.4.3 The role of demographic changes and changes within demographic groups

To examine the extent to which observed demographic changes explain the increase in mean time spent in child care and the growing inequality in time spent in child care, I follow Aguiar and Hurst (2007) using the Blinder-Oaxaca decomposition to decompose the changes in unconditional means and the John-Murphy-Pierce (JMP) decomposition to decompose the changes in dispersion.

The Blinder-Oaxaca decomposition of changes in unconditional means is performed as follows:

[5] Similar changes in the dispersion of time allocation are found using the sample that excludes households from Quebec.

$$\bar{Y}_{k2010} - \bar{Y}_{k1986} = W_{2010}'Y_{k2010} - W_{1986}'Y_{k1986} \tag{1}$$
$$= (W_{2010} - W_{1986})'Y_{k2010} + W_{1986}'(Y_{k2010} - Y_{k1986})$$

where $\bar{Y}_{kt}$ refers to unconditional mean time spent in activity k in year t. W_t is a vector of demographic weights in year t, and Y_{kt} is a vector of average hours that each demographic cell spends in activity k in year t. As seen in Eq. (1), when the difference in unconditional mean time spent in activity k between 1986 and 2010 is decomposed, it is explained in part explained by changing demographics ($(W_{2010} - W_{1986})'Y_{k2010}$) and in part by changes in mean time within demographic group ($W_{1986}'(Y_{k2010} - Y_{k1986})$). An alternative way to decompose the difference between the unconditional means would be $(W_{2010} - W_{1986})'Y_{k1986} + W_{2010}'(Y_{k2010} - Y_{k1986})$.

The results of the two decompositions are respectively reported in the Panels 1-2 of Table 3.6, which indicates that changes in child care hours within demographic groups increase total child care by 0.60 to 0.72 hours per day, dominating demographic changes, which decrease total child care by up to 0.13 hours per day. Compared to child care, demographic changes exhibit a stronger effect on market work, increasing total market work by 0.15 to 0.35 hours per day. This finding is consistent with the fact that the proportion of older and more-educated individuals has increased in the population, and on average, older and more-educated individuals work more in the labor market.

JMP decomposition was first presented in John et al. (1993) to decompose changes in wage inequality. Following Aguiar and Hurst (2007), I adapt JMP decomposition to examine changes in time allocation inequality as follows:

$$y_{it} = X_{it}\beta_t + u_{it} \tag{2}$$

where y_{it} denotes the time that individual i spends in child care (on the Designated Day) in year t. X_{it} includes 42 dummy variables indicating the 42 demographic cells described in section 3.4.1, and β_t represents the mean of child care time for each demographic cell. The residual u_{it} is considered as an inverse cumulative distribution function of the percentile θ_{it} of individual i with demographic characteristics X_{it} in the residual distribution, i.e. $u_{it} = F_t^{-1}(\theta_{it} \mid X_{it})$. According to the JMP framework, y_{it} is decomposed as follows:

$$y_{it} = X_{it}\beta + F^{-1}(\theta_{it} \mid X_{it}) + X_{it}(\beta_t - \beta) + [F_t^{-1}(\theta_{it} \mid X_{it}) - F^{-1}(\theta_{it} \mid X_{it})] \tag{3}$$

where $F^{-1}(\cdot)$ and β represent the residuals and the cell-means obtained from the regression that pools all samples together. In Eq. (3), the first item $X_{it}\beta + F^{-1}(\theta_{it} \mid X_{it})$ captures the effects on child care time of a varying demographic composition. The second item $X_{it}(\beta_t - \beta)$ captures additional changes in child care time because of changes in cell-means within demographic groups, and the final item $F_t^{-1}(\theta_{it} \mid X_{it}) - F^{-1}(\theta_{it} \mid X_{it})$ captures the effects of changes in the distribution of unobservable components.

Panel 1 in Table 3.7 shows the JMP decomposition results over the period 1986-2010. The first column reports total changes in the 90^{th}-10^{th}, 90^{th}-50^{th}, and 50^{th}-10^{th} percentile differentials. For instance, the difference in time spent in child care per day between the 90^{th} and 10^{th} percentiles increased by 1.45 hours, which is much greater than the increase in the 50^{th}-10^{th} percentile differential (0.42 hours). Changes in the observed demographics account for 38% of the increase in child care inequality (0.16/0.42) between the 50^{th} and 10^{th} percentiles but contribute little to the increase in the 90^{th}-10^{th} percentile differential (column 2). The increase in child care time within demographic groups accounts for 62% of the increase in the 50^{th}-10^{th} percentile differential and 37% of the growth in the 90^{th}-10^{th} percentile differential (column 3). Except for the 50^{th}-10^{th} percentile differential, unobservable components have dominant effects on inequality, increasing the 90^{th}-10^{th} and 90^{th}-50^{th} percentile differentials by 61% and 81%, respectively. Panel 2 and 3 perform the JMP decomposition for the periods 1986-1998 and 1998-2010, the results of which are similar to the results shown in Panel 1. To summarize, JMP decomposition results show that changes in cell-means (i.e. changes within demographic groups) dominate changes in the observed demographic trends in explaining the growing inequality in child care time.

3.5 Time allocation and education

To document the evolution of the relationship between child care time and parental education from 1986 to 2015, I use two approaches. The first approach reports mean time spent in child care for different educational categories. The mean time is adjusted by the fixed demographic weights, as described previously. The second approach uses a Tobit model that regresses time spent in child care on indicator variables for education and on a set of variables controlling for individuals' other characteristics, such as the age of the youngest child living in the household and respondents' age and working status. The model does not include the number of children and household income, due to a lack of consistent measurement in the GSS. Given that men and women might have systematically different patterns in allocating time to child care, the regression is run separately for men and women. The Tobit model is preferred to OLS because a considerable number of individuals (especially males) did not spend any time in child care on the Designated Day. A two-part model is used as a complement to the Tobit model, separately investigating factors associated with the probability of spending any time in child care and factors associated with the amount of time spent in child care conditional on spending time in child care.

Panels 1-4 in Table 3.8 respectively present average time spent in child care, market work, domestic work, and leisure from 1986 to 2010 for three samples (full sample, women, and men) by three educational categories: high school degree and less (≤12 years of education), between high school and university (13-15 years of education), and university degree and more (≥16 years of education).

Panel 1 shows that, first, both women and men exhibit an education gradient in child care: average hours spent in child care increase with individuals' education attainment across all years (the only exception occurred in 2010 when women with a high school degree or less spent more time in child care than women with an education level of between high school and university). Second, average time spent in child care increased continuously across all educational groups, ranging from 0.40 to 0.99 hours per day. Third, the gaps in child care time between educational groups did not increase over time. Between 1986 and 2010, individuals with a high school degree or less increased child care by 0.71 hours per day while individuals with a university degree or more increased child care by 0.51 hours per day.

Panel 2 indicates that market work hours are positively associated with educational attainment for the full sample and for women. For men, individuals with an education level between high school and university recorded the highest market work hours from 1986 to 2005. In addition, women with an education level of between high school and university substantially and continuously increased market work hours (from 2.87 hours in 1986 to

3.89 hours in 2010). Furthermore, for the full sample, the gaps in market hours between the lowest-education group and the other education groups increased moderately.

Panel 3 shows that domestic work hours are negatively associated with educational attainment for the full sample and for women. However, the differences in domestic work hours between education groups decreased for the full sample and for women.

Panel 4 finds that, in general, leisure time decreases with educational attainment. In addition, leisure time decreased across all education groups between 1986 and 2010. Women with an education level between high school and university recorded the highest reduction in leisure (by 1.03 hours per day).

As shown in Panels 5-7, the education-based gaps in total child care time also applied to some sub-categories of child care. From 1986 to 2010, more educated parents (both females and males) consistently spent more time on primary child care and recreational child care (one exception occurred in 2010 when women with a high school degree or less spent more time on recreational care than other education groups). However, the gaps in time spent on educational child care between education groups were initially small and disappeared in 2010 for both women and men.

Figure 3.2 investigates whether there has been a growing inequality in child care within educational groups, by comparing changes at each percentile point between 1986 and 2010 for the three educational groups (i.e. a replication of Figure 3.1 by education attainment). The figure shows that changes in child care increase with percentile, suggesting a growing inequality within educational groups for all educational groups. However, the pattern is not more pronounced for individuals with less education.

Table 3.9 reports the estimates of the Tobit model in each survey year, indicating that conditional on the observed individuals' characteristics, women with more than 15 years of education spend more time on child care than women with less than 13 years of education. The gap tends to decline and is not statistically significant in 2010. Men with 13-15 years of education and men with more than 15 years of education spend significantly more time in child care than men with less than 13 years of education. However, the magnitude of the gaps in 2010 is considerably smaller than in 1986. In addition, for all years, both the estimated education coefficients and the difference between the estimated education coefficients are greater for men than for women. This finding suggests that men exhibit a greater and steeper education gradient in child care than women.

The estimated coefficients on the other control variables indicate that time spent in child care is strongly and negatively associated with the age of the youngest child living in the household. Child care time barely shows a statistically significant relationship with age of respondents. Individuals spend more time in child care if working was not their main activity in the past week. Women significantly decrease time spent in child care on weekends.

Censoring ratios reported at the bottom of Table 3.9 reflects non-participation in child care on the Designated Day. Compared to females, whose censoring ratios dropped slightly between 1986 and 2010 (from 31% to 27%), males are marked by a continuous and substantial decrease in censoring ratios. In 1986, 60% of males did not spend any time in child care on the Designated Day; the figure decreased to 42% in 2010.

To determine whether the observed education-based gaps in child care time are quantitatively important, Table 3.10 presents the marginal effects of education on child care time predicted by the Tobit model as well as by the corresponding OLS estimates. The Tobit estimates suggest that, conditional on the observed characteristics, in 1986, women with more than 15 years of education on average spent 61% more time in child care compared to women with less than 13 years of education, but the gap in child care between the two education groups decreased to 7% in 2010. In 1986, men with 13-15 years of education and men with more than 15 years of education respectively spent 85% and 29% more time in child care compared to men with less than 13 years of education, while in 2010, the gaps dropped to 49% and 11%, respectively. The marginal effects predicted by the Tobit model are remarkably comparable to the OLS estimates in terms of both magnitude and statistical significance.

The Tobit model assumes that both the zeroes and the positive values in the dependent variable are generated by the same probability mechanism. A two-part model relaxes this strong assumption and has been shown to provide a better fit in many applications (Cameron and Trivedi, 2010). This study uses a two-part model to examine whether the education-based gap in child care time is explained primarily by the difference in the probability of spending any time in child care between education groups or by the difference in the amount of time spent in child care between education groups. Specifically, whether or not a parent spends time in child care is modeled through a binary probit regression, and the amount of child care time for parents who spend time in child care is modeled through an OLS regression.

Panel 1 in Table 3.11 reports the average marginal effects of education predicted by the binary probit model. In 1986, women and men with more than 15 years of education were 12% and 20% more likely to spend time in child care compared to their counterparts with less than 13 years of education, while in 2010, the gaps declined to 4% and 10%, respectively. For male parents, the gap in the probability of spending time in child care between the least educated group and the most educated group remained statistically significant between 1986 and 2010, while for female parents, the gap has disappeared by 2005. Panel 2 in Table 3.11 shows the OLS estimates of the association between education and the amount of time spent in child care, excluding parents who did not spend any time in child care on the Designated Day. Given that statistically significant coefficients on education only appear in a few years, consistent education-based gaps in the positive amount of child care time are not observed. In addition, in both part 1 and part 2 of the two-part model, the age of the youngest child living in the household is strongly and negatively associated with the dependent variables for both females and males (not shown in Table 3.11). In conclusion, the results of the two-part model indicate that the strong education-based gaps in child care time shown in Table 3.10 are explained primarily by the fact that more educated parents are more likely to spend time in child care rather than by the difference in the positive amount of child care time between education groups.

3.6 Discussion and conclusion

This study finds a continuous and important increase in child care time for both female and male parents in Canada from 1986 and 2010 and a persistent education gradient in parental time devoted to child care. The two findings may be inherently connected in that if, cross-sectionally, more education is associated with more child care time, then, in long run child, care time should increase along with a rise in educational attainment in the population.

The increase in child care time can be a good sign, given the strong and positive association between parental time spent with children and children's development. While the gaps in child care time between education groups have been persistently observed, it is encouraging that the magnitude of those gaps has declined. However, it is alarming that the dispersion in child care time has grown, which may induce inequality in children's development.

Limitations

The validity and the reliability of the time diary are essential to the findings of this study. Compared to other methods of measuring time-use, such as survey question estimates, the time diary is superior in terms of both validity and reliability and is usually preferred by researchers (Sayer et al., 2004; Kan and Pudney, 2008). However, the time diary does have limitations. First, the time diary does not indicate the quality of parental engagement in child care and does not include the indirect time that parents devote to children (Sayer et al., 2004). Second, the time diary requires respondents to make a great deal of effort to recall what they did and when, which might limit its accuracy. Third, the day selected for the time diary may not be representative of the respondent's normal activities (Kan and Pudney, 2008).

The gaps in child care time between educational groups are shown to withstand the controls for individuals' characteristics such as the respondent's age, the age of the youngest child, working status, and marital status. However, due to a lack of consistent measurement in the GSS, the model does not include the number of children and household income, which are potential third factors that correlate with parental education and affect child care time. It is unknown whether the observed education-based gaps in child care time hold when these potential third factors are controlled for.

Areas for future research

First, as seen in the Beckerian model, differences in the production function of child care, the opportunity cost of child care, preferences, and long-run expectations could result in variation of child care time by parents' socio-economic status. Future empirical research could examine the potential mechanisms and reveal the leading cause of variation in child care time.

Second, although ample evidence shows the positive association between parental time devoted to children and children's development, the evidence on the causality is mixed (Baker and Milligan, 2015; Kimmel ad Connelly, 2007; Milkie et al., 2015; Kalil and Mayer, 2016). In addition, not all types of parental time with children benefit child development (Hsin and Felfe, 2014). More evidence on these aspects will be helpful to determine whether a sheer increase in parental time with children and what types of time investment could most benefit children's development.

Third, a number of studies compare the difference in time allocation between countries at cross-sectional time points (e.g. Freeman et al., 2005; Sayer et al., 2004), but few studies compare the difference in trends in time allocation between countries. This may be because consistent time-use data for a long period are rarely available and different classifications of activities are used across surveys.

Fourth, in addition to time input, the expenditure on market goods is another important ingredient in the production of child care. It is of great interest to know whether the long-run increase in parental expenditure on child care is also relatively important, what the extent of the difference in child care expenditure between educational groups might be, and whether the education-based gaps in the expenditure on child care have increased over time. Long-running survey data on household expenditures such as Survey of Household Spending (SHS) might provide insights into these questions.

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Table 3.1 Time allocation (hours per day), 1986-2010

	1986	1992	1998	2005	2010	Change 2010-1986	Change in %
Panel 1: Full sample							
Child care	0.94	1.15	1.28	1.36	1.58	0.65	69%
Market work	4.64	4.49	5.00	5.22	4.78	0.14	3%
Domestic work	2.98	3.24	3.13	2.94	3.03	0.05	2%
Leisure	6.89	6.93	6.45	6.02	6.22	-0.67	-10%
Sleep	7.82	7.93	7.87	8.17	8.07	0.25	3%
Total	23.27	23.74	23.74	23.70	23.69	0.41	2%
Sample size	3,298	2,828	2,953	4,821	3,586		
Panel 2: Women							
Child care	1.28	1.57	1.64	1.80	2.08	0.81	63%
Market work	2.90	3.07	3.65	3.76	3.50	0.60	21%
Domestic work	4.12	4.13	3.99	3.75	3.75	-0.37	-9%
Leisure	6.94	6.84	6.42	6.02	6.07	-0.87	-13%
Sleep	7.99	8.07	8.02	8.35	8.28	0.28	4%
Total	23.23	23.68	23.72	23.67	23.68	0.45	2%
Sample size	1,871	1,632	1,673	2,837	2,079		
Panel 3: Men							
Child care	0.57	0.71	0.91	0.88	1.05	0.48	83%
Market work	6.49	5.99	6.45	6.78	6.15	-0.34	-5%
Domestic work	1.77	2.29	2.22	2.08	2.26	0.49	28%
Leisure	6.84	7.03	6.49	6.02	6.38	-0.46	-7%
Sleep	7.65	7.78	7.70	7.98	7.85	0.20	3%
Total	23.32	23.81	23.76	23.74	23.69	0.37	2%
Sample size	1,424	1,196	1,280	1,984	1,507		
Panel 4: Weekday							
Child care	0.97	1.17	1.30	1.42	1.69	0.72	74%
Market work	5.79	5.96	6.36	6.54	6.17	0.38	7%
Domestic work	2.82	3.00	2.82	2.58	2.70	-0.12	-4%
Leisure	6.07	5.91	5.54	5.17	5.28	-0.78	-13%
Sleep	7.52	7.62	7.62	7.93	7.79	0.27	4%
Total	23.16	23.67	23.64	23.63	23.62	0.46	2%
Sample size	2,496	1,992	2,110	3,410	2,555		
Panel 5: Weekend							
Child care	0.89	1.13	1.24	1.21	1.29	0.40	45%
Market work	1.44	1.09	1.62	1.87	1.50	0.06	4%
Domestic work	3.42	3.78	3.90	3.85	3.81	0.39	12%
Leisure	9.04	9.18	8.63	8.16	8.48	-0.55	-6%
Sleep	8.54	8.63	8.42	8.78	8.72	0.18	2%
Total	23.32	23.81	23.81	23.87	23.81	0.49	2%
Sample size	799	836	843	1,411	1,031		

Notes: All means are calculated using fixed demographic weights, as described in the text.

Table 3.2 Child care time by categories (hours per day), 1986-2010

	1986	1992	1998	2005	2010	Change 2010-1986	Change in %
Panel 1: Full sample							
Child care	0.94	1.15	1.28	1.36	1.58	0.65	69%
Primary	0.63	0.73	0.83	0.89	1.12	0.49	78%
Educational	0.14	0.18	0.19	0.16	0.11	-0.03	-25%
Recreational	0.16	0.24	0.27	0.31	0.35	0.19	117%
Sample size	3,298	2,828	2,953	4,821	3,586		
Panel 2: Women							
Child care	1.28	1.57	1.64	1.80	2.08	0.81	63%
Primary	0.92	1.02	1.09	1.24	1.52	0.60	65%
Educational	0.20	0.27	0.27	0.20	0.15	-0.05	-24%
Recreational	0.15	0.28	0.28	0.36	0.41	0.26	167%
Sample size	1,871	1,632	1,673	2,837	2,079		
Panel 3: Men							
Child care	0.57	0.71	0.91	0.88	1.05	0.48	83%
Primary	0.32	0.42	0.54	0.51	0.70	0.38	118%
Educational	0.08	0.09	0.09	0.11	0.06	-0.02	-27%
Recreational	0.17	0.20	0.27	0.26	0.29	0.12	68%
Sample size	1,424	1,196	1,280	1,984	1,507		
Panel 4: Weekday							
Child care	0.97	1.17	1.30	1.42	1.69	0.72	74%
Primary	0.67	0.75	0.85	0.95	1.20	0.53	79%
Educational	0.16	0.21	0.19	0.18	0.13	-0.04	-22%
Recreational	0.14	0.22	0.26	0.29	0.36	0.22	163%
Sample size	2,496	1,992	2,110	3,410	2,555		
Panel 5: Weekend							
Child care	0.89	1.13	1.24	1.21	1.29	0.40	45%
Primary	0.55	0.68	0.76	0.74	0.90	0.35	63%
Educational	0.09	0.14	0.17	0.11	0.06	-0.03	-37%
Recreational	0.25	0.30	0.31	0.36	0.33	0.09	35%
Sample size	799	836	843	1,411	1,031		

Notes: All means are calculated using fixed demographic weights, as described in the text.

Table 3.3 Market/domestic work time by categories (hours per day), 1986-2010

	1986	1992	1998	2005	2010	Change 2010-1986	Change in %
Panel 1: Full sample							
Market work	4.64	4.49	5.00	5.22	4.78	0.14	3%
Core market work	3.79	3.76	4.23	4.45	4.07	0.29	8%
Other market work	0.85	0.73	0.77	0.77	0.71	-0.14	-17%
Domestic work	2.98	3.24	3.13	2.94	3.03	0.05	2%
Core domestic work	2.07	2.44	2.35	2.21	2.25	0.17	8%
Shopping activities	0.91	0.80	0.78	0.73	0.78	-0.13	-14%
Sample size	3,298	2,828	2,953	4,821	3,586		
Panel 2: Women							
Market work	2.90	3.07	3.65	3.76	3.50	0.60	21%
Core market work	2.42	2.58	3.08	3.20	3.01	0.59	24%
Other market work	0.48	0.49	0.57	0.55	0.49	0.01	2%
Domestic work	4.12	4.13	3.99	3.75	3.75	-0.37	-9%
Core domestic work	3.06	3.20	3.04	2.84	2.85	-0.21	-7%
Shopping activities	1.06	0.93	0.95	0.91	0.90	-0.16	-15%
Sample size	1,871	1,632	1,673	2,837	2,079		
Panel 3: Men							
Market work	6.49	5.99	6.45	6.78	6.15	-0.34	-5%
Core market work	5.25	5.01	5.45	5.77	5.21	-0.03	-1%
Other market work	1.24	0.98	0.99	1.01	0.94	-0.31	-25%
Domestic work	1.77	2.29	2.22	2.08	2.26	0.49	28%
Core domestic work	1.02	1.63	1.61	1.54	1.60	0.58	57%
Shopping activities	0.75	0.66	0.61	0.54	0.67	-0.09	-12%
Sample size	1,424	1,196	1,280	1,984	1,507		
Panel 4: Weekday							
Market work	5.79	5.96	6.36	6.54	6.17	0.38	7%
Core market work	4.71	4.99	5.36	5.56	5.26	0.55	12%
Other market work	1.08	0.97	1.00	0.98	0.91	-0.18	-16%
Domestic work	2.82	3.00	2.82	2.58	2.70	-0.12	-4%
Core domestic work	1.95	2.20	2.13	1.96	2.01	0.06	3%
Shopping activities	0.86	0.81	0.69	0.62	0.69	-0.18	-21%
Sample size	2,496	1,992	2,110	3,410	2,555		
Panel 5: Weekend							
Market work	1.44	1.09	1.62	1.87	1.50	0.06	4%
Core market work	1.22	0.92	1.42	1.62	1.27	0.04	4%
Other market work	0.21	0.17	0.20	0.26	0.23	0.02	10%
Domestic work	3.42	3.78	3.90	3.85	3.81	0.39	12%
Core domestic work	2.38	2.98	2.89	2.85	2.79	0.41	17%
Shopping activities	1.04	0.80	1.01	1.00	1.02	-0.02	-2%
Sample size	799	836	843	1,411	1,031		

Notes: All means are calculated using fixed demographic weights, as described in the text.

Table 3.4 Leisure time by categories (hours per day), 1986-2010

	1986	1992	1998	2005	2010	Change 2010-1986	Change in %
Panel 1: Full sample							
Leisure	6.89	6.93	6.45	6.02	6.22	-0.67	-10%
Personal care	2.48	2.23	1.95	1.96	2.04	-0.44	-18%
Organization	0.26	0.37	0.30	0.26	0.30	0.04	17%
Entertainment	1.04	1.15	1.19	1.05	1.13	0.09	9%
Sports	0.58	0.80	0.79	0.78	0.85	0.27	46%
Media & communication	2.53	2.37	2.22	1.97	1.90	-0.63	-25%
Sample size	3,298	2,828	2,953	4,821	3,586		
Panel 2: Women							
Leisure	6.94	6.84	6.42	6.02	6.07	-0.87	-13%
Personal care	2.58	2.30	1.98	2.05	2.03	-0.55	-21%
Organization	0.32	0.39	0.36	0.25	0.29	-0.03	-9%
Entertainment	1.09	1.32	1.34	1.12	1.21	0.12	11%
Sports	0.59	0.72	0.69	0.72	0.68	0.09	16%
Media & communication	2.37	2.11	2.05	1.87	1.86	-0.51	-21%
Sample size	1,871	1,632	1,673	2,837	2,079		
Panel 3: Men							
Leisure	6.84	7.03	6.49	6.02	6.38	-0.46	-7%
Personal care	2.38	2.16	1.92	1.86	2.05	-0.33	-14%
Organization	0.19	0.36	0.24	0.26	0.32	0.12	63%
Entertainment	1.00	0.98	1.02	0.98	1.05	0.06	6%
Sports	0.57	0.89	0.90	0.84	1.03	0.45	78%
Media & communication	2.70	2.66	2.40	2.07	1.93	-0.76	-28%
Sample size	1,424	1,196	1,280	1,984	1,507		
Panel 4: Weekday							
Leisure	6.07	5.91	5.54	5.17	5.28	-0.78	-13%
Personal care	2.39	2.11	1.87	1.82	1.92	-0.47	-20%
Organization	0.21	0.29	0.26	0.18	0.19	-0.02	-7%
Entertainment	0.66	0.70	0.75	0.67	0.71	0.05	8%
Sports	0.47	0.59	0.61	0.66	0.70	0.23	49%
Media & communication	2.33	2.22	2.05	1.84	1.76	-0.58	-25%
Sample size	2,496	1,992	2,110	3,410	2,555		
Panel 5: Weekend							
Leisure	9.04	9.18	8.63	8.16	8.48	-0.55	-6%
Personal care	2.69	2.49	2.13	2.29	2.34	-0.35	-13%
Organization	0.37	0.56	0.39	0.45	0.59	0.23	61%
Entertainment	2.05	2.16	2.27	2.01	2.16	0.10	5%
Sports	0.85	1.24	1.23	1.10	1.16	0.31	37%
Media & communication	3.07	2.74	2.62	2.31	2.23	-0.84	-27%
Sample size	799	836	843	1,411	1,031		

Notes: All means are calculated using fixed demographic weights, as described in the text.

Table 3.5 Unconditional distribution of time-use categories (hours per day), 1986-2010

		1986	1992	1998	2005	2010	Change 2010-1986
Time-use category	Percentile						
Child care	30th	0.00	0.00	0.00	0.00	0.00	0.00
	45th	0.17	0.50	0.50	0.50	0.67	0.50
	60th	0.75	1.17	1.25	1.25	1.50	0.75
	75th	1.50	2.08	2.08	2.25	2.53	1.03
	90th	3.05	3.67	3.75	4.00	4.50	1.45
Market Work	30th	0.00	0.00	0.00	0.00	0.00	0.00
	45th	0.00	0.00	0.00	0.50	0.25	0.25
	60th	6.75	6.58	7.62	8.08	7.50	0.75
	75th	8.92	8.92	9.33	9.50	9.25	0.33
	90th	10.42	10.58	11.33	11.25	11.00	0.58
Domestic work	30th	1.00	1.25	1.17	1.00	1.17	0.17
	45th	2.08	2.33	2.17	2.00	2.02	-0.07
	60th	3.50	3.58	3.42	3.10	3.17	-0.33
	75th	5.17	5.17	4.92	4.67	4.75	-0.42
	90th	7.33	7.42	7.25	7.25	7.08	-0.25
Leisure	30th	4.83	4.58	4.25	3.83	3.83	-1.00
	45th	6.00	5.75	5.42	4.92	5.00	-1.00
	60th	7.33	7.25	6.75	6.17	6.25	-1.08
	75th	9.00	9.00	8.58	8.00	8.08	-0.92
	90th	11.67	12.00	11.50	11.17	11.25	-0.42
Sample size		3,298	2,828	2,953	4,821	3,586	

Table 3.6 Blinder-Oaxaca decomposition of changes in time use (hours per day)

	Unconditional change	Change due to different demographics	Change due to different cell means
Panel 1	$W_{2010}Y_{2010}$-$W_{1986}Y_{1986}$	(W_{2010}-W_{1986})Y_{2010}	W_{1986}(Y_{2010}-Y_{1986})
Child care	0.60	-0.13	0.72
Primary	0.46	-0.06	0.53
Educational	-0.03	-0.01	-0.02
Recreational	0.17	-0.06	0.22
Market Work	0.40	0.36	0.05
Leisure	-0.77	-0.12	-0.65
Domestic work	-0.07	-0.04	-0.03
Panel 2	$W_{2010}Y_{2010}$-$W_{1986}Y_{1986}$	(W_{2010}-W_{1986})Y_{1986}	W_{2010}(Y_{2010}-Y_{1986})
Child care	0.60	0.00	0.60
Primary	0.46	0.00	0.47
Educational	-0.03	0.01	-0.04
Recreational	0.17	-0.01	0.17
Market Work	0.40	0.15	0.25
Leisure	-0.77	-0.08	-0.69
Domestic work	-0.07	-0.15	0.08

Table 3.7 JMP decomposition of the change in child care distribution

Percentile differential	Total change	Contribution of changes in observed demographics	Contribution of changes in cell-means	Contribution of unobservables
Panel 1: 1986-2010				
90-10	1.45	0.01	0.54	0.89
90-50	1.03	-0.14	0.28	0.90
50-10	0.42	0.16	0.26	-0.01
Panel 2: 1986-1998				
90-10	0.70	-0.02	0.39	0.33
90-50	0.45	-0.12	0.26	0.30
50-10	0.25	0.10	0.12	0.03
Panel 3: 1998-2010				
90-10	0.75	0.01	0.25	0.50
90-50	0.58	-0.06	0.15	0.49
50-10	0.17	0.07	0.10	0.00

Table 3.8 Time allocation by education (hours per day)

	Full sample			Women			Men		
Educational categories	≤12	13-15	≥16	≤12	13-15	≥16	≤12	13-15	≥16
Panel 1: Child care									
1986	0.82	0.89	1.17	1.14	1.19	1.63	0.49	0.53	0.75
1992	0.88	1.27	1.32	1.25	1.66	1.84	0.49	0.81	0.84
1998	1.06	1.30	1.56	1.45	1.57	2.04	0.65	0.98	1.12
2005	1.11	1.43	1.55	1.55	1.81	2.13	0.66	0.98	1.02
2010	1.54	1.56	1.68	2.14	1.95	2.26	0.91	1.09	1.15
Change 1986-2010	0.71	0.67	0.51	0.99	0.76	0.63	0.42	0.57	0.40
Panel 2: Market work									
1986	4.35	4.69	4.94	2.73	2.87	3.20	6.03	6.84	6.53
1992	4.31	4.46	4.77	2.76	3.00	3.67	5.91	6.19	5.78
1998	4.78	4.91	5.47	3.42	3.47	4.34	6.20	6.61	6.50
2005	5.04	5.23	5.45	3.41	3.88	4.02	6.73	6.84	6.77
2010	4.33	4.91	5.16	2.71	3.89	3.83	6.02	6.11	6.38
Change 1986-2010	-0.01	0.22	0.22	-0.02	1.02	0.63	-0.01	-0.73	-0.15
Panel 3: Domestic work									
1986	3.26	2.92	2.72	4.62	3.97	3.70	1.86	1.68	1.82
1992	3.32	3.28	3.07	4.26	4.10	4.00	2.35	2.31	2.20
1998	3.27	3.19	2.86	4.27	3.98	3.62	2.23	2.24	2.17
2005	3.00	3.06	2.66	3.96	3.79	3.36	2.00	2.19	2.01
2010	3.11	3.08	2.84	4.14	3.59	3.51	2.05	2.46	2.22
Change 1986-2010	-0.15	0.15	0.12	-0.48	-0.38	-0.19	0.20	0.78	0.40
Panel 4: Leisure									
1986	6.97	7.02	6.57	6.92	7.12	6.62	7.02	6.89	6.52
1992	7.35	6.76	6.67	7.34	6.73	6.33	7.35	6.80	6.99
1998	6.71	6.46	6.09	6.47	6.62	5.94	6.96	6.27	6.23
2005	6.27	5.89	5.89	6.27	5.93	5.82	6.27	5.85	5.95
2010	6.47	6.19	5.95	6.22	6.09	5.82	6.73	6.30	6.07
Change 1986-2010	-0.50	-0.83	-0.62	-0.70	-1.03	-0.80	-0.29	-0.59	-0.45
Panel 5: Primary care									
1986	0.55	0.60	0.79	0.82	0.84	1.24	0.27	0.32	0.38
1992	0.56	0.83	0.78	0.81	1.10	1.14	0.29	0.50	0.46

1998	0.68	0.85	0.98	0.94	1.07	1.34	0.41	0.59	0.65
2005	0.76	0.90	1.04	1.12	1.20	1.51	0.38	0.55	0.62
2010	1.05	1.13	1.21	1.48	1.46	1.69	0.61	0.73	0.77
Change 1986-2010	0.50	0.53	0.42	0.67	0.62	0.45	0.33	0.41	0.39
Panel 6: Educational care									
1986	0.12	0.14	0.18	0.19	0.20	0.21	0.05	0.06	0.15
1992	0.14	0.18	0.25	0.21	0.26	0.38	0.07	0.08	0.12
1998	0.18	0.16	0.23	0.30	0.22	0.33	0.05	0.10	0.14
2005	0.14	0.17	0.17	0.19	0.19	0.23	0.09	0.14	0.11
2010	0.12	0.10	0.11	0.17	0.14	0.16	0.06	0.05	0.07
Change 1986-2010	0.00	-0.04	-0.07	-0.01	-0.07	-0.06	0.01	-0.01	-0.08
Panel 7: Recreational care									
1986	0.15	0.15	0.20	0.14	0.15	0.18	0.17	0.14	0.22
1992	0.18	0.26	0.28	0.23	0.29	0.32	0.14	0.23	0.25
1998	0.20	0.28	0.35	0.21	0.28	0.37	0.18	0.29	0.34
2005	0.22	0.36	0.34	0.25	0.42	0.40	0.18	0.30	0.30
2010	0.37	0.34	0.36	0.48	0.36	0.42	0.24	0.31	0.31
Change 1986-2010	0.21	0.19	0.16	0.34	0.20	0.24	0.08	0.17	0.09

Notes: All means are calculated using fixed demographic weights, as described in the text.

Table 3.9 Tobit estimates of education gradient in child care, conditional on other characteristics

	Dependant variable: ln(minutes per day spent in child care)									
	1986		1992		1998		2005		2010	
	Women	Men	Women	Men	Women	Men	Women	Men	Women	Men
Education attainment (≤12 years omitted)										
13-15 years	0.12	0.86**	0.52***	0.76**	0.05	1.03***	0.28**	0.82***	0.14	0.20
	（0.68）	(2.39)	(3.36)	(2.52)	(0.30)	(3.41)	(1.97)	(2.99)	(0.78)	(0.59)
≥16 years	0.73***	2.14***	0.81***	1.06***	0.54***	1.61***	0.38**	1.18***	0.08	0.82**
	(3.22）	(5.01)	(3.58)	(2.86)	(3.02)	(4.88)	(2.28)	(4.07)	(0.45)	(2.39)
Age of the youngest child (age <5 omitted)										
5-9 years old	-1.20***	-1.38***	-0.89***	-1.43***	-0.98***	-1.37***	-1.00***	-1.02***	-0.86***	-0.98***
	(-6.01)	(-3.48)	(-6.04)	(-4.21)	(-7.51)	(-4.45)	(-7.41)	(-4.28)	(-6.67)	(-3.70)
10-14 years old	-3.12***	-3.78***	-3.23***	-3.20***	-3.00***	-3.85***	-2.50***	-3.23***	-2.71***	-3.01***
	(-11.38)	(-6.97)	(-14.39)	(-7.41)	(-12.88)	(-9.68)	(-13.96)	(-10.94)	(-13.10)	(-9.27)
> 14 years old	-4.84***	-6.55***	-5.63***	-6.93***	-9.58***	-10.95***	-9.80***	-13.06***	-8.59***	-8.73***
	(-11.18)	(-6.64)	(-13.53)	(-10.11)	(-12.78)	(-12.79)	(-14.56)	(-12.48)	(-13.97)	(-13.87)
Age of respondent (25-34 years old omitted)										
35-44 years old	-0.12	-0.12	-0.08	0.16	-0.05	-0.24	-0.1	0.26	-0.23*	-0.12
	(-0.67)	(-0.34)	(-0.54)	(0.51)	(-0.37)	(-0.84)	(-0.75)	(1.09)	(-1.87)	(-0.48)
45-54 years old	-1.22***	-0.43	-0.13	-1.20**	-0.14	-0.20	-0.19	-0.59*	-0.27	-0.39
	(-2.94)	(-0.62)	(-0.36)	(-2.03)	(-0.42)	(-0.41)	(-0.78)	(-1.69)	(-1.20)	(-1.09)
55-64 years old	0.81	-3.04*	0.04	-0.30	-2.16	0.24	-0.58	-0.08	0.25	0.42
	(0.78)	(-1.90)	(0.02)	(-0.26)	(-1.30)	(0.11)	(-0.70)	(-0.09)	(0.40)	(0.43)
Not working	0.90***	1.16***	0.87***	0.83**	0.74***	0.83**	0.80***	0.91***	0.82***	0.55*
	(5.13)	(2.63)	(5.44)	(2.06)	(5.61)	(2.33)	(6.80)	(2.80)	(6.60)	(1.88)
Weekend	-0.95***	0.35	-0.64***	-0.20	-0.70***	-0.20	-1.11***	-0.29	-0.89***	-0.41*
	(-4.86)	(0.98)	(4.01)	(-0.66)	(-4.47)	(-0.72)	(-8.48)	(-1.31)	(6.37)	(-1.86)
Sample size	1860	1422	1632	1196	1645	1253	2834	1983	2076	1,501
Uncensored	1290	568	1214	597	1181	664	1988	1024	1513	868
Left-censored	570	854	418	599	464	589	846	959	563	633
Censoring ratio	31%	60%	26%	50%	28%	47%	30%	48%	27%	42%
Pseudo R-squared	0.126	0.089	0.161	0.098	0.225	0.136	0.195	0.129	0.246	0.144

Notes: *t* statistics in parentheses; * p<0.10, ** p<0.05, *** p<0.01. Estimates are weighted using sample weights provided by the GSS. The other regressors include a set of dummies for marital status (married/common-law, single, separated/divorced/widowed), a dummy variable indicating whether there are less than four members in the household, and a set of dummies for provinces.

Table 3.10 Marginal effects of education on child care time, predicted by Tobit and OLS

	Dependant variable: ln(minutes per day spent in child care)									
	1986		1992		1998		2005		2010	
	Women	Men	Women	Men	Women	Men	Women	Men	Women	Men
Panel 1: Tobit estimates										
Education attainment (≤12 years omitted)										
13-15 years	0.10	0.29**	0.45***	0.37**	0.04	0.48***	0.22**	0.31***	0.12	0.11
	(0.68)	(2.35)	(3.38)	(2.55)	(0.30)	(3.49)	(1.98)	(3.07)	0.79	0.60
≥16 years	0.61***	0.85***	0.71***	0.53***	0.47***	0.80***	0.29**	0.48***	0.07	0.49**
	(3.19)	(4.47)	(3.55)	(2.80)	(3.03)	(4.91)	(2.29)	(4.12)	0.45	(2.53)
Panel 2: OLS estimates										
Education attainment (≤12 years omitted)										
13-15 years	0.09	0.26*	0.38***	0.35**	0.03	0.53***	0.16*	0.36***	0.05	0.15
	(0.75)	(1.9)	(3.55)	(2.50)	(0.30)	(3.65)	(1.81)	(3.08)	(0.45)	(0.96)
≥16 years	0.55***	0.82***	0.59***	0.51***	0.38***	0.86***	0.25**	0.53***	0.02	0.47***
	(3.52)	(4.59)	(3.78)	(2.87)	(2.98)	(5.16)	(2.37)	(4.17)	(0.14)	(2.73)
Sample size	1,860	1,422	1,632	1,196	1,645	1,253	2,834	1,983	2,076	1,501

Notes: *t* statistics in parentheses; * p<0.10, ** p<0.05, *** p<0.01. The other regressors are the same as in Table 3.9.

Table 3.11 Two-part model estimates

	1986 Women	1986 Men	1992 Women	1992 Men	1998 Women	1998 Men	2005 Women	2005 Men	2010 Women	2010 Men
Panel 1: Part one	Binary probit Dependant variable: Parent spends time in child care = 1									
Education attainment (≤12 years omitted)										
13-15 years	0.02	0.08**	0.07***	0.07**	0.00	0.11***	0.04*	0.08***	0.04*	0.02
	（0.82）	(2.55)	(2.81)	(2.26)	(0.05)	(3.30)	(1.87)	(3.01)	(1.78)	(0.52)
≥16 years	0.12***	0.20***	0.10***	0.11***	0.09***	0.17***	0.03	0.12***	0.04	0.10**
	(3.30）	(5.12)	(3.18)	(2.77)	(3.92)	(4.71)	(1.42)	(4.21)	(1.43)	(2.55)
Sample size	1,860	1,422	1,632	1,196	1,645	1,253	2,834	1,983	2,076	1,501
Pseudo R-squared	0.291	0.181	0.367	0.211	0.514	0.290	0.421	0.270	0.530	0.307
Panel 2: Part two	OLS Dependant variable: ln(minutes per day spent in child care) if minutes spent in child care > 0									
Education attainment (≤12 years omitted)										
13-15 years	-0.04	-0.17	0.13*	0.14	0.02	0.13	0.03	0.02	-0.19**	0.07
	（-0.69）	(-1.54)	(1.88)	(1.39)	(0.22)	(1.07)	(0.59)	(0.29)	(-2.38)	(0.69)
≥16 years	0.12	-0.12	0.26***	0.12	-0.02	0.23*	0.20***	0.03	-0.19**	0.04
	（1.44）	(-0.94)	(2.58)	(0.93)	(-0.26)	(1.88)	(3.08)	(0.29)	(-2.16)	(0.40)
Sample size	1,290	568	1,214	597	1,181	664	1,988	1,024	1,513	869
R-squared	0.236	0.084	0.247	0.064	0.194	0.133	0.247	0.090	0.330	0.164

Notes: Estimates shown in Panel 1 refer to average marginal effects predicted by a binary probit model. *t* statistics in parentheses; * p<0.10, ** p<0.05, *** p<0.01. Estimates are weighted using sample weights provided by the GSS. Robust standard errors are used. The other regressors in part one and in part two are the same as in Table 3.9.

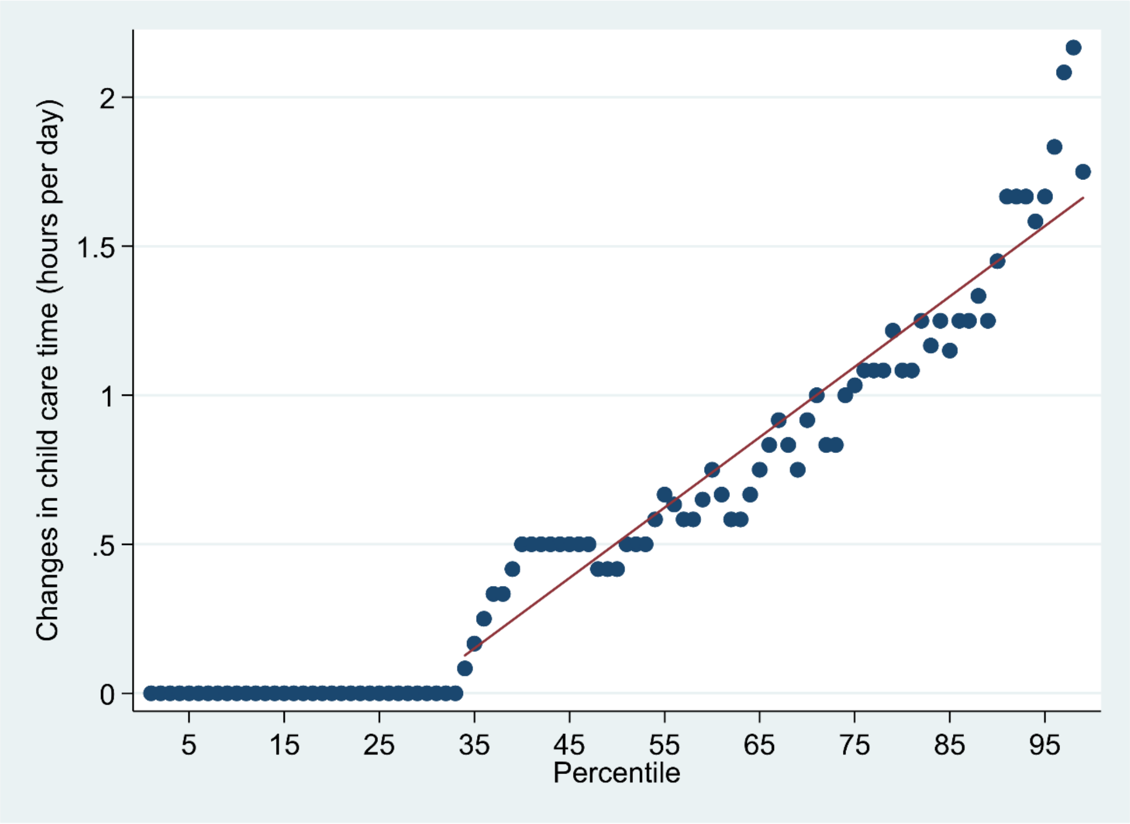

Figure 3.1 Change in child care time at each percentile point, 1986-2010

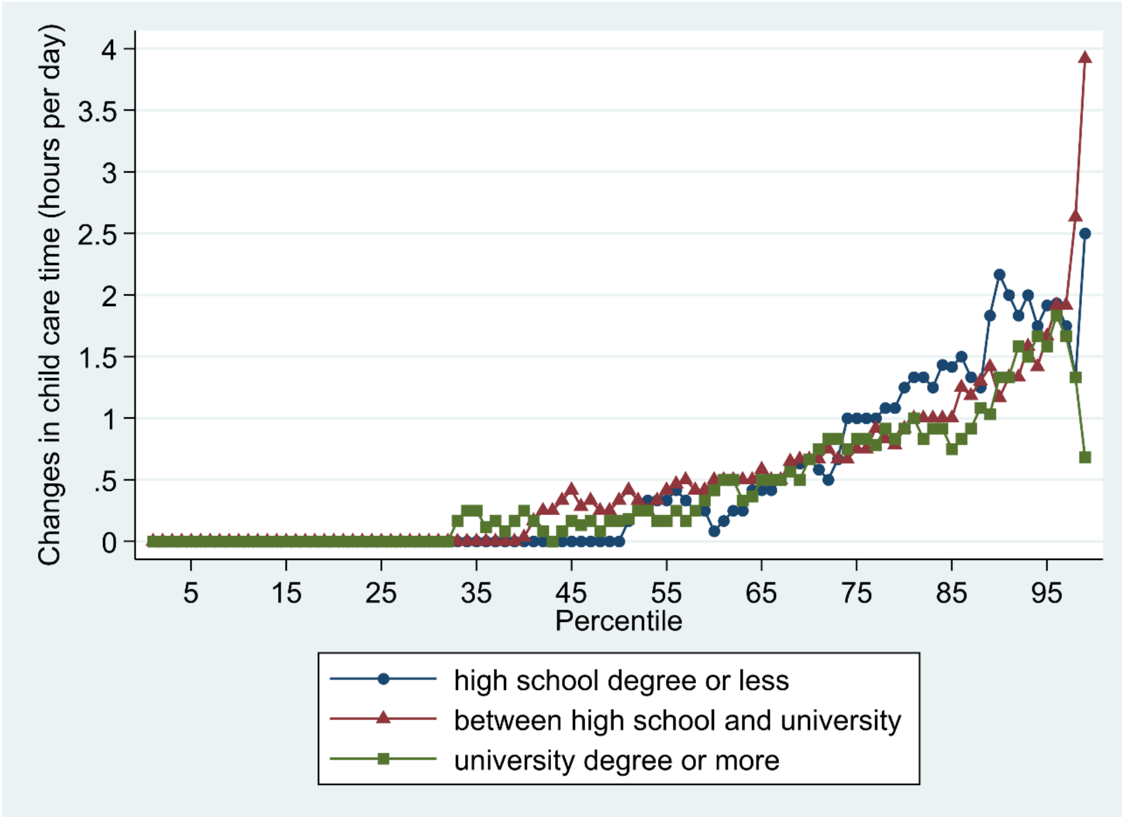

Figure 3.2 Change in child care time at each percentile point by education, 1986-2010

Appendix

Theoretical framework

In a standard Beckerian model, an individual's utility derives from a range of final consumption goods Z_i:

$$U = U\left(Z_{hp}, Z_l, Z_c\right) \tag{1}$$

where Z_{hp}, Z_l, and Z_c represent home produced final goods, leisure, and child care, respectively.

Each final consumption good is produced through a combination of market goods and time:

$$Z_i = f_i\left(\mathbf{x}_i, T_i\right) \tag{2}$$

where $\mathbf{x}_i$ is a vector of market goods used to produce Z_i, and T_i represents time spent in producing Z_i.

Individuals face both time and budget constraints:

$$T_{hp} + T_l + T_c = T - T_w \tag{3}$$

$$\sum_i \mathbf{p}_i \mathbf{x}_i = V + wT_w \tag{4}$$

where T_{hp}, T_l, T_c, and T_w represent time spent in home production, leisure, child care, and market work, respectively. $\mathbf{p}_i$ is a vector of prices of $\mathbf{x}_i$. w is the wage per unit of T_w. V is income other than earnings from labor market.

Individuals are assumed to maximise (1) subject to (2), (3) and (4). The demands for inputs $\mathbf{x}_i$ and T_i are derived from the demands for Z_i.

Table A3.1 Time-use classifications

Primary categories	Sub-categories	Examples of activities included
Child care	Primary child care	Basic baby/child care (putting children to bed, getting children ready for school, personal care for children); Medical care; Other child care; Travel for child care
	Educational child care	Helping, teaching, and reprimanding; Reading/conversation with children
	Recreational child care	Playing with children
Market work	Core market work	Work for pay; Overtime work; Looking for work; Unpaid work in business/farm
	Other market work	Travel during/to/from work; Waiting/delays at work; Meals/snacks at work; Idle time before or after work; Coffee/other breaks; Other uncodeable work activities
Domestic work	Core domestic work	Meal preparation; Meal clean-up; Outdoor cleaning; Laundry, ironing, folding; Mending; Home repairs, maintenance; Gardening, pet care; Other uncodeable housework; Travel for domestic work
	Shopping activities	Everyday shopping (food, clothing, gas); Shopping for durable goods (house, car); Personal care services (hairdresser); Government and financial services; Medical and dental care; Waiting and queuing for purchase; Other uncodeable services; Travel for goods and services
Leisure	Personal care	Washing, dressing, packing; Meals at home/snacks/coffee; Restaurant meals; Relaxing, thinking, resting; Other personal care or private activities; Travel for personal care
	Organization	Professional/union/general meetings; Political and civic activities; Child, youth, family organization; Religious meetings; Religious services/prayer/read Bible; Fraternal and social organizations; Volunteer work, helping; Other uncodeable organizations; Travel for organizations
	Entertainment	Sport events; Pop music, fairs, concerts; Movies; Opera, ballet, drama; Visits, entertaining friends/relatives; Socializing at bars, clubs; Other social gatherings; Travel for entertainment
	Sports & hobbies	Sports, physical exercise, coaching; Hunt, fish, camp; Walk, hike; Hobbies; Domestic home crafts; Music, theatre, dance; Games, cards, arcade; Pleasure drives, sightseeing; Other uncodeable sport or active leisure; Travel for sports and hobbies
	Media & communication	Radio; Television, rented movies; Records, tapes; Books, magazines, newspapers; Talking, conversion; Letters and mail; Other uncodeable media or communication; Travel for media or communication
Sleep		Night/essential sleep; Naps/incidental sleep

Conclusion

This thesis investigates three factors that potentially influence child well-being: family income, family structure, and time spent in child care.

The first essay in this thesis studies the evolution of the gradient (relationship) between family income and child health. Using the Canadian National Longitudinal Survey of Children and Youth (NLSCY), we find that income gradient in child health is statistically significant and becomes more pronounced as children age. This conclusion is consistent with some previous studies and the results are more robust in that the Health Utilities Index Mark 3 is used as an alternative measure of child health, which is conventionally measured using ordinal self-rated health or health rated by the person most knowledgeable of child. In addition, the strong gradient withstands some "third factor" explanations such as parental health and children's health at birth. However, contrary to previous U.S. evidence that attributes part of the gradient to the protective effect of family income on the incidence and severity of children's health problems at birth and chronic conditions, our results suggest that children from low-income families do not suffer more from poor health at birth or recover more slowly from poor health at birth and that higher income does not reduce the incidence of chronic conditions or buffer the adverse effects of chronic conditions. The contrast between Canadian and U.S. children may reflect the effects of universal health insurance in Canada. Furthermore, using local unemployment rates to instrument for family income, we find that family income has a statistically significant and economically meaningful causal effect on children's health and that OLS estimates may underestimate the positive impact of family income on children's health. Our findings suggest that universal health insurance may cushion the adverse effects of poor health at birth and chronic conditions but does not eliminate the strong income-related inequality in child health.

Also using the NLSCY, the second essay investigates whether children persistently living in single-parent families exhibit worse outcomes than children persistently living in intact families and whether a parental separation affects children's future outcomes. Children's outcomes under investigation include mental health, general health, and educational attainment. Descriptive regression results show that, compared to children persistently living in intact families, children persistently living in single-parent families have poorer mental and general health and are more likely to repeat a grade and have lower math scores. The differences in children's outcomes across family structures, which are statistically significant and quantitatively important, are strongly associated with the differences in family income and parental involvement. Following the children who lived with two biological parents in Cycle 1 (1994/95) for six years, this study finds that the children who experienced a parental separation during the period exhibited worse outcomes in Cycle 4 (2000/01) compared to the children whose parents remained together. A number of these disadvantages withstand additional controls for pre-existing family conditions such as social-economic status and family dysfunction. In addition, little evidence is found to suggest that a parental separation mitigates the adverse effects of family dysfunction on children's future outcomes. Moreover, in terms of mental health, boys are more sensitive than girls to a parental separation. Furthermore, using a sibling fixed-effect approach substantially reduces the associations between children's outcomes and parental separation predicted by the OLS estimates, but several gaps, especially in mental health, remain statistically significant and quantitatively meaningful.

The third essay uses five cross-sectional data sets on the subject of time use taken from the General Social Survey (GSS) to document trends in Canadians' time allocation between 1986 and 2010. Controlling for demographic composition, this study finds a continuous and dramatic increase in time spent in child care, which is accompanied by stable market/domestic work hours and a decline in leisure time. The increase in child care time applied to all gender and education groups. Women increased time spent in market work and decreased time spent in domestic work, while men behaved in the reverse. In addition to the increase in the average time spent in child care, the inequality in child care time increased considerably. Decomposition results show that changes in time allocation within demographic groups dominate changes in demographics in explaining the increasing average time spent in child care and the growing inequality in child care time. Lastly, more highly educated parents are found to spend more time in child care. The observed gaps in child care time among education groups are statistically significant, quantitatively important, and more pronounced for fathers than for mothers. However, the magnitude of the educational-based gaps in child care time is found to decline.