# Intergenerational Transmission of Socio-Economic Status and Intragenerational Mobility Over the Early Adult Life Course of Canadian Women and Men

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# Contents

# Abstract

The objective of this paper is to provide evidence of the relationship between intergenerational income transmission and intragenerational economic mobility. More specifically, we aim to provide novel results on whether the rate of income growth over age is higher among children of more or less privileged social origins in Canada, and what factors may account for eventual differences. Among those factors, we examine the role of education, as well as factors related to the early adult life course, post labour market entry, including parenthood and couple status. We find that although inequalities based on parental income levels are observed in the early life course, they are exacerbated by the steeper income growth experienced by children of higher income parents between 22 and 35 years old, especially among men. While these patterns seem to be associated with differences in educational attainment, we also find an important role for labour force attachment over the early life course. We find significant gender differences in these patterns, driven in part by flatter income growth among more privileged women compared with more privileged men. This last pattern is in part driven by the negative association between parenthood and income among women, and gender differences in labour force attachment.

# Introduction

In Canada, research shows that the children of parents in the top 10% income bracket have, on average, an income that is 20 percentiles higher than children of parents whose income is in the bottom 10% once they become adults themselves (Corak, 2020). This characteristic places Canada roughly in the middle range of OECD countries' intergenerational social mobility (the change, or lack therefore, in income between parents and the later labour market earnings of their children) (Corak, 2013).

Social scientists often study intergenerational social mobility by examining how parents may pass on their (dis)advantage to children, or, the intergenerational transmission of socioeconomic status (SES). For example, parents from different SES backgrounds have varying levels of resources to invest in the development of their children's skills and education (Bailey & Dynarski, 2011; Kornrich & Furstenberg, 2013; Schneider et al., 2018), as well as their social and cultural capital, and socialization (Bourdieu & Passeron, 1964; Friedman & Laurison, 2020; Lareau, 2003; Rivera, 2015). One mechanism that has received much attention among scholars and policymakers is education, which has been found to account for around 50% of the association between parental and child income in Canada (Simard-Duplain & St-Denis, 2020c).

These contributions generally suggest that disparities emerging early in the life course can at least partly account for inequalities found in adulthood. That is, inequalities emerge as a result of a cumulative process driven by factors observed early in childhood. However, relatively less is known about mechanisms that drive intergenerational income transmission later in the life course, especially after adult children's entry on the labour market. This is a critical oversight, as income disparities emerge in part as a result of the trajectories of individuals on the labour market, such as during the job matching and wage setting process, when human, social, and cultural capital is converted into economic capital (earnings, wealth, job security, etc.).

This blind spot in research carries significant implications. First, it prevents a full understanding of how inequalities in early life course outcomes translate into disadvantages on the labour market over the course of one's career. Second, the early life course is often marked by couple formation and transitions to parenthood, the impact of which can differ substantially for men and women. While we know that mothers tend to suffer a wage penalty (Budig & England, 2001; Fuller, 2018; Zhang, 2010), the interplay between this dynamic and gender differences in social mobility has rarely been investigated.

In this paper, we examine the income trajectories of young adults of different social origins. More specially, we aim to contribute to the literature with three major focuses:

1. We ask whether there is a divergence or a convergence in income growth over the life course of individuals of different social origins, and what is the role of educational attainment in this process.
2. We investigate the role of labour force attachment throughout the early career of Canadians as a driver of divergence (or convergence) in income growth rates by social origin.
3. Finally, we aim to explore the factors behind gender differences in intergenerational income transmission by focusing on how certain life course events can account for the lower level of intergenerational income transmission experienced by women, such as couple formation and parenthood.

We do so by leveraging the intergenerational family files constructed by Statistics Canada as part of the linkage of two important datasets—the Longitudinal and International Study of Adults (LISA) and the T1 Family File. Merging these data sources allows for the study of intergenerational mobility dynamics. We use longitudinal data on the income of respondents born between 1964 and 1980, and estimate young adults' income growth when they were aged between 22 to 35 years old, letting it vary by parental income level.

We find that while income inequalities based on parental income are observed throughout the early adult life course, these differences are exacerbated by the steeper income growth experienced among the children of higher income parents—particularly men—between 22 and 35 years. While these patterns seem to be associated with differences in educational attainment, we also find an important role for post-labour market entry factors such as labour force attachment. Finally, we find that the presence of children in the household and weaker labour force attachment accounts for a substantial portion of the gender gap in intergenerational social mobility. At the same time, we highlight a new aspect of gender differences in intergenerational income transmission: women born in lower income families experience a much larger penalty at 22 years old than men relative to their counterparts born in higher income families.

The rest of the paper is organized as follows: First, we review the literature establishing a link between social mobility and life course processes. Second, we present our data and our methodological approach. Third, we report our empirical results in detail. We conclude with a discussion of our results and their implications.

## *Explaining the intergenerational transmission of socio-economic status*

Research in the field of social stratification and inequality has sought to unpack the mechanisms underpinning the observed association between parental SES and child outcomes throughout youth and adulthood. These mechanisms include the development of social and cultural capital, parenting practices, and the effect of schooling (Bourdieu & Passeron, 1964; Bowles & Gintis, 1976, 1976; Coleman et al., 1966; Lareau, 1987). The literature also largely focuses on the role of intermediate outcomes on child SES, such as academic achievement, cognitive and non-cognitive skills, and personality traits (Hauser et al., 1983; Jencks, 1977; Sewell et al., 1969), and educational attainment (Blau & Duncan, 1967; Hout, 1988).

Starting with foundational contributions to the status attainment literature (Blau & Duncan, 1967), research has attempted to quantify the role of various mechanisms using mediation or decomposition models. These models aim to decompose estimates of intergenerational transmission into a part that can be explained by observed factors and a direct, unexplained association. For example, the status attainment model of Blau and Duncan (1967) posits that the overall relationship between parental and child SES is mediated in part by the level of education achieved by children (Breen & Jonsson, 2005; Karlson & Birkelund, 2019; Simard-Duplain & St-Denis, 2020c; Sullivan et al., 2017). The connection here is therefore two-fold: (1) parental SES is correlated with child educational attainment, and (2) child educational attainment is correlated with child SES.

Following the same intuition, more complex path analysis, structural equation modelling, and decomposition methods have been used to quantify the role of a wide range of factors observed in childhood and youth beyond education. For example, several studies have sought to estimate the extent to which intergenerational mobility can be explained by cognitive and non-cognitive skills (Betthäuser et al., 2019; Blanden et al., 2007; Hsin & Xie, 2017; Jackson, 2006; Karlson & Birkelund, 2019).

This research builds on the insight that inequalities observed early in the life course have a cumulative impact later on (DiPrete & Eirich, 2006; Elder, 1998). Two different types of empirical studies conceptualize social mobility more explicitly as a process that unfolds over time in a sequential fashion. First, research on education transitions documents how social origins influence the sequence of credentials obtained through post-secondary education (PSE) (Mare, 1980, 1981; Zarifa, 2012) and on non-linear pathways through postsecondary education (Bukodi et al., 2019; Goldrick-Rab, 2006). This literature is mostly interested in pre-labour market dynamics during childhood and youth.

A second strand of research emphasizes the role of mechanisms observed later in the life course, after children have reached adulthood and entered the labour market. This perspective can be traced to early status attainment scholarship that proposed to narrow in on career trajectories and transitions (Sørensen, 1975; Spilerman, 1977). To a certain extent, some studies did adopt this type of life course perspective by including measures of the first occupation and its relationship with the occupation held at "maturity" later in life (Blau & Duncan, 1967; Featherman & Hauser, 1978; Ornstein, 1981). However, most of the recent social mobility literature that does focus on labour market and career dynamics neglect to adopt a life course perspective. Unfortunately, this knowledge gap largely prevents us from documenting the accumulation of inequalities over the careers of individuals, especially in the context of intergenerational social mobility.

Of what literature is available, a small number of studies have directly focused on the role of observed job characteristics in accounting for the intergenerational transmission of socioeconomic status (Friedman & Laurison, 2020; Simard-Duplain & St-Denis, 2020c; Torche, 2011). For example, job skill intensity and job quality account for up to 25 percent of the portion of intergenerational income mobility that is not correlated with education (Simard-Duplain & St-Denis, 2020c). Yet in these studies, job characteristics are measured at one point in time and are not explicitly conceptualized as part of a career trajectory.[1] Likewise, a few decomposition studies narrow in on labour market dynamics by exploring the role of variations in returns to education and skills across countries or US regions (Björklund et al., 2017; Rothstein, 2019). In this case, education and skills are measured at one point in time, as are the earnings returns to these individual characteristics.

## *Linking inter- and intra-generational social mobility*

A number of studies have estimated growth curve models to estimate the relationship between parental socioeconomic status and child intragenerational mobility in socioeconomic status. For example, Bukodi & Goldthorpe (2011) find that in the UK, children from non-salariat/lower class families initially report lower occupational SES scores but catch up to those from salariat/higher class backgrounds. Another UK study focusing on children with postsecondary education (PSE) find limited differences by parental social class at entry, and a process of catching up within fields of study (Jacob & Klein 2019). In contrast, studies of Germany and Italy find that inequalities based on social origins are either relatively fixed at labour market entry with little chance for convergence (Barone et al., 2011; Hillmert, 2011; Manzoni et al., 2014) or widen with age (Ballarino et al., 2020).

1 Other studies find that children tend to work for the same employer as their parents (Corak & Piraino, 2011; Kramarz & Skans, 2014).

These growth curve model studies, although contradictory[2], are operationalized to follow the fundamental insights of the early literature on careers and status attainment (Spilerman, 1977), on cumulative disadvantages (DiPrete & Eirich, 2006), and on social mobility as a process (e.g. Mare, 1981). They highlight how intergenerational social mobility unfolds over the adult life course, as observed by convergence or divergence in SES over the career of individuals[3]. At the same time, the growth curve models literature describes SES trajectories without documenting the role of career dynamics and other characteristics and events of the adult life course (for exception, see Flores et al. (2020), who show that variation in lifetime earnings growth operates through the number of years worked). Given the persistent impact of factors such as non-employment and job insecurity on income and socioeconomic status (Fuller, 2008; Gangl, 2006), this is an important omission.

In this paper, we address this shortcoming by combining insights from growth curve modelling with insights from the literature focusing on the role of job characteristics in accounting for intergenerational income transmission. More specifically, we formulate three hypotheses on the intergenerational transmission of SES over the early life course of Canadians based on our review of the literature in the previous sections:

1. Parental income is only weakly associated with children's income at the start of the adult life course, but these differences grow over time in a cumulative fashion.
2. Differences in educational attainment by social origins do not only account for average differences in income, but also account for differences in income growth rates between children of lower and higher-income families.
3. Children born to lower income parents are more likely to experience weak labour force attachment over their career, which accounts for divergences in income growth rate by social origins over the early life course.

## *Gender differences in intergenerational social mobility patterns*

Hypothesis 3 above is our operationalization of a life course perspective on the role of career dynamics in intergenerational social mobility. Apart from career dynamics, we also integrate another important life course dimension into our analysis, family formation and fertility. This dimension allows us to also focus on gender differences in processes related to social mobility. This focus on gender is motivated by existing findings of weaker intergenerational income transmission in father-daughter pairs than father-son pairs (Chadwick & Solon, 2002; Chen et al., 2017). The relationship between daughters' individual status attainment and family-level measures such as total family income (Simard-Duplain & St-Denis, 2020c) or class (Beller, 2009) is also weaker than that of sons.

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2 Inconsistent results across studies might be driven by different institutional settings across selected countries (Mayer, 2009), and by differences in variables and methods.

3 To that extent, this literature goes beyond the largely methodological contribution of research on bias in the estimates of inter-generational income transmission that considers the weaker relationship between parental and child income in young adulthood as a source of error (Chen et al., 2017; Haider & Solon, 2006) rather than part of an intragenerational mobility process that needs to be explained.

The literature aiming to unpack this dynamic has predominantly focused on the role of mothers' employment status and SES to explain variation in daughters' status attainment (Beller, 2009; Hayes & Miller, 1993; Kalmijn, 1994; Rosenfeld, 1978; Stevens, 1986). However, few studies have attempted to account for gender differences in social mobility by considering the role of life course events in the daughters' generation, such as parenthood (motherhood and its associated penalty). Recent studies of the relationship between mothers and daughters' employment probabilities (Binder, 2021; van Putten et al., 2008) do not systematically investigate the role of motherhood or childbirth as a key mechanism or outcome variable in the daughters' generation.

Our study is most similar to that of Raaum et al. (2008), who show that mothers with more affluent husbands exhibit lower employment participation in the US and the UK, which accounts for the weaker association between parental earnings and the earnings of their adult daughters. However, that study does not focus on income growth trajectories, but only earnings levels at around 40 years old.

Meanwhile, the growth curve studies mentioned above document how inequalities unfold in early adulthood, but rarely report results on gender differences in this process. Some studies restrict their analyses to men (Ballarino et al., 2020; Wolbers et al., 2011), while others do not disaggregate patterns by gender (Jacob & Klein, 2019). Those that provide gender-specific results yield contradictory results, with one study showing weaker divergence in occupational SES score by class origin for women than men in early adulthood in the UK (Manzoni et al., 2014) and another showing earlier and stronger divergence in lifetime earnings for women than men across European countries (Flores et al., 2020). Neither study consider the role of parenthood in these trends.

This is an important omission because motherhood is another feature of the early life course that has an impact on income and income growth. Parenthood may be correlated with labour force attachment patterns, especially when the child is younger. At the same time, we may expect further influence of the presence of children on the age-income slopes of women. This is because mothers are viewed by some employers as less committed, and are in turn put on career tracks where they are more likely to face a glass ceiling and lower upward mobility prospects at work (Acker, 1990; Correll et al., 2007; Roth, 2006). Indeed, research has found that women from elite backgrounds are penalized in hiring compared to men with similar social origins due to a weaker perceived commitment of women to their employer than men (Rivera & Tilcsik, 2017). This is likely to stunt income growth among more privileged women over their early life course in comparison with men.

In light of these shortcomings, we aim to fill the gap by shedding light on gender differences in income mobility. We formulate two additional hypotheses:

4. We will find weaker differences in income growth rates by parental income level among women than men, as a result of flatter income growth profiles among women of privileged social origins in comparison with men of similar backgrounds.
5. This weaker difference in income growth rate among women of different social origins relative to men will be in part explained by the negative association between motherhood and income. We expect to find a role for motherhood beyond its impact through observed differences in labour force attachment between fathers and mothers.

# Data and Methods

We use data from the Longitudinal and International Study of Adults (LISA), Wave 3 (2016), linked with administrative data from the T1 Family Files (T1FF), 1982-2015. Each LISA respondent is matched to their tax data through an anonymous linkage key, allowing us to construct a longitudinal administrative dataset including an observation for each year when a LISA respondent filed their taxes.[4] This way, we can measure the income and other characteristics of LISA respondents as reported in their tax records between 1982 and 2015.

The T1FF data is also processed to construct a family file linked to each LISA respondent, which includes a roster of tax filers who reported living at the same address as the respondent in a year when they both filed (spouses, parents, and siblings). Individuals in that roster can be linked to their tax records from 1982 to 2015. We use this feature of the data to build an intergenerational dataset linking LISA respondents to their parents (for technical details on the features of these linkages, see Hemeon, 2016; Simard-Duplain & St-Denis, 2020b, 2020a).

## Measures and Sample

We use the log of parental and child total income (pre-taxes) to measure SES. For parental income, we follow the approach most widely used in the literature and calculate their permanent income by using the log of average income over five years when their child (the LISA respondent) was 15 to 19 (Corak & Heisz, 1999). We drop observations whose permanent income was below $500. Then, we combine the income of both parents, when present (i.e. family income). Child income is measured with individual total income. To better understand the pathways and trajectories leading to disparities in permanent income levels at prime age (after 30), we keep T1FF observations when the respondent (children) was between 22 and 35 years old.

Two sample restrictions are in place. First, we restrict the sample to LISA respondents in the 1964 to 1980 birth cohorts so that all cohorts in the sample have the same age range (22-35). Second, LISA respondents reporting less than $500 of total income on more than half of the years between 22 and 35 years old (including years when not filing or not matched to a T1FF observation) are excluded from the analysis.

4 In some years, no linkage can be established because of non-filing. In other years (or for some individuals, in all years), no linkage can be established because the linkage is based on deterministic matching that leaves some LISA respondents unmatched with their tax records even when they exist.

Apart from parental income, we include four other key covariates. First, we use the LISA survey data to measure the educational attainment of respondents by allocating them into one of four categories based on their highest certificate, diploma, or degree: (1) high school certificate or equivalent, or less; (2) trade, vocational, or apprenticeship certificate or diploma; (3) college, cégep, and other non-university and university certificates and diploma below the bachelor's degree; (4) bachelor's degree or more.

Second, we develop a measure of weak labour force attachment between 22 and 35 years old from T1FF data[5]. This is done because no labour supply survey variable retrospectively reports labour force participation and employment patterns for respondents prior to 2012, the first wave of the survey. We derive a variable capturing the cumulative number of years with weak labour force attachment at each age between 22 and 35 years old.

Lastly, we also include two variables capturing individuals' conjugal and parenthood status. The former is a within-person time-varying dummy variable indicating whether the respondent has a common-law or married spouse in a given year. The latter is a categorical variable capturing the age group of the oldest child[6] (including adopted children) of each respondent, as available in LISA survey data.

## Analytical Strategy

Our objective is to examine whether children from different socioeconomic backgrounds experience different rates of income growth over the early adult life course. We therefore rely on growth curve models to estimate the extent to which children's income growth varies by parental income. Growth curve models are a type of mixed-effects model that allows us to include time-varying and time-invariant variables as predictors of change in an outcome, in which case, child income, thereby enabling us to study income growth dynamically (Singer & Willett, 2003) (for technical details, please see Appendix 1).

5 We derive a dummy variable for each year of data that takes a value of 1 if any of the following conditions are met: 1) Having an employment income level lower than $14,700. This corresponds to the annual employment income an individual would make working 30 hours a week for 49 weeks a year at a rate of $10.00 an hour. We consider this to be a conservative earnings threshold for an individual with weak labour force attachment. Individuals with negative income are not counted because self-employed workers can experience substantial income losses while also being strongly attached to the labour market. 2) Reporting an amount of Non-Taxable Income (Social Assistance or Workers' Compensation Payments) or Disability Amount for Self (physical or mental impairment noticeably restricting the tax filer's activities of daily living) of $500 or more on a given year. Net Federal Supplements are also included, but these are related to the Old Age Supplement, which our sample members are ineligible for, due to their age. This aims to capture major spells outside of the active labour force and other obstacles to full participation. 3) Reporting an amount of $500 or more on a given year in Employment Insurance benefits. This aims to capture involuntary job losses that led to prolonged non-employment spells. It also captures other lengthy spells of joblessness or absence from work such as those associated with maternity and parental leaves.

6 Categories: (1) No child; (2) 0-5 years old; (3) 6-14 years old; (4) 15-18 years old.

In our models, we regress child income on child's age and the interaction between age and parental income to understand how income increases by age (also referred to as income growth rate or age-income profile), and how this relationship varies by parental income level. We then explore two key mechanisms that might account for the observed relationships between income growth and parental income: the role of education, and that of labour force attachment.
To do so, we first introduce education and its interaction with age into the model, which is a time-invariant variable that differs from person to person. Next, we add labour force attachment. We can then understand how much education and labour force attachment each explains the differential income growth by parental income by looking at how the interaction between age and parental income changes after adjusting for education and labour force attachment. For example, a diminished coefficient size for the "parental income x age" interaction would mean that gaps in income growth between children from rich and poor families stem partly from different levels of educational attainment of these children, or from the different number of years with weak labour market attachment of these children.

To understand gender differences, our second set of models follows the same steps of adjusting for education and labour force attachment, but we also include gender-related controls. For example, a negative coefficient of the three-way interaction between gender, age and parental income would mean that intergenerational income transmission over the early adult life course is weaker among daughters compared to sons. Again, we first include education as a covariate to examine the extent to which differential income growth based on parental income can be accounted for by higher income growth rates associated with higher education attainment. Next, we focus on the role of motherhood in explaining the gap between women from higher and lower income families by adding the dummies for age group of a woman's oldest child (or absence of children) interacted with gender. This will allow us to assess the influence of motherhood penalty, if any, on differences in income growth by social origin among women and in comparison with their male counterparts.

# Results

## *Establishing the link between intergenerational income transmission and intra-generational income mobility*

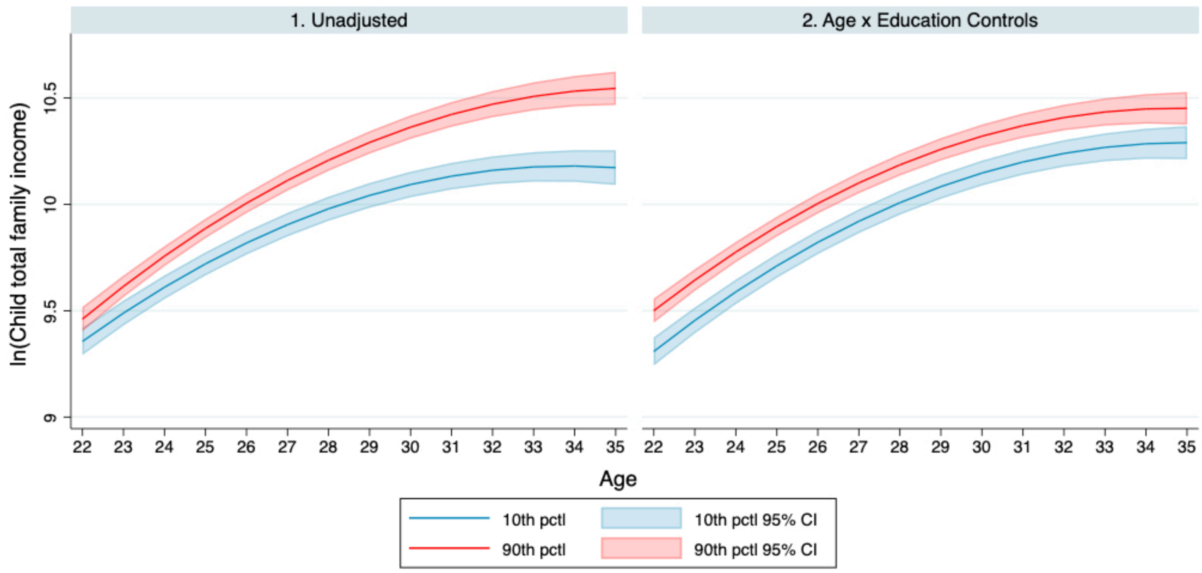
We regress child income on child age in a multilevel mixed-effect model framework. We estimate growth curve models where the key parameter is the relationship between age and income. In the first specification, we test hypothesis 1. The specification includes a random intercept and a random slope on age, as well as a cross-level interaction between age and parental income. We estimate the model with unstructured covariance. Figure 1 reports average adjusted predictions from that model (see Table A1 for all model parameters). It plots the natural log of child income over age 22 to 35 years old holding parental total family income at the 10$^{th}$ and 90$^{th}$ percentile values. In other words, Figure 1 shows the gap in income between children born from parents in the 10$^{th}$ and 90$^{th}$ income percentile at different ages, allowing to track divergences as incomes grow over the life course. Its key components are the starting point at age 22 (intercept) and the steepness of income trajectories (income growth slope). Figure 2 provides complementary information: log-log elasticities varying by age, which show how the association between parental and child income varies by age. An increasing gap over age between the 10$^{th}$ and 90$^{th}$ parental income percentile values in Figure 1 will translate into a positive slope in Figure 2. In both panels, the confidence intervals are reported at the 95% level.

We find that at 22 years old, a difference in child income by parental income is already observed, although the confidence intervals in Figure 1 overlap (between children from families with income in the 10$^{th}$ and 90$^{th}$ percentile). That difference grows substantially and non-linearly in size over time to reach approximately .4 log points at 35 years old. That is, an increase from the 10$^{th}$ to the 90$^{th}$ percentile in permanent parental total family income is associated with a 40% increase in child individual total income. At 22, the gap was negligible. The estimates reported in Figure 2, Panel A (Model 1), show a statistically significant log-log association (elasticity) of 0.063 at baseline age (22 years old). The elasticity grows by 0.012 points a year (as shown by the statistically significant age x parental income interaction term in Table A1, Model 4) to reach more than 0.20 points. That is, a 100 percent increase in parental total family income (averaged when the child is 15 to 19 years old) is associated with a 20 percent increase in child income at 35 years old.

This is evidence that although early in their life course, children from higher- and lower-income families experience limited inequalities in their personal income, they are placed on trajectories associated with diverging age-income slopes. This is consistent with hypothesis 1. Most notably, Panel 1 of Figure 1 shows that by 30 years old, income growth has all but stalled for children from families with income at the 10$^{th}$ percentile, while a higher rate of growth is observed among those from families with income at the 90$^{th}$ percentile.

Figure 1.

## Average adjusted predictions, 1964-1980 birth cohorts




*Source: LISA (2016) and T1FF (1982-2015)*

# Education

Next, we consider hypothesis 2 and ask whether this divergence may be driven by the relationship between age and income across the different levels of educational attainment respondents acquire. Therefore, we begin by adding education as another fixed-effect person-level variable in our model. In Figure 1, Panel 2,[7] we introduce a cross-level interaction between age and education (and education dummies). We can see that adding these controls greatly reduces the gap in average adjusted predictions between children from families at the 10$^{th}$ and 90$^{th}$ income percentile at older ages, but increases the gap slightly at 22 years old.[8] Overall, income growth rates between children of lower and higher income parents become similar and the gap visible around labour market entry remains relatively constant over the life course (see also Figure 2, Panel B, Model 1).[9]

7 Corresponding to Model 6 in Table A1.

8 Average adjusted predictions are estimated with the -margins- Stata command. The output is the predicted value of the dependent variable averaged over all respondent at specific values (in this case, parental income 10$^{th}$ and 90$^{th}$ percentile, and child age), holding all other covariates at their means.

9 In Table A1 (Model 6), we report that the parental income x age coefficient loses statistical significance, meaning that net of the age x education interaction, there is no difference in income growth rate by parental income level.

This confirms the importance of life course dynamics over explanations that would focus on the influence of education estimated at a single point in time: the size of the gap between children of parents in the $10^{th}$ and $90^{th}$ income percentile of total family income is partly accounted for by average differences in income growth rates across levels of education. Higher income children having higher growth rate due to a greater likelihood of higher educational attainment. At the same time, higher levels of educational attainment are associated with an initially lower income level, which is compensated for by a higher growth rate later in the life course. This dynamic is driving the smaller gap in child income at 22 years old in the unadjusted model.

## Labour Force Attachment

To unpack the dynamics observed above, we consider the role of labour force attachment. Model 2 in both panels of Figure 2 reports age-specific log-log associations net of a control capturing the number of years with weak labour force attachment (LFA), squared. A shift of the curves closer to zero means that weak labour force attachment accounts for part of the association between parental and child income.

More specifically, when comparing results from models 1 and 2 in Panel A,[10] we find that LFA controls account for a large share of intergenerational income transmission over the life course, with the curve becoming less steep in Model 2 in comparison with Model 1. That is, accumulation of years of weak LFA by children of lower-income families is associated with an income penalty and accounts not only for overall intergenerational income transmission, but also for the divergence in incomes between lower and higher income children over their early adult life course.

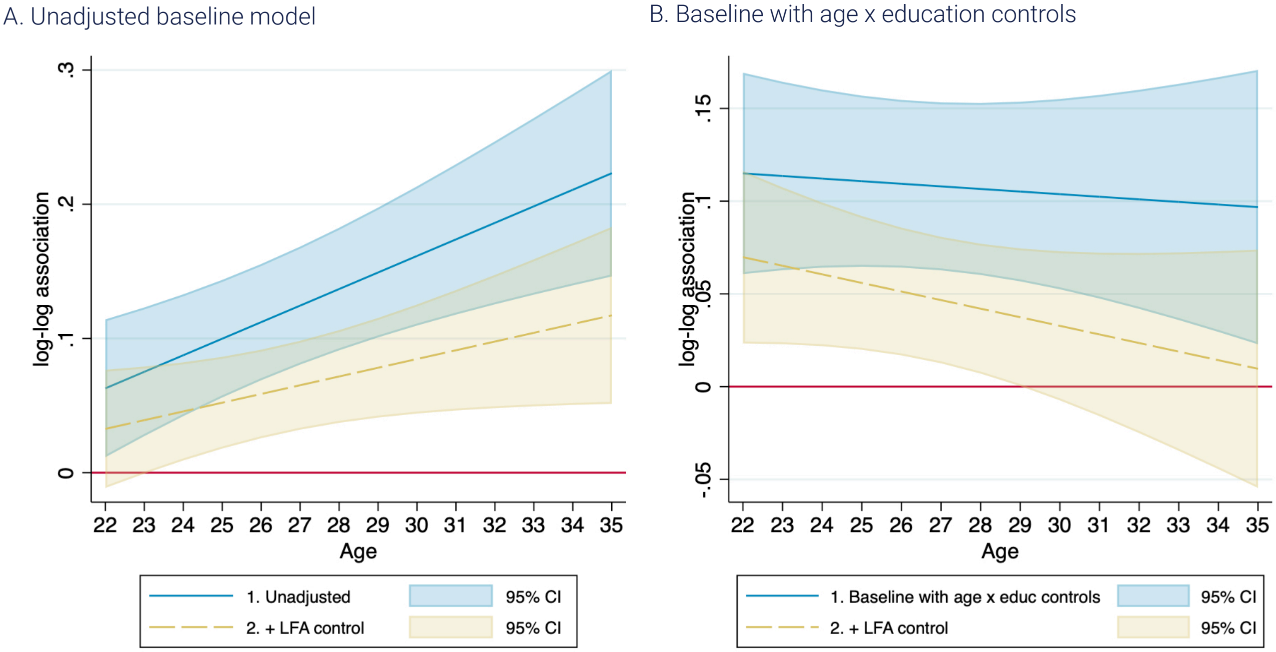
In Panel B, we compare the model with age x education controls (Model 2 in Figure 1) with a model adding LFA controls to that specification and find similar patterns: net of LFA controls, we observe a convergence in the income of lower and higher income children over the life course. In other words, the social origins gap in income can be accounted for by the accumulation of years with weak LFA to a larger extent later in the life course.

In sum, these results support hypothesis 3. Children born to lower income parents are more likely to experience weak labour force attachment over their career, which accounts for divergences in income growth rate by social origins over the early life course. This highlights the importance of considering career-related mechanisms, especially those that capture cumulative disadvantage such as our cumulative measure of LFA.

10 Full regression output is reported in Table A1. Model 2 estimates in Figure 2.A are obtained from Model 7. Model 2 estimates in Figure 2.B are obtained from Model 8.

Figure 2.

## Average marginal effects (elasticities) net of controls, 1964-1980 birth cohorts




*Source: LISA (2016) and T1FF (1982-2015)*

# Gender Differences

Next, we explore gender differences in child's income trajectories. We do so by adding a binary gender variable to each model and interacting it with age and parental income separately, as well as a three-way interaction for parental income x age x gender. In Figure 3, we report average adjusted predictions by parental income level and gender, and elasticities by gender. These are derived from regression estimates reported in Tables A2, Model 4, and A3, Model 2.

First, the unadjusted estimates of income growth (left panels of Figure 3, "1. Unadjusted") show a divergence in income by social origin over the life course only among men, starting from a small and not statistically significant elasticity at 22 to an elasticity of over 0.25 at 35 years old. Among women, high elasticity is observed at 22 years old, but we find little to no divergence in income growth by social origin (the differences in intercept and slope relative to men are statistically significant). In addition, the lack of divergence among women appears related to the weak income growth rate of women born to higher-income parents, as shown in the upper-left panel of Figure 3. That is, while women from lower-income families experience similar income growth to their male counterparts, income growth among women from high-income families is lower and almost flat starting at 30 years old, unlike their male counterparts.

Second, the role of education appears substantially different for women and men. In Figure 3, right panels ("2. Age x Education controls"), controlling for education and its interaction with age fully accounts for intergenerational income transmission among women at 35 years old, while for men the patterns are similar to those in the unadjusted model (smaller but constant elasticity over the early adult life course net of the education x age interaction). At the same time, this pattern appears to be driven by the fact that net of the controls, the income growth of women born to parents in the 90th income percentile flattens at an even earlier age than in the unadjusted model. The controls have little influence on the growth rate of women born to parents in the 10th income percentile relative to their male counterparts. This translates into a greater gap between men and women from similar family backgrounds within educational attainment levels. Meanwhile, the income gap by social origin at 22 years old for women remains large and unaccounted for.

In sum, the results are broadly consistent with hypothesis 4, but a surprising pattern is observed among women (a large income gap by social origin at 22 years old that decreases with age). This pattern suggests that dynamics occurring later in the life course of women may contribute to an attenuation of the relationship between parental and daughters' income by the time they reach 35 years old.

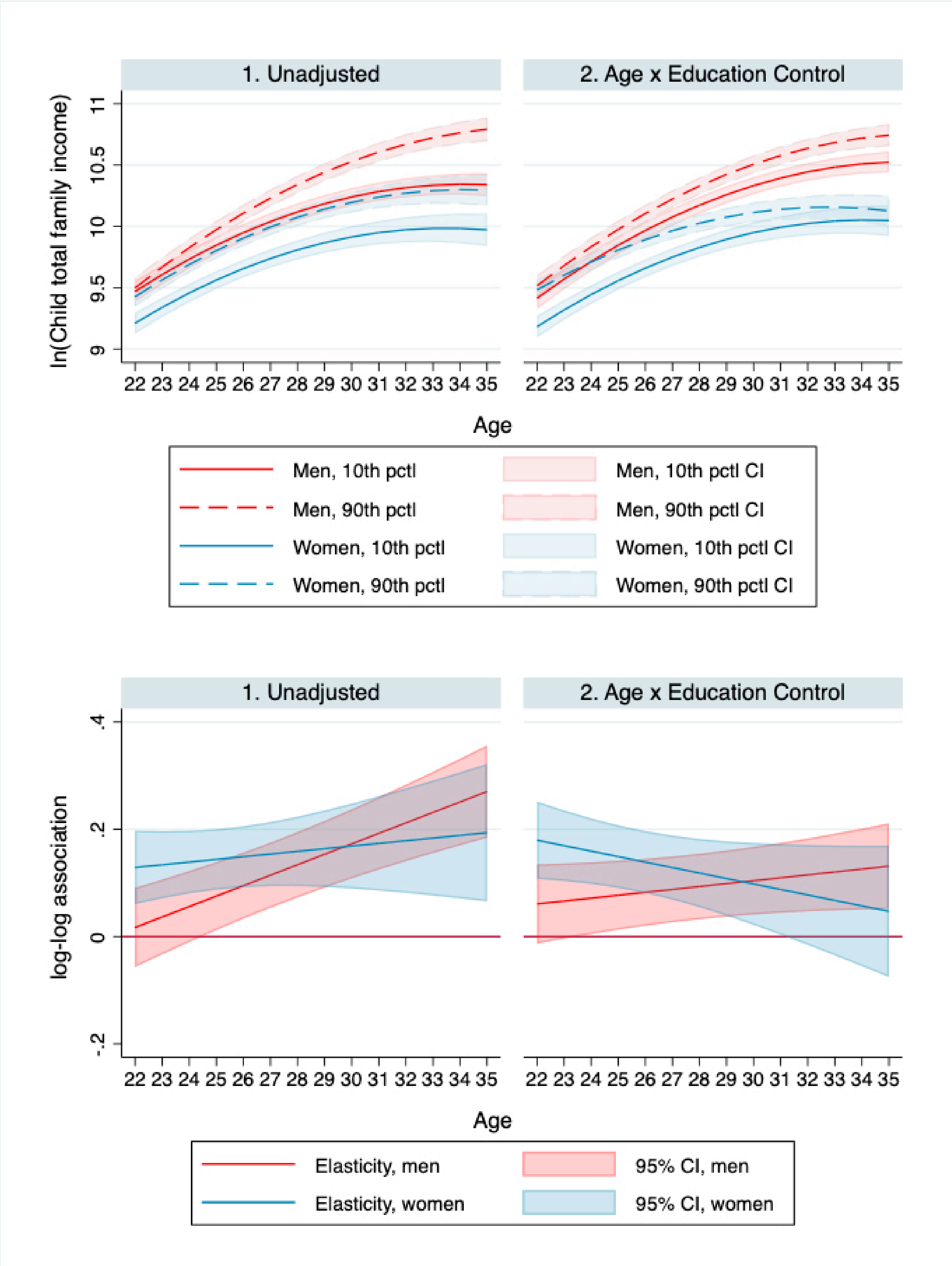
### *Accounting for the gender gap in intergenerational income transmission*

We further explore the patterns observed in Figure 3 by considering the role of weak labour force attachment, and of couple status and the presence of children. In Figure 4, we report adjusted differences in income relative to men born to parents in the 90th total family income percentile. Using estimates from tables A3 and A4 to generate adjusted predictions (holding all covariate constant at 0), we visualize income gaps by social origin within gender, and gender income gaps by social origin.

In Panel A, we report results adjusting for different measures of labour force attachment (LFA), couple status, and the presence of children, in comparison with a baseline model not adjusting for education. The baseline specification in Panel B includes education dummies and their interaction with age, with the same controls then added. A line moving closer to the reference group relative to the baseline specification indicates that the controls included in the model account for the income difference between a given gender/parental income group and the reference group.

Figure 3.

## Average adjusted predictions and average marginal effects (elasticities) in gender interaction models, 1964-1980 birth cohorts

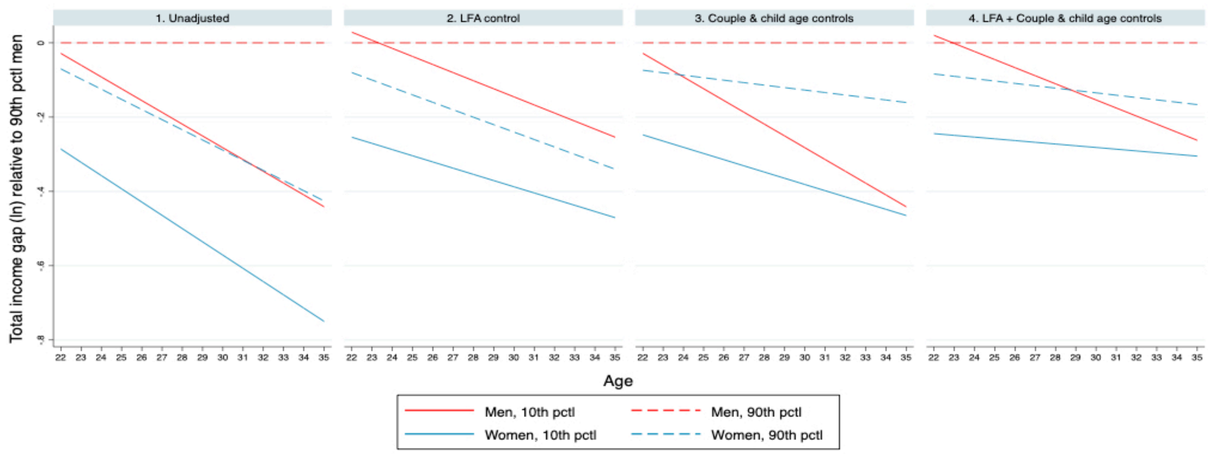



*Source: LISA (2016) and T1FF (1982-2015)*

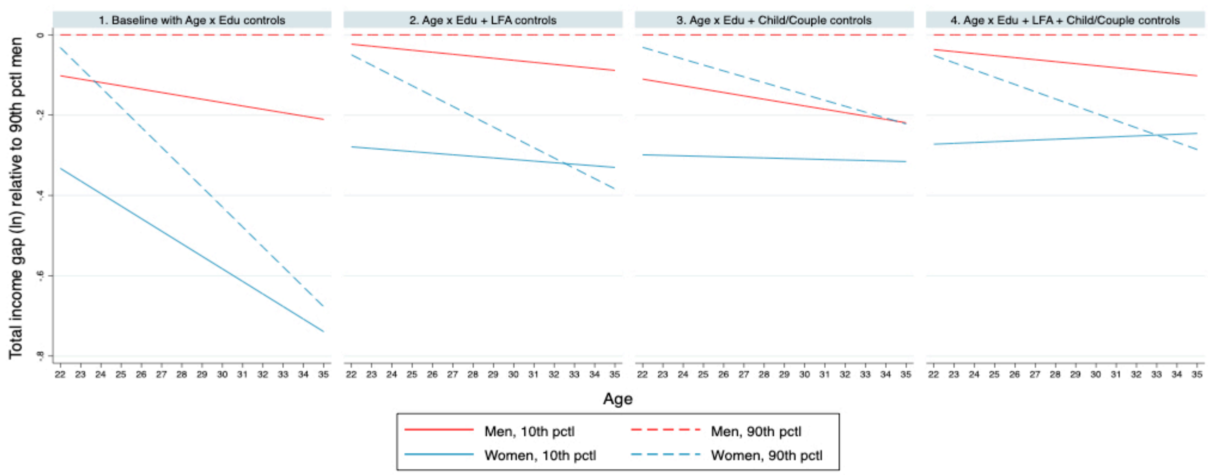
Figure 4.

## Difference in average adjusted predictions relative to men in 10th percentile of parental income, 1964-1980 birth cohorts

A. Unadjusted baseline model




B. Baseline with age x education controls




*Source: LISA (2016) and T1FF (1982-2015)*

We focus our interpretation on Panel B. First, we find that controlling for LFA in Model 2 accounts for half of the gap between men born from parents in the $10^{th}$ and $90^{th}$ income percentile at 35 years old. It also fully closes the gap between women from parents in the $10^{th}$ and $90^{th}$ income percentile. Importantly, controlling for LFA also accounts for approximately 50% of the gap between men and women at both the $10^{th}$ and $90^{th}$ parental income percentile at 35 years old. This reinforces our initial findings from Figure 2 showing an important role for LFA as a mechanism driving the divergence of income growth trajectories by social origin in Canada.[11]

11 In Panel A, we find a much weaker role of LFA among women, suggesting that little difference emerges in LFA patterns by social origins among women over their early life course overall, although differences emerge within educational attainment categories. The same is not true for men, for whom we find a similar impact of LFA in Panel A and B.

Note however that controlling for LFA does not account for the income gap by social origins at early ages among women, meaning that differences in labour force attachment levels accounts for the gap that persists among women later in their career, but not at labour market entry. This may be because our LFA variable intends to capture cumulative patterns of labour force attachment and that LFA patterns is not the primary source of difference in the employment profile of women born in low versus high income families in their early life course.

Second, the presence of children and couple status (Model 3) accounts for a large share of the difference in income growth between women and men born to parents in the 10$^{th}$ and 90$^{th}$ family income percentile. This means that maternity and couple formation are important mechanisms generating income gaps between men and women regardless of their social origins (although the gap between men and women in the 10$^{th}$ parental income percentile is smaller than at the 90$^{th}$ percentile when controlling for the presence of children and couple status). Note that thes variables have little impact at younger ages, meaning that they do not explain the initial gender gap (which is inexistent among men and women in the 90$^{th}$ percentile of parental income). Rather, they account for the divergence in the income attainment of men and women over their life course. Specifications with all controls (Model 4) show that the presence of children and couple status accounts for a greater share of the gap between men and women at the 10$^{th}$ and 90$^{th}$ percentile of parental income, and that this effect is concentrated at older ages. This is relatively consistent with the expectations formulated in hypothesis 5, expecting to find an additional role for parenthood and couple status in addition to LFA. However, these variables do little to help explain the strong relationship between parental and daughters' income at the start of our age range. Only the subsequent gender divergence in income growth profiles is accounted for.[12]

12 Also note that children and couple controls have little impact on the income gap by social origins among men. As show in Table A2, the interaction between gender and the presence of children is large and negative while the baseline coefficients (for men) are small and positive (fatherhood premium).

# Conclusion

The objective of this paper was to provide evidence of the relationship between intergenerational income transmission and intragenerational economic mobility. More specifically, we aimed to provide novel results on whether age-income slopes are steeper among children of higher-income families in Canada, and what factors may account for eventual differences. Among those factors, we examined the role of education, as well as factors related to the early adult life course, post labour market entry, including labour force attachment, couple status and parenthood.

First, we find a divergence in income with age between children from lower and higher income families, a trend more pronounced among men. Second, we find that this dynamic is driven in part by the fact that children from higher income families tend to achieve a higher level of education, and higher education levels are associated with steeper age-income slopes. Third, we provide evidence of the crucial roles of factors posterior to labour market entry.

The cumulative influence of differences in labour force attachment by parental income level over the life course accounts for a large proportion of the differences in age-income profiles by parental income level, but does not fully explain the divergence among men.

The presence of children accounts for some of the observed gender differences in income growth. In particular, the lower level of intergenerational income transmission at the end of the early life course among women from higher income parents can be attributed to their greater likelihood of having young children, which is associated with an important income penalty especially visible at older ages for more privileged women (who experience childbirth later in their life course).

Together, these findings point at the existence of important cumulative inequality dynamics that unfold over the adult life course, rooted in inequalities in parental income measured in adolescence. While education tends to take place predominantly at the beginning of the adult life course, which appears to be a factor related to differences in the rate of income growth by parental income especially among men, labour force attachment and family characteristics also play important roles.

In contrast with the UK literature (Bukodi & Goldthorpe 2011; Jacob & Klein 2019), we do not find evidence of a process of catching up among men initially facing a disadvantage rooted in their family socioeconomic status or their educational attainment. To the contrary, our results point at persistent inequalities over time, in line with Flores et al. (2020), although not among individuals with the same level of educational attainment. We suspect that this is driven by our use of income as a measure of socioeconomic status, which allows for greater heterogeneity between individuals than occupational indices or big social classes.

To conclude, interventions that could contribute to attenuate the impact of inequalities occurring early in the life course, especially those related to educational attainment and labour force attachment, may contribute to equalizing opportunities among individuals of different social origins. Our results suggest that such interventions may attenuate disparities emerging earlier in the life course, during schooling and the early career. In terms of family policies, those supporting the labour force participation of mothers and measures aimed at reducing disadvantages experienced by employed mothers may contribute to closing the gender income gap. At the same time, if designed in a way that predominantly benefit women from privileged social origins, they may exacerbate inequalities between women from lower and higher income backgrounds.

Future research should explore the role of other characteristics, experiences and events unfolding over the adult life course in social mobility, such as adult education and re-skilling, job loss, or geographic mobility. It is very likely that our cumulative measure of labour force attachment indirectly captured the effect of several of these factors. In the absence of more detailed longitudinal survey or administrative data on employment trajectories such as those allowing to measure job changes, occupational transitions, and overqualification episodes, it is challenging to document precisely which specific factors may account for divergences in income emerging over the life course of Canadians of different social origins.

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# Appendix 1: Tables

Table A1.

## Growth curve models with varying slopes by parental permanent income level and education, 1964-1980 birth cohorts

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| Age | | 0.150 *** | 0.150 *** | 0.016 | 0.016 * | 0.120 ** | 0.227 *** | 0.307 *** |
| Age squared | | -0.006 *** | -0.006 *** | -0.006 *** | -0.006 *** | -0.006 *** | -0.011 *** | -0.011 *** |
| ln(parental total family income) | | | 0.124 *** | 0.063 * | 0.044 | 0.115 *** | 0.033 | 0.07 ** |
| ln(parental total family income) x Age | | | | 0.012 ** | 0.012 ** | -0.001 | 0.007 † | -0.005 |
| Education | | | | | | | | |
| High school or less (reference) | | | | | 0.000 | 0.000 | | 0 |
| Trades, vocational or apprenticeship certificate or diploma | | | | | 0.176 ** | 0.055 | | 0.053 |
| College, non-university, or other certificate or diploma below Bachelor | | | | | 0.110 * | -0.037 | | -0.075 |
| Bachelor degree or more | | | | | 0.171 *** | -0.277 *** | | -0.212 *** |
| Education x Age | | | | | | | | |
| High school or less (reference) x Age | | | | | | 0.000 | | 0 . |
| Trades, vocational or apprenticeship certificate/diploma x Age | | | | | | 0.023 *** | | 0.024 ** |
| College, non-university, or other certificate/diploma below Bachelor x Age | | | | | | 0.028 *** | | 0.024 *** |
| Bachelor degree or more x Age | | | | | | 0.087 *** | | 0.076 *** |
| Cumulative Weak LFA, cumulative years | | | | | | | -0.326 *** | -0.325 *** |
| Cumulative Weak LFA, cumulative years squared | | | | | | | 0.015 *** | 0.016 *** |
| Constant | | 9.412 *** | 8.059 *** | 8.727 *** | 8.813 *** | 8.274 *** | 9.304 *** | 8.998 *** |
| Level 2 (between person) variance component | | | | | | | | |
| var(Constant) | 0.3512 *** | 0.5083 *** | 0.5087 *** | 0.5060 *** | 0.5189 *** | 0.4894 *** | 0.3183 *** | 0.3093 *** |
| Level 1 (person-year) variance component | | | | | | | | |
| var(Age) | | 0.0079 *** | 0.0079 *** | 0.0078 *** | 0.0078 *** | 0.0066 *** | 0.0073 *** | 0.0064 *** |
| var(Residual) | 0.5502 *** | 0.3130 *** | 0.3130 *** | 0.3130 *** | 0.3131 *** | 0.3131 *** | 0.2954 *** | 0.2955 *** |
| ICC | 0.390 | 0.619 | 0.619 | 0.618 | 0.624 | 0.610 | 0.519 | 0.511 |
| cov(Age,Constant) | | -0.0358 *** | -0.0367 *** | -0.0362 *** | -0.0379 *** | -0.0322 *** | -0.0314 *** | -0.0287 *** |
| BIC | 159871260 | 134203637 | 134081632 | 134033429 | 133860021 | 133232295 | 127775068 | 127074175 |
| Log pse-likelihood | -79935614 | -67101782 | -67040774 | -67016667 | -66929948 | -66616069 | -63887476 | -63536998 |
| chi-squared | | 1029.466 | 1047.931 | 1072.888 | 1116.087 | 1445.385 | 2144.061 | 2616.337 |
| p-values | | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0 | 0 |

*Source: LISA (2016) and T1FF (1982-2015)* *** p<0.001, ** p<0.01, * p<0.05, † p<0.1

Table A2.

## Growth curve models with varying slopes by parental permanent income level and gender, 1964-1980 birth cohorts

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| Age | 0.150 *** | 0.160 *** | 0.016 | -0.051 | 0.153 *** | -0.051 | 0.149 *** |
| Age squared | -0.006 *** | -0.006 *** | -0.006 *** | -0.006 *** | -0.011 *** | -0.006 *** | -0.011 *** |
| Male (reference) | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Female | -0.256 *** | -0.152 *** | -0.681 | -1.377 * | -1.492 ** | -1.089 † | -1.344 ** |
| Age x Female | | -0.021 *** | | 0.136 † | 0.155 * | 0.145 † | 0.157 * |
| ln(parental total family income) | | | 0.054 | 0.017 | -0.017 | 0.017 | -0.012 |
| ln(parental total family income) x Age | | | 0.012 ** | 0.019 *** | 0.013 ** | 0.019 *** | 0.013 ** |
| ln(parental total family income) x Female | | | 0.038 | 0.112 * | 0.121 ** | 0.087 † | 0.108 * |
| ln(parental total family income) x Age x Female | | | | -0.014 * | -0.015 * | -0.013 † | -0.014 * |
| Cumulative Weak LFA, cumulative years | | | | | -0.323 *** | | -0.310 *** |
| Cumulative Weak LFA, cumulative years squared | | | | | 0.015 *** | | 0.014 *** |
| Not in a couple (reference) | | | | | | 0.000 | 0.000 |
| In a couple | | | | | | 0.031 | 0.000 |
| No child present (reference) | | | | | | 0.000 | 0.000 |
| Child present, 0-5 years old | | | | | | 0.043 * | 0.023 |
| Child present, 6-14 years old | | | | | | 0.010 | -0.012 |
| Child present, 15-18 years old | | | | | | 0.099 | 0.044 |
| Child present,0-5 x Female | | | | | | -0.481 *** | -0.258 *** |
| Child present, 6-14 x Female | | | | | | -0.471 *** | -0.203 *** |
| Child present, 15-18 x Female | | | | | | -0.594 *** | -0.313 ** |
| Constant | 9.534 *** | 9.485 *** | 8.955 *** | 9.299 *** | 9.920 *** | 9.302 *** | 9.861 *** |
| Level 2 (between person) variance component | | | | | | | |
| var(Constant) | 0.5050 *** | 0.5024 *** | 0.5016 *** | 0.4977 *** | 0.309 *** | 0.481 *** | 0.309 *** |
| Level 1 (person-year) variance component | | | | | | | |
| var(Age) | 0.0078 *** | 0.0077 *** | 0.0078 *** | 0.0076 *** | 0.007 *** | 0.008 *** | 0.008 *** |
| var(Child present) | | | | | | 0.100 *** | 0.084 *** |
| var(Residual) | 0.3130 *** | 0.3130 *** | 0.3130 *** | 0.3130 *** | 0.296 *** | 0.302 *** | 0.288 *** |
| ICC | 0.617 | 0.616 | 0.616 | 0.614 | 0.511 | 0.614 | 0.518 |
| cov(Age,Constant) | -0.0371 *** | -0.0365 *** | -0.0375 *** | -0.0368 *** | -0.032 *** | -0.037 *** | -0.034 *** |
| cov(Child present,Constant) | | | | | | 0.019 *** | 0.034 *** |
| cov(Age,Child present) | | | | | | -0.009 *** | -0.010 *** |
| BIC | 133984035 | 133926464 | 133784479 | 133704343 | 127496432 | 132309542 | 126868128 |
| Log pse-likelihood | -66991975 | -66963185 | -66892182 | -66852103 | -63748137 | -66154650 | -63433933 |
| chi-squared | 1148.13 | 1194.416 | 1205.891 | 1266.352 | 2337.036 | 1685.075 | 2442.514 |
| p-values | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |

*Source: LISA (2016) and T1FF (1982-2015)    *** p<0.001, ** p<0.01, * p<0.05, † p<0.1*

Table A3.

## Growth curve models with varying slopes by parental permanent income level, gender, and education 1964-1980 birth cohorts

| | (1) | | (2) | | (3) | | (4) | | (5) | |
|---|---|---|---|---|---|---|---|---|---|---|
| Age | -0.052 | | 0.058 | | 0.230 | *** | 0.057 | | 0.226 | *** |
| Age squared | -0.006 | *** | -0.006 | *** | -0.011 | *** | -0.006 | *** | -0.011 | *** |
| Male (reference) | 0.000 | | 0.000 | | 0.000 | | 0.000 | | 0.000 | |
| Female | -1.418 | * | -1.420 | ** | -1.485 | ** | -1.128 | * | -1.335 | ** |
| Age x Female | 0.137 | † | 0.137 | † | 0.161 | * | 0.137 | † | 0.157 | * |
| ln(parental total family income) | -0.016 | | 0.061 | | 0.014 | | 0.066 | † | 0.022 | |
| ln(parental total family income) x Age | 0.020 | *** | 0.005 | | 0.003 | | 0.005 | | 0.003 | |
| ln(parental total family income) x Female | 0.113 | * | 0.119 | * | 0.123 | ** | 0.094 | † | 0.110 | ** |
| ln(parental total family income) x Age x Female | -0.015 | * | -0.016 | * | -0.016 | * | -0.013 | † | -0.015 | * |
| Education | | | | | | | | | | |
| High school or less (reference) | 0.000 | | 0.000 | | 0.000 | | 0.000 | | 0.000 | |
| Trades, vocational or apprenticeship certificate/ diploma | 0.151 | ** | 0.040 | | 0.036 | | 0.028 | | 0.020 | |
| College, non-university, or other certificate/ diploma below Bac. | 0.176 | *** | -0.007 | | -0.041 | | -0.014 | | -0.045 | |
| Bachelor degree or more | 0.260 | *** | -0.250 | *** | -0.183 | *** | -0.295 | *** | -0.212 | *** |
| High school or less (reference) x Age | | | 0.000 | | 0.000 | | 0.000 | | 0.000 | |
| Trades, ... certificate/diploma x Age | | | 0.020 | ** | 0.022 | ** | 0.020 | ** | 0.022 | ** |
| College, ... certificate/diploma below Bac. x Age | | | 0.033 | *** | 0.026 | *** | 0.034 | *** | 0.026 | *** |
| Bachelor degree or more x Age | | | 0.094 | *** | 0.079 | *** | 0.094 | *** | 0.080 | *** |
| Cumulative Weak LFA, cumulative years | | | | | -0.319 | *** | | | -0.306 | *** |
| Cumulative Weak LFA, cumulative years squared | | | | | 0.015 | *** | | | 0.015 | *** |
| Not in a couple (reference) | | | | | | | 0.000 | | 0.000 | |
| In a couple | | | | | | | 0.024 | | -0.004 | |
| No child present (reference) | | | | | | | 0.000 | | 0.000 | |
| Child present, 0-5 years old | | | | | | | 0.050 | ** | 0.031 | |
| Child present, 6-14 years old | | | | | | | 0.043 | | 0.022 | |
| Child present, 15-18 years old | | | | | | | 0.181 | ** | 0.121 | † |
| Child present,0-5 x Female | | | | | | | -0.474 | *** | -0.253 | *** |
| Child present, 6-14 x Female | | | | | | | -0.446 | *** | -0.187 | ** |
| Child present, 15-18 x Female | | | | | | | -0.556 | *** | -0.287 | ** |
| Constant | 9.500 | *** | 8.902 | *** | 9.647 | *** | 8.860 | *** | 9.563 | *** |
| Level 2 (between person) variance component | | | | | | | | | | |
| var(Constant) | 0.5207 | *** | 0.4835 | *** | 0.3033 | *** | 0.4625 | *** | 0.3008 | *** |
| Level 1 (person-year) variance component | | | | | | | | | | |
| var(Age) | 0.0076 | *** | 0.0063 | *** | 0.0063 | *** | 0.0062 | *** | 0.0067 | *** |
| var(Child present) | | | | | | | 0.0970 | *** | 0.0818 | *** |
| var(Residual) | 0.3131 | *** | 0.3132 | *** | 0.2955 | *** | 0.3020 | *** | 0.2881 | *** |
| ICC | 0.624 | | 0.607 | | 0.507 | | 0.605 | | 0.511 | |
| cov(Age,Constant) | -0.0397 | *** | -0.0329 | *** | -0.0289 | *** | -0.0322 | *** | -0.0305 | *** |
| cov(Child present,Constant) | | | | | | | 0.0095 | *** | 0.0268 | *** |
| cov(Age,Child present) | | | | | | | -0.0067 | *** | -0.0078 | *** |
| BIC | 133476694 | | 132745164 | | 126720275 | | 131360931 | | 126107248 | |
| Log pse-likelihood | -66738263 | | -66372482 | | -63360027 | | -65680313 | | -63053461 | |
| chi-squared | 1393.273 | | 1797.599 | | 2967.433 | | 2232.175 | | 3108.836 | |
| p-values | 0.000 | | 0.000 | | 0.000 | | 0.000 | | 0.000 | |

*Source: LISA (2016) and T1FF (1982-2015)* *** p<0.001, ** p<0.01, * p<0.05, † p<0.1

# Appendix 2: Analysis

## Multilevel analysis and growth curve modelling

Multilevel analysis of longitudinal individual data focuses on two sources of variation in the outcome of interest (income). First, income varies from year to year over the life course of a person: it grows with promotions, may decrease following life course events such as layoffs, childbirth, or retirement, and may fluctuate more-or-less randomly from year to year. Nevertheless, some individuals will earn more than others on average throughout their life course. The second source of variation in income is the variation between individual average income levels. This variation is generally due to differences in the distribution of personal (and contextual) characteristics and experiences across individuals. Growth curve models aim to parse out the variation in income that is driven by within-person fluctuation and the variation in income that is driven by average differences between individuals.

### *Baseline specification: Random-intercept and random-slope growth curve model*

To estimate the relationship between parental income and child's income over the early adult life course, we regress child income at all ages on parental permanent income. In the longitudinal LISA dataset, one person is observed at many ages. Person-years observations (1st level), *ij*, are nested within a person (2nd level), *j*, so that we have 14 years of data for each child. For that reason, the error in a regular OLS model would be correlated within person, violating an assumption of OLS regression. For that reason, we use mixed-effects models, also called multilevel models (Raudenbush & Bryk, 2002; Snijders & Bosker, 2012).

In an OLS framework, we would first estimate the following relationship between age and the log of child total income (*xtirc_c*):

$$ln(xtirc\_c_i) = \beta_0 + \beta_1 age_i + \epsilon_i \tag{1a}$$

This would only be true if we were using cross-sectional data with one observation per person *i*, each observed once at a single year of age. In a multilevel framework, the first-level equation for the same relationship is:

$$ln(xtirc\_c_{ij}) = \beta_{0j} + \beta_{1j} age_{ij} + e_{ij} \tag{1b}$$

Where i denotes a person-year (first-level) and *j* denotes a person (second-level). In this analysis, a person is a child, observed at several years of age.

Now, there may be average between-person differences in income, at the second level. In this case, we let the intercept vary randomly between persons, so that we have:

$$\beta_{0j} = \gamma_{00j} + u_{0j} \tag{2}$$

Which allows us to express equation 1 as:

$$ln(xtirc\_c_{ij}) = \gamma_{00} + \beta_{1j}age_{ij} + u_{0j} + e_{ij} \tag{3}$$

This is essentially the same specification as Equation 1b, but with a person-year error term (within-person), $e_{ij}$ , and a between-person error term, $u_{oj}$. In the regression output, this is reported as an unexplained variance component for the model constant, var(Constant), and a residual, within-person unexplained variance, var(Residual). Note that $u_{oj}$ can be interpreted as a person-level fixed-effect that could be extracted for each person-level observation.

So far, the only independent variable in the model is age, which varies within person. The coefficient $B_{1j}$ is an estimate of the average age-income slope. The use of this type of specification with a time variable in a mixed-effect model is generally referred to as a growth curve model (Snijders & Bosker, 2012).

Mixed-effects models also allow for independent variables that only vary between person (between 2nd-level units). In the context of a growth curve model, these are time-invariant variables that can account for between-person differences in average income. More specifically, we are able to test whether between-person differences in income may be driven by differences in parental income measured at 15-19 years old. Our measure of parental income is a person-level (second-level characteristic), which does not vary at the first level (within a person). In order to estimate the association between parental and child income, we let the first-level intercept vary depending on parental income level. This will move each person-specific intercept. Now let's re-write equation 2 as:

$$\beta_{0j} = \gamma_{00} + \gamma_{01}ln(xtirc\_p_j) + u_{0j} \tag{4}$$

We re-write equation 3 as:

$$ln(xtirc\_c_{ij}) = \gamma_{00} + \beta_{1j}age_{ij} + \gamma_{01}ln(xtirc\_p_j) + u_{0j} + e_{ij} \tag{5}$$

In this case, the intercept varies randomly with the person-level (2nd level) error term, but in equation 2, the error term was plausibly correlated with parental income. In contrast. fixed-effects models net out its effect but do not allow us to estimate its impact (the effect of $ln(xtirc\_p_j)$ would be sucked into the individual fixed-effect parameter alongside with the rest of person-invariant attributes).

More importantly, we use mixed-effect models to answer our research question: does the effect of age on income (age-income slope) varies across individuals based on their level of parental income. If we assumed that the effect of age varied randomly across individuals, then we would do the same as with the intercept and replicate our approach in Equation 2, yielding:

$$\beta_{1j} = \gamma_{10j} + u_{1j} \tag{6}$$

And complexifying the overall specification as the random-intercept, random-slope specification:

$$ln\left(xtirc_{c_{ij}}\right) = \gamma_{00} + (\gamma_{10j} + u_{1j})age_{ij} + \gamma_{01}\,ln\left(xtirc_{p_j}\right) + u_{0j} + e_{ij} \tag{7}$$
$$= \gamma_{00} + \gamma_{10j}age_{ij} + u_{1j}age_{ij} + \gamma_{01}\,ln\left(xtirc_{p_j}\right) + u_{0j} + e_{ij}$$

This means we assume that the error term in equation 5 was correlated with age, and that, from equation 1:

$$\epsilon_i = u_{0j} + u_{1j}age_{ij} + e_{ij}$$

So the random-slope specification also unbiases the error term.

However, we make a stronger hypothesis. We claim that the effect of age may vary not only randomly according to individual fixed-effects. In fact, we assume that the effect of age varies by parental income status. The mixed-effects model can now be expressed this way:

$$\beta_{1j} = \gamma_{10} + \gamma_{11}ln\left(xtirc_{p_j}\right) + u_{1j} \tag{8}$$

And the overall specification as the random-intercept, random-slope specification this way:

$$ln\left(xtirc_{c_{ij}}\right) = \gamma_{00} + \left(\gamma_{10} + \gamma_{11}ln\left(xtirc_{p_j}\right) + u_{1j}\right)age_{ij} + \gamma_{01}ln\left(xtirc_{p_j}\right) + u_{0j} + e_{ij} \tag{9}$$
$$= \gamma_{00} + \gamma_{10}age_{ij} + \gamma_{11}ln\left(xtirc_{p_j}\right) \times age_{ij} + u_{1j}age_{ij} + \gamma_{01}ln\left(xtirc_{p_j}\right) + u_{0j} + e_{ij}$$

If we re-order the terms, we get:

$$= \gamma_{00} + \gamma_{10} age_{ij} + \gamma_{01} ln\left(xtirc_{p_j}\right) + \gamma_{11} ln\left(xtirc_{p_j}\right) \times age_{ij} + u_{1j} age_{ij} + u_{0j} + e_{ij}$$

Here, $y_{10}$ is an estimate of the relationship between age and child income (age-income slope), and $y_{01}$ is an estimate of the relationship between parental income and child income generally found in models of intergenerational income transmission based on log-log elasticities (Becker; Solon; Corak & Heisz 1999). A positive log-log coefficient can be interpreted as an association between parental and child income where children with higher income parents have a higher level of income on average than children of lower-income parents.

Finally, $y_{11}$ is a cross-level interaction coefficient that captures the variation in the age-income slope by parental income level. A positive coefficient means that the rate of income growth over age is stronger for children of higher income parents. This can be interpreted as an increase in inequality based on parental income over the life course.

The role of life course variables in explaining the association between parental and child income

Next, we ask: how does the age-income profile vary by level of education? Does this account for the association between parental and child income as well as the difference in the steepness of age-incomes slopes between children with different levels of parental income?

We do so by adding a new term at the person-level (2nd level) for education, yielding the following equations:

$$\beta_{0j} = \gamma_{00} + \gamma_{01} ln(xtirc\_p_j) + \gamma_{02} educ_j + u_{0j} \tag{10}$$

$$\beta_{1j} = \gamma_{10} + \gamma_{11} ln\left(xtirc_{p_j}\right) + \gamma_{12} educ_j + u_{1j} \tag{11}$$

$$ln\left(xtirc_{c_{ij}}\right) = \gamma_{00} + \left(\gamma_{10} + \gamma_{11} ln\left(xtirc_{p_j}\right) + \gamma_{12} educ_j + u_{1j}\right) age_{ij} + \gamma_{01} ln\left(xtirc_{p_j}\right) + \gamma_{02} educ_j + u_{0j} + e_{ij} \tag{12}$$

Here, the new specification lets the intercept and the slope for age vary by education in addition to parental income. Accordingly, $y_{12}$ is another cross-level interaction coefficient. If education is correlated with child income, with parental income, and with the interaction between age and parental income, the estimates for $y_{11}$ and $y_{01}$ will decrease. In other words, a decrease in would mean that any difference in the steepness of age-income slopes by parental income is driven by the fact that children with parents of a given income level experience a specific rate of income growth over time due to their overrepresentation in a specific educational attainment category (to the extent that we do find a significant coefficient for $y_{12}$, that is, a difference in the steepness of the age-income slopes by educational attainment). The size of the change in $y_{11}$ is a quantification of the mediating role of that association (here, mediating in a non-causal sense).

Finally, person-year independent variables (level 1) can also be introduced in the model, such as our variables for labour force attachment and the age of the oldest child. Their impact on can be interpreted the same way.

## *Varying age-income slopes by gender*

For analyses by gender, we estimate a model with interaction terms between gender (binary variable) and age, gender and parental income, and a three-way interaction between gender, age and parental income:

$$\begin{aligned} ln(xtirc\_c_{ij}) = {} & \gamma_{00} + \gamma_{10} age_{ij} + \gamma_{01} ln(xtirc_{pj}) + \gamma_{02} sex + \gamma_{11} ln(xtirc_{pj}) \times age_{ij} \\ & + \gamma_{13} ln(xtirc_{pj}) \times sex_{cj} + \gamma_{14} age_{ij} \times sex_{cj} + \gamma_{15} ln(xtirc_{pj}) \times age_{ij} \times sex_{cj} \\ & + u_{1j} age_{ij} + u_{0j} + e_{ij} \end{aligned} \tag{13}$$