Parental Education Mitigates the Rising Transmission of Income between Generations

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February 19, 2020: Draft, please do not cite or circulate.

Abstract

This article provides evidence on the causal relationship between maternal education and the intergenerational transmission of income. Using a novel linkage between intergenerational income tax data and Census data for individuals born between 1963 and 1985 and their parents, we show that rank mobility has decreased over time, and that this decline was sharpest for children of mothers without a high school diploma. Using variation in compulsory schooling laws, we show that rank mobility increases as the percentage of mothers with a high school diploma increases. We find weaker evidence that mobility increases with the percentage of mothers with a university degree.

JEL codes: J62, D63

Keywords: social mobility, intergenerational income transmission, income inequality, education, Canada

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1 Introduction

Understanding and ensuring equality of opportunity is a priority for many public policy decision makers and citizens alike. The potential mechanisms through which income is transmitted across generations are many. Identifying which of these factors matter most for equality of opportunity is key to designing public policies aimed at fostering intergenerational mobility.

Chetty et al. (2014a) and Corak (2017) show that intergenerational income mobility varies greatly across locations within the United States and Canada. These spatial differences in mobility tend to correlate strongly with segregation, income inequality, school quality, social capital, family stability, and educational attainment. Yet, it remains unclear whether these factors causally affect the degree of income transmission across generations, and therefore whether public policy can effectively promote equal access to economic opportunities.

To make progress on this question, we examine how aggregate education of the parents, more specifically the mothers, influences income rank mobility. To do so, we exploit plausibly exogenous variation in maternal education generated by changes in compulsory schooling laws over time across Canadian provinces. Children of different birth cohorts had mothers born in different years and thereby exposed to different laws. Similarly, the mothers of children born in the same calendar year but in different provinces faced different legal minimum schooling-leaving ages. In practice, we use policy variation over time and space in a two-stage least squares model that seeks to identify the impact of aggregate maternal education on income mobility.

We develop a novel data linkage between Canadian tax data and Census data. The tax data cover the universe of children born during a period spanning over 20 years, allowing us to track changes in income mobility over two decades with a high degree of precision. To identify the level of education of each parent in the data, tax files were matched with multiple waves of the Canadian Census. This allows us to calculate the average level of parental education each children was exposed to. We organize our empirical analyses in three parts.

First, we describe differences in intergenerational income mobility by level of parental education. On average, children of educated mothers attain higher incomes than children of less educated mothers at every point in the parental income distribution. In other words, parental education boosts children income ranks above and beyond what would be expected on the basis of parental income alone. This relative advantage is stronger in the bottom half of the income distribution.

Then, we characterize the evolution of mobility by level of education over 20 years. Mobility was greater for cohorts of children born in the early 1960s than for those born in the 1980s. This reduction in mobility was particularly pronounced for families with low education. A naive simulation exercise indicates that increases in average parental education over the study period have attenuated the observed reduction in relative mobility, which suggests that aggregate education may fuel relative intergenerational income mobility.

In the third part, we use changes in aggregate maternal education induced by compulsory schooling laws to estimate the causal effect of maternal education on relative income mobility. Increases in overall levels of education can affect mobility in several ways. First, increasing the supply of educated parents can reduce the returns to education in the parent generation, thereby partly closing the gap in parental financial resources between children of low- and high-education parents. It can also reduce the relative value of the human capital benefits children of educated parents enjoy above and beyond the extra financial resources. Finally, aggregate maternal education could directly modulate the importance of parental financial resources for children outcomes, conditional on individual parental education.

Our estimates reflect the impact that increasing maternal education has on the strength of the parent-child income transmission in society. In our setting, we isolate the local effect of changes in education induced by compulsory schooling laws. We find that a 1-percentage-point increase in the fraction of mothers with a high school diploma reduces the parent-child rank-rank slope (the intergenerational income correlation) by 3.2%, thus increasing socioeconomic mobility. There is less evidence of a causal impact of the fraction of mothers holding a bachelor degree. A decomposition analysis suggests that maternal education mostly affects mobility by shaping the strength of parent-child income link within education groups, rather than by decreasing the relative value of the benefits children of educated parents individually enjoy.

Our work builds upon a long line of research on intergenerational mobility in economics that trace its roots back to Becker and Tomes (1979, 1986) and Loury (1981); sociologists go even further back, with Blau and Duncan (1967), Featherman et al. (1975), Goldthorpe (1980), Goldthorpe and Hope (1974), and Sewell and Hauser (1975), contributions that focus on the intergenerational transmission of social status as proxied by occupational prestige. Parental education is also commonly used as a measure of social origins, by economists and sociologists alike (Blanden 2013; Bradbury et al. 2015; Bukodi and Goldthorpe 2013; Goldthorpe 2013).

The development of large longitudinal administrative data, particularly intergenerationnally-linked tax data, has placed the focus of recent literature on the intergenerational transmission of income, especially the correlation between parental income rank and child income rank (Chetty et al. 2014a). Chetty et al. (2014a) show that there are important differences within the United States in terms of rank mobility and the opportunities available to children from different socioeconomic backgrounds. Corak (2017) does the same for Canada, while Connolly et al. (2019a) highlight the fact that high-mobility and low-mobility areas exist in both countries, but that the population residing in low-mobility areas is much larger in the U.S., leading to much lower nationwide mobility rates. Another important finding is that mobility rates appear to be on decline when comparing successive birth cohorts, both in Canada (Connolly et al. 2019b) and in the U.S. (Chetty et al. 2017; Davis and Mazumder 2019), a decline that correlates with increasing income inequality. This correlation between high inequality and high intergenerational transmission rates, dubbed the "Great Gatsby Curve," has now been documented in a variety of settings, such as a cross-country, cross-sectional one (Corak 2013) or a within-country, over-time one (Connolly et al. 2019a). Yet the investigation of causal links between various factors or policies and intergenerational mobility is still an area that demands further research. Recent examples in this emergent line of research include Biasi (2019) and Rothstein (2019).

The previous studies tend to look at private outcomes, albeit some that are transmitted from parents to their children. Our contribution is more general, as we aim to estimate the overall impact of education on mobility. In this sense, both private and social returns are captured in our analysis. Broadly speaking, social returns to education should take such spillovers into account (Heckman et al. 2018). Spillovers from higher education can, for example, make plants more productive (Moretti 2004b) and increase wages, even when controlling for one's own education level (Moretti 2004a)– a finding however debated by Lange and Topel (2006), on the basis of a failure to account for endogeneity issues implied by a spatial equilibrium. Aryal et al. (2019) revisit the private/public returns to schooling question. They extend their model to take into account local spillovers and use variation induced by compulsory schooling laws in Norway to estimate a social return to schooling of 5%, and a private one of 7.2%. Other, non-pecuniary, benefits from compulsory schooling laws have also been found, such as less crime (Lochner and Moretti 2004), better health (Lleras-Muney 2005), lower rates of teen pregnancy (Black et al. 2005a), and better cognitive abilities later in life (Banks and Mazzonna 2012). Our approach encompasses both private and social returns, taking into account income for both children and parents, and the rank-rank relationship between the two generations.

We further contribute to a rich literature on the effect of compulsory schooling laws. Effects of such policies have been documented for different outcomes and in various settings (for a short review, see Lavecchia et al. 2016). The literature is particularly large for the United States (Acemoglu and Angrist 2000; Angrist and Krueger 1991; Oreopoulos et al. 2006; Stephens and Yang 2014, among others), though not confined to it. For example, Oreopoulos (2006) looks at the Canadian context, while Grenet (2013) studies such laws in the United Kingdom and France, and Pischke and Von Wachter (2008) focus on Germany. Compulsory schooling laws dictate a combination of school entry and minimum school leaving ages, thereby forcing or giving incentives to people from the lower part of the educational attainment distribution to stay in school longer than they otherwise would. The first-order effect of such laws is thus to increase schooling of the individuals subject to them, which in turn raises their earnings (Acemoglu and Angrist 2000; Angrist and Krueger

1991; Oreopoulos 2006).[1] Intergenerational effects are also identified using compulsory schooling laws: Oreopoulos et al. (2006) find that increased parental education reduces the probability that a child repeats a grade, whereas Black et al. (2005b) find that a mother's education affects the educational attainment of their sons but not their daughters.

The remainder of this paper is structured as follows. We first present the new data linkage we use, including descriptive statistics on intergenerational income transmission and the first part of our empirical analysis. We continue with the 2SLS methodology. We then offer a presentation of the findings, and a final section containing a conclusion. An appendix follows.

2 Linking the Intergenerational Income Database to Census data

A non-trivial challenge that researchers face when measuring mobility is the need to have data on two successive generations with measures of socioeconomic status and ideally, in the case of income, for a large number of years to get closer to the true permanent income and away from possible transitory shocks (Chen et al. 2017; Grawe 2006; Mazumder 2016). Until recently, mobility estimates for the U.S. were based mostly on survey data of limited sample sizes, such as the Panel Study of Income Dynamics (Corak 2004; Solon 1992). Recent work by Chetty et al. (2014a,b) uses administrative federal tax data in the U.S. to provide mobility estimates at a subnational level, the commuting zone, that would have previously been impossible with survey data. One drawback of tax data is the limited number of sociodemographic variables available on tax returns. This can be overcome by linking tax data to other sources, such as Census data. Chetty et al. (2019) does that, linking federal income tax returns to Census data and the American Community Survey, in order to study race and economic opportunity in the United States.

Most of the estimates on intergenerational income transmission in Canada are based on administrative tax files from Statistics Canada's Intergenerational Income Database (IID) (Chen et al. 2017; Corak and Heisz 1999). The IID provides tax data for all Canadians born between 1963 and 1985 (except for those born in 1971, 1976 and 1981) and their parents from 1978 onwards. Several contributions have been made using these data (Chen et al. 2017; Connolly et al. 2019a; Corak 2006; Corak and Heisz 1999; Grawe 2004, 2006; Oreopoulos 2003; Oreopoulos et al. 2008, among

[1] Stephens and Yang (2014) question the robustness of the U.S.-based aforementioned studies, since effects are significantly smaller when allowing year-of-birth effects to vary across regions. However, Lavecchia et al. (2016) conclude that Stephens and Yang's study "suggests a need for additional research to determine whether these laws really did generate large returns." For instance, it is likely the case that the impact of compulsory schooling laws are gradual, in which case trends over-adjust for time-varying effects (Goodman-Bacon 2018). We examine the validity of this research design in the Canadian context in Section 4.

others). The IID is based on Statistics Canada's T1 Family File[2] and contains detailed tax data on close to six million individuals filing their tax returns in Canada and their parents. Table 1 below presents the number of observations by birth cohort, where cohorts are labelled using the year of the match between children and their parents in the tax data.

[Insert Table 1 here.]

Tax files, however rich they are in terms of coverage, do not contain information on education. To identify parental education, this project relies on a new data linkage between the IID and Census data. Using this combined dataset, we are able to provide the first-ever detailed picture of the evolution of mobility across Canada by parental education level. In partnership with Statistics Canada, we have developed this new linkage that we call the IID+. Statistics Canada has, over recent years, been promoting a new approach to the generation of data, based on existing administrative data files that can be coupled with one another (and with other survey data) using keys that are generated from record IDs and stored in a key registry. This process, known as the Social Data Linkage Environment, opens up new possibilities, in this case by supplementing the IID with data from the Canadian Census of population. The Census contains information on the respondent's place of birth (down to the province), immigration status, and educational attainment, among others. One in five Canadians is asked to complete the so-called long-form Census, so the merge with the IID does not capture all individuals in the IID data. However, the link with the Census is attempted for multiple waves: the 1991, 1996, 2001, 2006, 2011,[3] and 2016 Censuses, each time trying to find a match with either the children or the parents of the IID. Depending on the birth cohort, we are able to find one of the parents in one of the six Censuses for 62% to 71% of the individuals present in the IID. Our overall match rate is 68 percent.

The differences in rank mobility measured using the IID or the IID+ are negligible. When child income is measured between the ages of 30 to 36, and parental income is measured when the child is 15 to 19 years old, the largest difference we observe on the rank-rank slope is 0.0043 in absolute value (less that 2% of the average value) and the smallest is 0.0003. If child income is instead measured between the ages of 27 to 31 inclusively, the largest difference is 0.0038 in absolute value and the smallest is 0.00035. Clearly, interpretation of results using the IID+ leads to extremely similar conclusions to those using the IID. The risk of bias from using the restricted sample, the IID+, for which information on the parents is available in one of the Censuses, is therefore minimal

[2] The T1 is the form that Canadians use to submit their annual tax return to the Canada Revenue Agency. The T1 Family File (T1FF) is a compilation of all T1 forms submitted each year in which family links between individuals have been identified by Statistics Canada.

[3] In 2011, the National Household Survey replaced the Census. Potential issues about representativeness of this survey do not affect the quality of our linkage.

when studying rank mobility. The IID+ thus consists of more than four million parent-child pairs, forming a nationally-representative sample of individuals born from 1963 to 1985.

From the IID, we have information on the child's year of birth and sex, the mother's year of birth, whether there are two parents in the family at the moment of the parent-child link or only a single parent, and the province of residence at the time of the link.[4] From the Census, we obtain information on the mother's educational attainment and the mother's province of birth. The detailed tax records allow us to compute various income measures pertaining to both the (adult) child and the parents. Our measures are all based on total before-tax income, as defined by the Canada Revenue Agency. Total income thus includes market income (income from all sources, including earnings, self-employment income, and investment income) and government transfers (including pensions, employment insurance benefits, and social assistance payments). Child income is measured as an average over a given number of years, all relative to the child's age. We compute the average annual total income when the child is between the ages of 25 and 29 (inclusively), 27 and 31, 30 and 34, and 30 and 36. We try different ages to be able to offer comparisons with other estimates in the literature and to test the sensitivity of our findings to the age band used. Our main results are based on child income measured between aged 30 and 36 to better capture lifetime income. However, since the youngest individuals in our data are observed only up until age 31 (birth year is 1985 and last tax year available is 2016), we also presents robustness checks using the different income measures stated above. We also base our parental income measure on total income, and we compute the average family income (the sum of both the mother's and the father's income). The choice of years over which to take this average can either be relative to the child's age or the mother's age. We do both, and compute average parental income when the child is aged 10 to 19 or 15 to 19, as well as when the mother is aged 40 to 49 or 45 to 49. In the main analysis, we use the percentile rank of the income variables, where percentile ranks are always computed within a given birth year of the child. We further restrict our sample by only keeping observations for which the average total income (of both the child and the parents) is greater than or equal to $500, a standard practice in the literature using the IID.

[Insert Figure 1 here.]

Since our analysis relies on variation in maternal education across provinces and years of birth, we need to exclude from our analysis parent-child pairs in which the mother is not born in Canada. As a first descriptive tool, Figure 1 shows the evolution of the intergenerational rank mobility coefficient (β) by year of birth of the child for three samples: our complete sample (of linked IID-Census

[4] The parent-child pairs in the IID are identified when the child is between 16 to 19 years old, so the time of the link corresponds to the child's late teenage years. See Corak and Heisz (1999), Chen et al. (2017) or Connolly et al. (2019a) for more on the construction of the IID and the parent-child linkages in the Canadian tax files.

data), the subsamble of children of immigrant mothers, and the subsample of Canadian-born mothers. In previous analyses based on the IID, children of immigrants could not be distinguished from those of Canadian-born parents, so the series represented by the blue circles is the one that most closely resembles previous estimates, for example those of Connolly et al. (2019b). The gradual rise in the intergenerational rank correlation–thus the decrease in mobility–is apparent, with a particularly steep increase between the children born in the late sixties and those of the mid seventies. The red squares pertain to children of immigrants. While all series follow a similar trend over time, it is clear that the children of immigrants have much higher rates of intergenerational mobility, with β coefficients just above 0.2 for the latest cohort of children, compared to 0.27 for the children of Canadian-born mothers. The green diamonds show the context in which our study is based: a sample of children from mothers born in Canada. Our current focus is on children of Canadian-born mothers because we are able to identify a credible source of exogenous variation for the education of their mothers. Studying the differential patterns between immigrant and non-immigrant mothers is the subject of a companion paper currently under work.

3 Individual Maternal Education and Children Income

We further split our sample of children of Canadian-born mothers by education level of the mother. We use three broad categories of educational attainment: the mother does not have a high school diploma, she has a high school diploma but no bachelor degree, or she has both a high school diploma and a bachelor degree. Figure 2 focuses on the children of Canadian-born mothers (the green diamonds of Figure 1) and shows the progression of the rank-rank correlation by education of the mother. Again, all three series follow a similar pattern of increase over time, but the rise is much more pronounced for parent-child pairs in which the mother has no high school diploma. This group consistently displays higher rank-rank correlations, meaning lower intergenerational mobility, relative to children of mothers with a high school degree. By the mid seventies, this difference is also significant relative to children of mothers with a bachelor degree.

[Insert Figure 2 here.]

Maternal Education Over Time Table 2 presents descriptive statistics on the parent-child pairs in our sample.[5] Just under 16% of our parent-child pairs consist of a single mother and a child. The average mother's age at child birth is 26.6. Three quarters of the mothers have at least

[5]Additional statistics can be found in Appendix Table B1.

a high school diploma, and 10.6% have also a bachelor degree in addition to a high school diploma.

[Insert Table 2 here.]

Table 3 shows that mothers' educational attainment has increased over time. We can see that 40% of children born in 1963 have a mother with no high school diploma, a percentage that drops to 24% by the midpoint of our sample period (1974), and to 15% for the 1985 birth cohort. Correspondingly, the percentage of children whose mother has high school qualifications but no postsecondary degree goes from 54% to 70% over the same time period, while the figures for mothers with a bachelor degree or more have gone from 6% to 15%. Clearly, mothers over our observation period increased their education level: the percentage of mothers with only a high school degree increased by 16 percentage points and the percentage with at least a bachelor degree by 9 percentage points.

[Insert Table 3 here.]

Mobility by Education Group Mothers of children born in 1963 were themselves born between 1913 and 1949. Twenty-two years later, the mothers' years of birth span from 1935 to 1971. The average maternal age at child birth for the kids in our sample has not changed drastically between the 1963 and the 1985 birth cohorts, going from 26.5 to 27.7. It is worth noting here that we consider all children born in those years, not just those that were the first borns. Thus even if a mother's age at first child birth might be trending upwards, average age for a given child birth has not seen the same increase. The first half of the twentieth century was a period of rising education (Oreopoulos 2006), a phenomenon that is reflected in our data. Going back to Figure 2, the mobility of children with a low-educated mother has clearly gone down (the blue circles), but the proportion of children that this category represents has also dropped by more than half. Figure 2 shows that the variance in the point estimates for beta of mothers with a bachelor degree decreases over time (the confidence intervals get narrower); this is in line with the increase in the proportion of mothers with a bachelor degree.

Table 4 presents quintile transition matrices for three birth cohorts, situated at the beginning, the middle, and the end of our sample, separately by the mother's education category. The distribution of the education categories within a birth cohort are given just above the matrices themselves as a reminder. The probability to remain in the bottom quintile for children of parents who were themselves in the bottom quintile has increased in families with mothers who do not have a high school diploma (top panel). It starts at 33%, and increases to 39% in 1974 then to

42% in 1985, for an overall increase of 9 percentage points. The probability they reach the third or fourth quintile of the income distribution has also declined over the period. The overall weight of this group has decreased over time since mothers are becoming more educated, but their mobility has clearly decreased, and this decline is in part due to the fact that these children are increasingly trapped at the bottom of the income distribution and unable to reach higher rungs of the income distribution. For children of mothers with a high school diploma only (middle panel) and children of mothers with at least a bachelor degree (bottom panel), we also observe an increasing stickiness at the bottom, from 26% to 32%, and from 27% to 37%, respectively. The increases are also large. Overall stickiness at the bottom is increasing, but it is largest for mothers without a high school diploma. For children of highly educated mothers, the probability to remain at the top of the ladder has declined over the period. This has contributed to an increase in mobility of that group. The overall weight of the group is smaller, but its share is increasing over time as mothers gain education.

[Insert Table 4 here.]

To continue our descriptive presentation of the data, we present in Figure 3 a series of binned scatterplots, where each dot is the mean child percentile rank for a given parental income rank. A linear fit going through those dots thus represents the rank-rank relationship. There are three panels, one for each broad maternal education group, and each panel has two series: one for the 1963 to 1966 birth cohorts combined (the gray triangles) and one for the 1982 to 1985 birth cohorts (the blue circles). We see that the decline in mobility–the increase in the rank-rank slope–stems from low child ranks for the bottom quintile of the parental income distribution: the blue circles are clearly below the gray triangles up until about parental income rank 20.

[Insert Figure 3 here.]

Figure 4 shows binned scatter plots of children mean income rank against parental income rank, separately by level of education. The size of the symbols represents the relative number of observations in each cell within educational categories. Private returns to education (for parents) are large: the mass is dramatically shifted to the right for college-educated parents, and somewhat to the left for parents with no high school diploma in 1963-66. In the later cohorts (1982-85), the weight is more evenly distributed for college-educated parents given large increases in the number of people completing bachelor degrees. In contrast, the income distribution of parents with no high school diploma is concentrated at lower income ranks.

[Insert Figure 4 here.]

In both periods, average income ranks of children of educated parents lie above those from lesser educated families throughout the entire income distribution. Children benefit from their parents' human capital directly, above and beyond what would be expected on the basis of parental financial resources alone.

The overall decrease in relative income mobility between 1963-66 and 1982-85 is largely accounted for by changes in rank-rank slopes *within* education groups. Appendix Figure A1 shows that the rank-rank slope conditional on education dummies increases sharply over time, from 0.203 to 0.249, a 23% increase. To put this in perspective, the unconditional rank-rank slope for the whole population increased from 0.229 to 0.270, a 18% increase. This implies that observed changes in the private intergenerational returns to education and in the fraction of educated parents helped attenuate the overall decrease in relative mobility over time. Appendix Figures A2 and A3 show the variation over time in the private returns to education (the average difference in parental income ranks between education groups) and in the intergenerational benefits associated with greater human capital, conditional on parental income (the vertical distance between series for different education groups).

Composition Changes and Mobility The left panel of Figure 5 shows the rank-rank relationship in the Canadian population as a whole, separately for children born in 1963-66 and those born in 1982-85. As a first pass to illustrate the mechanical association between maternal education and intergenerational mobility, we compute a counterfactual series for the 1982 to 1985 birth cohorts. To get to this counterfactual, we take the educational attainment distribution of the mothers of the 1963-66 birth cohorts, and apply those weights to the education-specific child income percentiles of the 1982-85 cohorts. In other words, the counterfactual shows us what the rank-rank relationship may have looked like for the 1982-85 birth cohorts if maternal education had stayed at the 1963-66 levels.[6]

The counterfactual distribution is shown by red plusses. We see that the deviations from the true distribution are more pronounced in the bottom half of the parental income distribution, such that the slope of the counterfactual relationship is higher than the actual value: 0.281 compared to 0.27. Our conclusion from this exercise is that the increases in education brought forward a decrease in the rank-rank slope of 0.011, and that the decline in socioeconomic mobility would have been larger had parental education not exerted a downward pressure on the rank-rank slope. This naive simulation exercise is informative and suggestive, but falls short of identifying causal

[6] One caveat to keep in mind is that under this naive accounting method the number of children in each percentile of the income distribution need not be equal across percentiles

links. For that, we turn to our main empirical strategy, which we discuss in the next section.

[Insert Figure 5 here.]

4 The Causal Effect of Aggregate Maternal Education on Relative Mobility

As in Connolly et al. (2019a) and Chetty et al. (2014a), we measure intergenerational mobility using a rank-rank specification. More specifically, we write child i's income rank in her cohort-specific distribution as a function of her parents' income rank in their cohort-specific distribution. Our research design relies on temporal and spatial variation across provinces. We therefore allow the rank-rank relationship to vary flexibly across province-by-birth-cohort cells:

$$y_{ipct} = \alpha_{pc} + \beta_{pc} x_{ipct} + \epsilon_{ipct} \tag{1}$$

where y_{ipct} is the child's income rank and x_{ipct} is parental income rank, p denotes the province of residence, c the birth cohort of the child, and t the mother's year of birth. As is customary in the literature, we refer to α_{pc} as *absolute* mobility, and to β_{pc} as *relative* mobility.

Our interest is mainly in explaining variation in β_{pc}. In our data, we observe 10 provinces and 20 birth cohorts, and therefore recover 200 estimates of β_{pc}. We plot these coefficient estimates in Figure A4.[7] Relative mobility decreases across the board over the two decades we consider, but does so at different rates across provinces. For instance, Alberta and Saskatchewan saw large increases in β_{pc} between 1963 and 1985 – from 0.17 to 0.3 and from 0.17 to 0.27, respectively – whereas β_{pc} increased by 0.02 points, from 0.27 to 0.29, in Newfoundland and Labrador. There is also substantial cross-sectional variation, with Manitoba exhibiting the lowest rates of relative mobility in the country over the entire period. The two sources of variation – over time and across provinces – are quantitatively important. Average differences across provinces account for 50% of the variance of β_{pc}, and average differences across birth cohorts account for 30%.

Econometric specification With estimates of β_{pc} in hand, we then examine the relationship between relative mobility and aggregate parental education:

$$\beta_{pc} = \Theta \bar{e}_{pc} + \mathbf{\Gamma} \boldsymbol{X}_{pc} + \upsilon_{pc} \tag{2}$$

[7] See also Connolly et al. (2019b) for a detailed paper documenting changes in mobility over the same time period.

where Θ captures the relationship between mobility and aggregate education $\bar{e}_{pc} = \frac{\sum e_{ipct}}{N_{pc}}$, and e_{ipct} is the education of child i's mother. We further include a set of control variables $\boldsymbol{X}_{pc}$, notably cohort and province fixed effects. Numerous omitted factors that correlate with education and mobility may bias the estimated coefficient. Hence, we develop an instrumental variable strategy leveraging temporal and geographic differences in compulsory education laws, similar to Acemoglu and Angrist (2000). Legal school-entry age and school-leaving age for the parent generation, CL_{pt}, vary across provinces p and mothers' years of birth t.[8] Note that children of a given cohort are born to mothers born in different years and therefore subject to different laws. To accommodate this feature, we estimate the relationship between β_{pc} and $\bar{e}_{pc}$ directly in the microdata and use the following two-stage least squares (2SLS) specification:

$$\beta_{pc} = \Theta^{2SLS}\bar{e}_{pc} + \boldsymbol{\Gamma}\boldsymbol{X}_{pc} + \upsilon_{iptc} \tag{3}$$

$$\bar{e}_{pc} = \theta CL_{pt} + \boldsymbol{\chi}\boldsymbol{X}_{pc} + u_{ipct} \tag{4}$$

where $\boldsymbol{X}_{pc}$ includes full sets of fixed effects for provinces p, child birth cohort c, and mother birth year t. The first-stage equation is a difference-in-differences specification with variation in treatment intensity and treatment timing.[9]

One possible issue with this specification is that the year of birth of the child, which is implicitly a function of the mother's age at birth once we condition on mother's year of birth, is itself an outcome of changes in compulsory schooling laws. We therefore also report results for alternative models in which these children birth-cohort fixed effects are omitted.

Results We begin with a visualization of the relationship between relative rank mobility β_{pc} and average mother's education. Figure 6 plots residual mobility against residual parental education. To generate this binned scatter plot, we first residualize all variables on province and birth-cohort fixed effects. The number of bins is selected via the method developed by Cattaneo et al. (2019). While a negative relationship between the fraction of mothers holding a high school diploma and the rank-rank measure is clearly apparent, there is much less of an association with the fraction of mothers holding a bachelor degree.

Main results on the causal effect of aggregate maternal education on relative mobility are presented in Table 5. Throughout, standard errors are clustered two-way at the mother year-of-birth level and the mother province-of-birth level to account for serial correlation. Column (1) reports OLS results from a specification that only includes province and birth-cohort fixed effects

[8] Appendix Figure A5, reproduced from Oreopoulos (2006), shows the variation in the sets of compulsory schooling laws over the time period when the parents in our data are of schooling age.

[9] This approach is numerically equivalent to first estimating the effect of schooling laws on individual education, $e_{ipct} = \theta CL_{pt} + \boldsymbol{\chi}\boldsymbol{X}_{pc} + u_{ipct}$, and then using the fitted values from that first-step as instruments for $\bar{e}_{pc}$.

as controls. These estimates correspond to the relationship shown in Figure 6. The point estimates imply that a 1-percentage-point increase in the share of high school graduates among mothers is associated with a 0.006 point reduction in the rank-rank income relationship (a 2.3% decrease at the mean). This relationship is statistically significant at conventional levels. Consistent with the visual evidence, the coefficient on the share of mothers with a bachelor degree is small and statistically insignificant (-0.0027, s.e. 0.0037). In column (2), we add fixed effects for the mother's year of birth, a conditioning variable that is essential for the validity of instrument, but which turns out to have little impact on our point estimates. We additionally control for the child's gender and for an indicator of single parenthood.

Columns (3) through (8) report 2SLS results for a variety of econometric specifications. In columns (3) to (5) we parameterize CL_{pt} using legal instruction time dummies (7 years, 8 years, 9 years, 10 years, and less than 7 years the omitted variable). In columns (6) to (8) we instead use legal entry age dummies (6 years old, 7 years old, 8 years old, more than 6 the omitted variable) with legal dropout age dummies (14 years old, 15 years old, 16 years old, less than 14 the omitted variable). The effect of high school education on mobility is large, varying between -0.008 and -0.012, and is always precisely estimated. The in-sample standard deviation in the fraction of mothers with a high school diploma is 10 percentage points. The point estimates therefore imply that a 1 standard deviation increase in high school education increases relative mobility of about 0.08-0.12 point, roughly equivalent to a move from the 10th to the 90th percentile of the unconditional distribution of β_{pc}. Alternatively, a 1-percentage-point increase in the share of high school graduates among mothers raises mobility by 3.2% relative to the mean. We also find some evidence of a positive, albeit much weaker, relationship between college education and relative mobility. Including provincial linear time trend (columns (5) and (8)) does not change our estimates which suggest that our instrumental variable strategy is robust to this alternative specification.

[Insert Table 5 here.]

To verify the validity of these results, we present in Table 6 estimates of the first-stage relationships between compulsory schooling laws and average maternal education. Odd numbered columns show first-stage results for the fraction of mothers with a high school diploma, and even numbered columns show corresponding estimates for the fraction of mothers holding a bachelor degree. In columns (1) to (4), we use legal entry age and legal dropout age dummies, while in columns (5) to (8), we use legal instruction time dummies. In all specifications, year-of-birth fixed effects and province-of-match fixed effects are included. Other characteristics, such as maternal year of birth, are included in columns (3), (4), (7), and (8). Therefore, first stage estimates presented in columns (1) and (2), and in columns (3) and (4), correspond to 2SLS results shown in of columns (6) and

(7) of Table 5, respectively. As can be seen, legal entry age and legal dropout age significantly predict the percentage of mothers with a high school diploma, in both columns (1) and (3). The effect on maternal bachelor percentage is less clear. The signs of the coefficients are opposite to what we would expect. The signs and magnitude are positive and increasing with dropout age and decreasing with entry age if only the year fixed effects or the province fixed effects are included. This suggests that the birth year and province fixed effects absorb most of the changes in the percentage of mothers with a bachelor degree. When legal instruction time dummies are used instead, we find similar results. The F-statistics range from 16.02 to 233.05 for the percentage with high school diploma, and from 15.2 to 41.88 for bachelor degree. It is sometimes missing; this is due to the small number of clusters we use to compute the standard errors. The F-statistics of the Sanderson-Windmeijer multivariate test, when estimated, support the idea that the instruments are more predictive of the high school percentage than the bachelor percentage. Both F-statistics are above 20 when we only cluster our standard errors on maternal year of birth. We plan to estimate our model at a finer geographical level, this will increase our number of geographical clusters.

Our results are robust to a variety of changes. Using different measures of children income rank and/or parental income rank does not change our results (Appendix Table B2. The coefficient on the percentage of mothers with a high school degree is always statistically significant and ranges from -0.007 to -0.014, while the one on the percentage of mothers with a bachelor degree ranges from -0.006 to -0.014, but this coefficient is never statistically different from zero when using instruction time dummies. We have used two sets of instrument dummies so far, but we can also have used our instruments linearly (column (3) of Appendix Table B3). Again, our main results continue to hold. The way in which we choose to cluster our standard errors matters. If we use two-way clusters, our standard errors are much larger than if we use group-level clusters. So far we have presented estimations using two-way clusters, with maternal province of birth and maternal year of birth. Two-way clusters using the children's year of birth and province of match produces similar standard errors (column (2) of Appendix Table B4). Using group-level clusters where a group is the interaction of maternal year and province of birth (column (3)) or child year of birth and province of match (column (4)) produces smaller standard errors. It is not clear at which level we should cluster. The number of provinces is small, which causes some issues. Using wild-cluster bootstrap will be our next step.

[Insert Table 6 here.]

5 Channels Linking Aggregate Maternal Education and Mobility

In this section, we examine whether differences in relative mobility tend to be due to differences in the intergenerational private returns to education, or to external effects that do not operate via the mechanisms that link individual parental education to individual children income.

For instance, consider a "long" regression of children income on parental income and parental education, as well as a Mincer equation for the parent generation that captures the returns to education:

$$y_{ipct} = a_{pc} + \lambda_{pc} x_{ipct} + \pi_{pc} e_{ipct} + \varepsilon_{1,ipct} \tag{5}$$

$$x_{ipct} = c_{pc} + r_{pc} e_{ijct} + \varepsilon_{2,ipct} \tag{6}$$

It can be shown that relative mobility β_{pc} is the sum of a term that reflects transmission of income that is unexplained by individual differences in education, and a term related to the returns to education:

$$\beta_{pc} = \lambda_{pc} + \pi_{pc} r_{pc} \frac{Var(e_{ipct})}{Var(x_{ipct})} = \lambda_{pc} + \pi_{pc} R_{pc} \tag{7}$$

where R_{pc} is the coefficient from the projection of e_{ipct} onto x_{ipct} (the "reverse" regression). The combined term $\pi_{pc} R_{pc}$ therefore captures variation in the private returns to education (π_{pc} and r_{pc}) as well as variation in educational attainment inequality via the variance of e_{ipct}.

As a first step, we decompose the variance of β_{pc} to examine whether differences in relative mobility are mostly due to how individual differences in parental education affect children outcomes ($\pi_{pc} R_{pc}$), or to differences in the conditional income rank-rank relationship (λ_{pc}). We find that a whopping 94% of the variance in β_{pc} is accounted for by variation in rank-rank slopes within education groups (λ_{pc}).[10] That is, differences in mobility across provinces and over time are largely due to differences in mobility conditional on individual maternal education. Changes in the intergenerational private returns to education account for less than 10% of the unconditional variation in β_{pc}.

[Insert Table 7 here.]

Then, we investigate through which channel the relationship between mobility β_{pc} and average education $\bar{e}_{pc}$ operates. We do so by putting λ_{pc}, $\pi_{pc,hs} R_{pc,hs}$, and $\pi_{pc,bacc} R_{pc,bacc}$ on the left-hand side in equation 3. Results are shown in Table 7. Columns (1) and (5) reproduce our main results of the effect of education on mobility β_{pc}, for two different methods of coding the instruments.

[10] Conditional on province and birth-cohort fixed effects, this percentage is 92.6%.

By construction, the coefficients reported in columns (2), (3) and (4) sum up to the "total" effect reported in column (1) because β_{pc} is equal to the sum of these three components. Interestingly, both levels of education are positively associated with relative mobility within education groups (negatively associated with λ_{pc}). However, the fraction of college-educated mothers is also positively associated with educational inequality and private returns to college education, $\pi_{pc,bacc}R_{pc,bacc}$. Naturally, since few mothers have a bachelor degree, any increase in the supply of college-educated mothers increases the variance in education attainment, and thereby tends to reduce mobility. In contrast, the effect of the supply of high-school-educated mothers on educational inequality and the private returns to a high school education, $\pi_{pc,hs}R_{pc,hs}$, reinforces its effect on λ_{pc}, resulting into a larger total effect on relative mobility. This follows from the fact that more than half the population has at least a high school diploma, so any increase in the supply of high-school-educated mothers decreases the variance in educational attainment.

To summarize, increases in education both at the high school and college level help increase mobility *within* education groups. That is, the income ranks of children born to more educated groups of mothers are less dependent on parental financial resources. But only high school education significantly affects *unconditional* income mobility. This is because the supply of college-educated mothers also affects educational inequality and private returns to education in a way that tends to reduce unconditional rank mobility.

6 Conclusion

Just as rising socioeconomic inequalities over the last few decades has garnered attention, so has now the increasing rate of transmission of those inequalities from one generation to the next. Across a variety of countries, settings, and measures, children from low socioeconomic backgrounds find it harder to move up the income distribution in adulthood. While the development of administrative data, in particular tax data, has allowed researchers to paint very detailed portraits of intergenerational mobility and its correlates, few studies have tackled causal mechanisms. Our research seeks to assess the causal role of aggregate parental education on the intergenerational correlation between parental income rank and child income rank. We leverage a novel data linkage and present informative descriptive evidence on the evolution of both rank mobility for cohorts for children born between 1963 and 1985 in Canada and the educational attainment of their mothers. We also exploit plausibly exogenous variation in maternal education coming from the variation over time and space of compulsory schooling laws to identify the causal effect of aggregate maternal education on relative mobility using a two-stage least squares estimation. We finally investigate the channels through which this causal effect might operate.

We focus on aggregate education and its link with rank mobility, and not on how more educated parents influence their children's outcomes, because we are interested in the aggregate effect on a society (encompassing both the private and the social returns to education). Our dependent variable is the rank-rank slope, which is inherently an aggregate measure: it characterizes the joint distribution of the parental and child income ranks. We find that the overall decrease in relative income mobility between the early sixties and the mid eighties is largely accounted for by changes in rank-rank slopes within maternal education groups. The group with the largest increase is the one with the lowest educational attainment: the rank-rank slope for parent-child pairs in which the mother does not even have a high school diploma has shot up, from 0.218 to 0.303. This is combined with the fact that aggregate maternal education has increased: the percentage of mothers without high school credentials has shrunk from 40% to 15%. Our IV estimates indicate that a 1-percentage-point increase in the share of high school graduates among mothers is associated with a 0.006 point reduction in the rank-rank income relationship (a 2.3% decrease at the mean). Our instruments have less bite on the percentage of mothers with a bachelor degree, and we refrain from over-interpreting the coefficients associated with this variable. Our results are robust to various specification changes, including changing how the instruments are used, the computation of the standard errors, or the income measures used.

Our results are informative in a historical perspective: the generations of parents in our data lived through a time of rapidly rising educational attainment, a consequence of which appears to be the mitigation of other forces driving up the intergenerational transmission of socioeconomic status. Yet our findings can be useful in other settings, including in developing countries which have yet to experience this rising tide of education, whether it is brought forward through compulsory schooling laws or other advancements. Our findings also turn the spotlight on a segment of the current population for whom the opportunities are ever more unequal than before: those who leave school without a high school diploma. Not only will their own labor market earnings reflect their low level of education, their children will also on average stay on lower rungs of the income distribution, even at equal parental income rank.

This leads us to conclude that policies aimed at increasing the educational attainment of today's youth should have the long-run consequence of improving the overall equality of opportunities. A high school diploma should be seen as a minimum level of education necessary to promote mobility. Policies that seek to boost school perseverance, particularly for children from low socioeconomic background, are probably key. Also linked to those are the upstream interventions that take place in early childhood, such as access to early childhood education, and especially high-quality early childhood education. Some of the gains of such education policies will be felt more quickly, and more privately, but our research suggests that there are also longer term and aggregate benefits for the society as whole.

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7 Figures

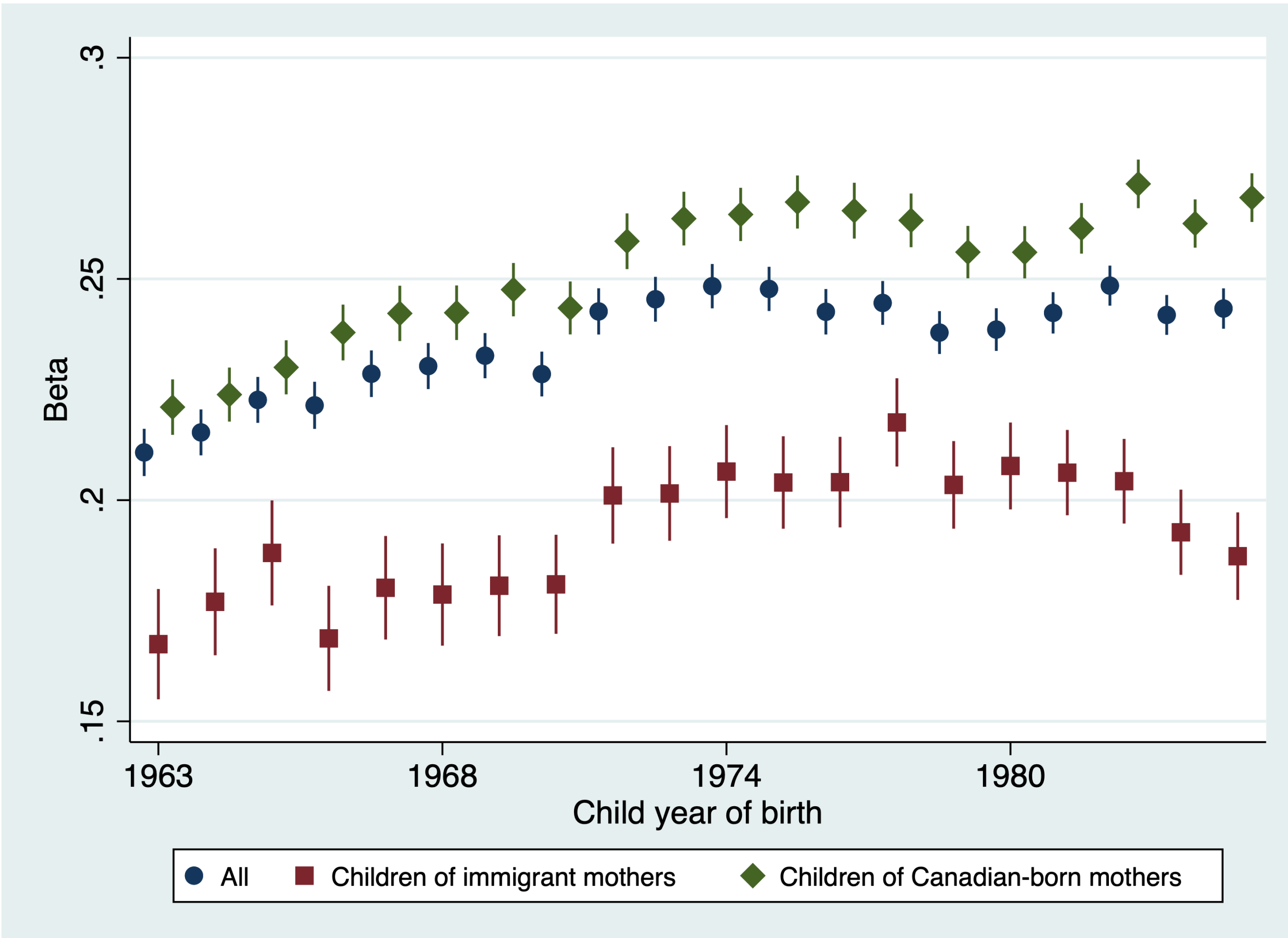

Figure 1: Intergenerational rank mobility by birth year and immigrant status of the mother

Source: Authors' calculations based on the IID+
Note: Each point in this graph represents the intergenerational rank mobility (β) estimated for a given child birth year, where child income is measured at ages 30 to 36 and parental income is average annual family income when the child is aged 15 to 19. The vertical bars denote 95% confidence intervals.

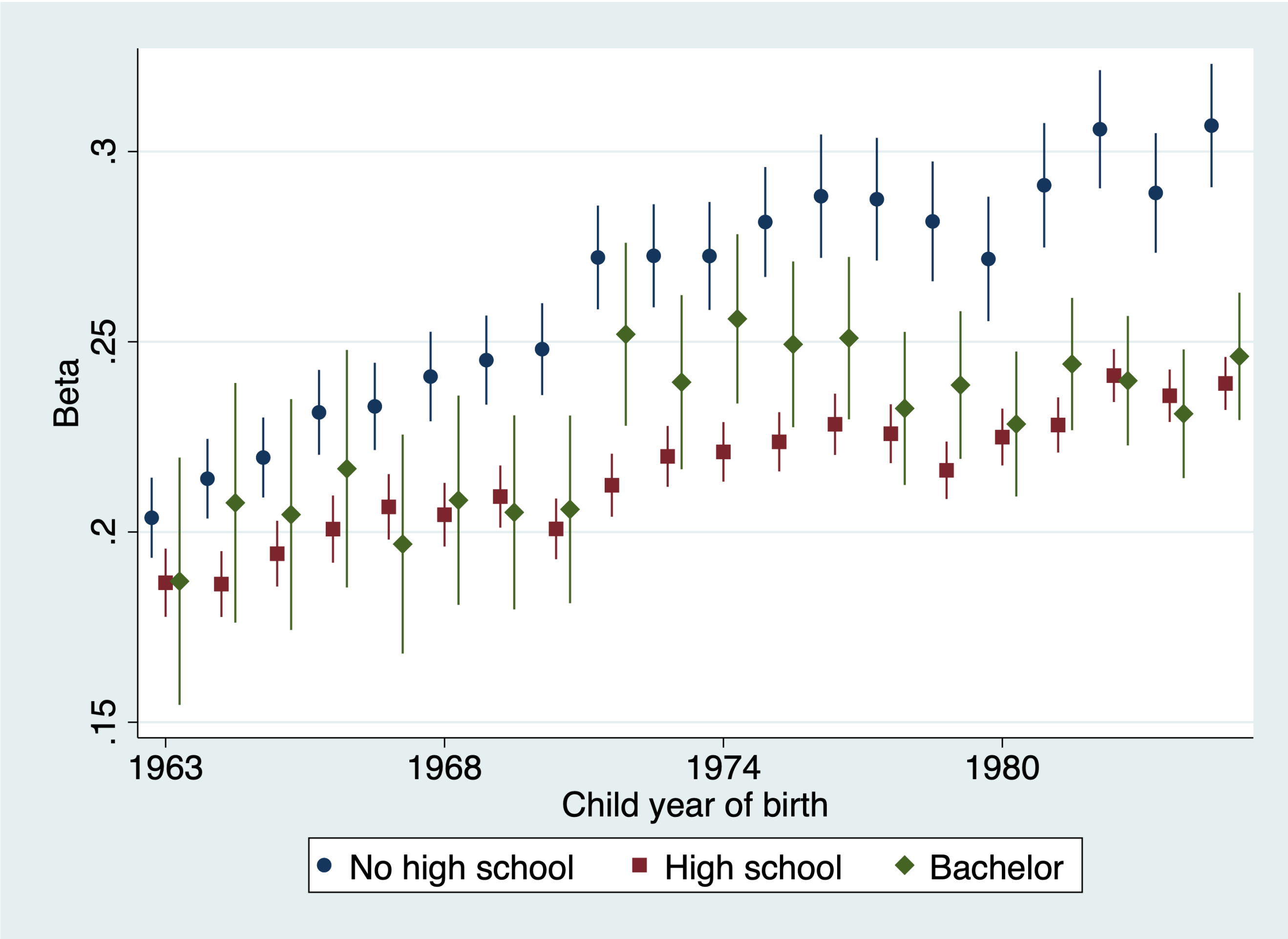

Figure 2: Intergenerational rank mobility by birth year and educational attainment of the mother

Source: Authors' calculations based on the IID+

Note: Each point in this graph represents the intergenerational rank mobility (β) estimated for a given child birth year, where child income is measured at ages 30 to 36 and parental income is average annual family income when the child is aged 15 to 19. The vertical bars denote 95% confidence intervals.

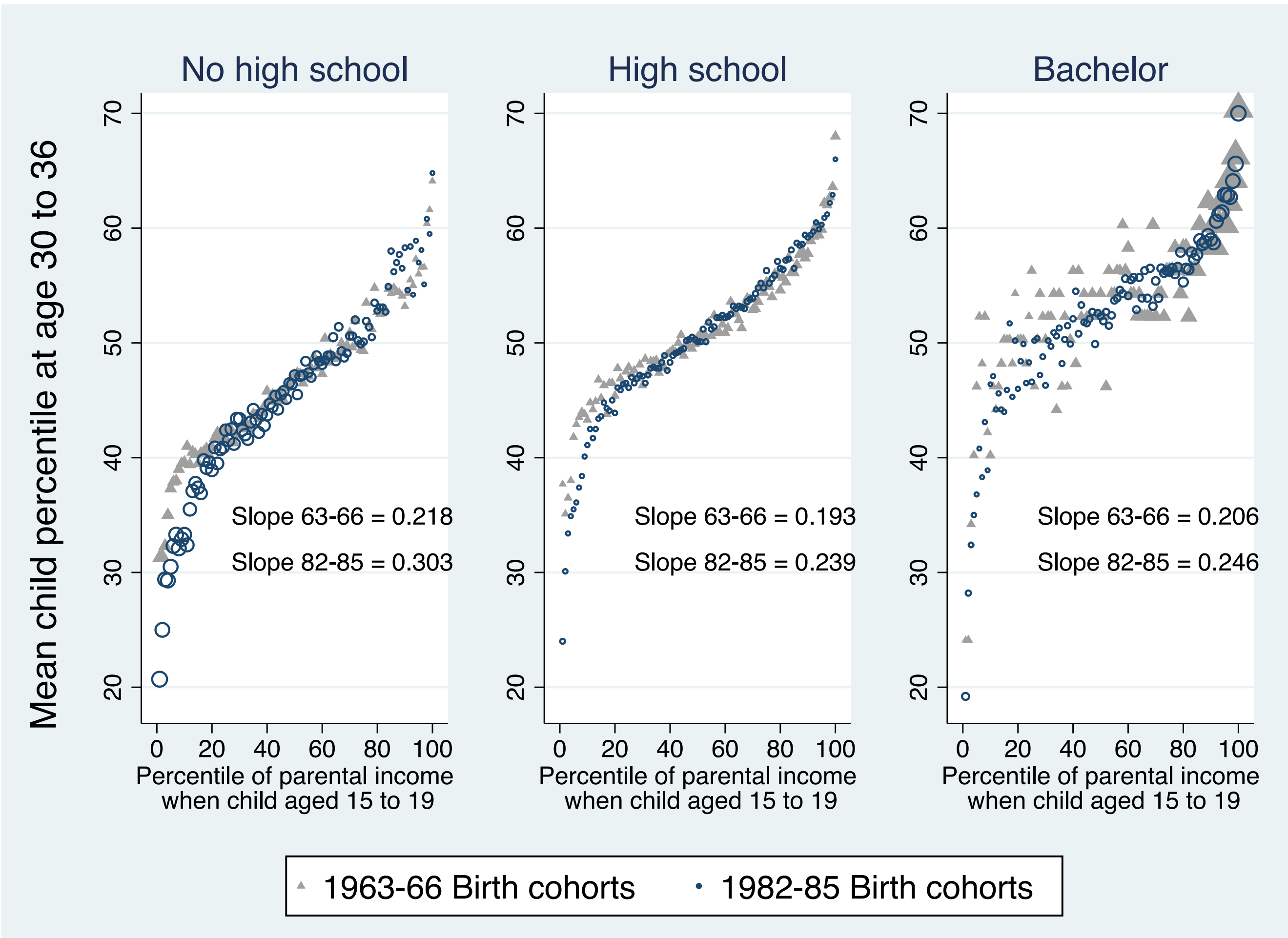

Figure 3: Intergenerational rank mobility by maternal education, 1963-66 and 1982-85 birth cohorts

Source: Authors' calculations based on the IID+

Note: Each point in this graph represents the mean child percentile rank for a given parental income rank, where child income is measured at ages 30 to 36 and parental income is average annual family income when the child is aged 15 to 19. The markers are weighed using the number of children. The slopes are from linear rank-rank regressions.

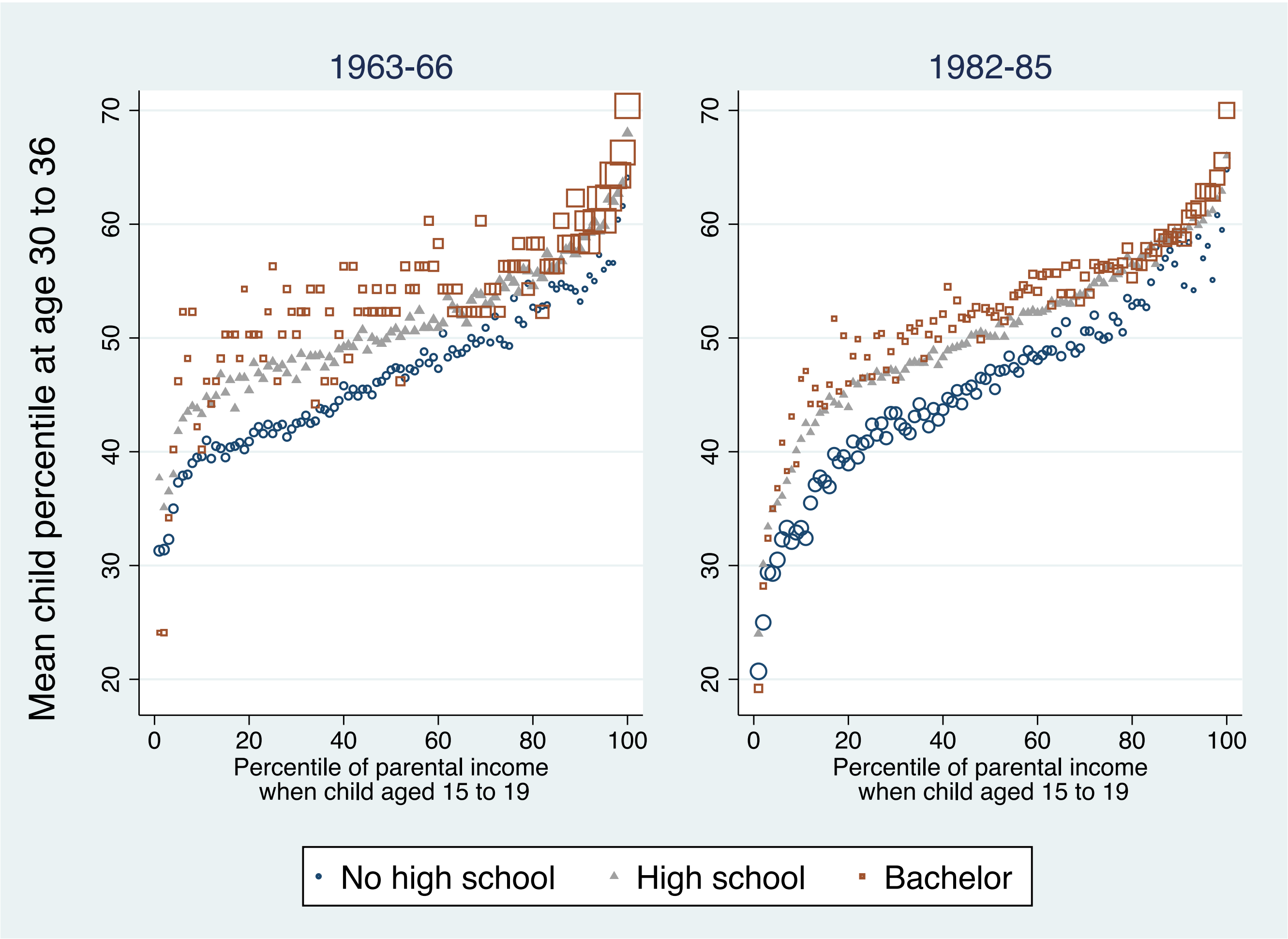

Figure 4: Intergenerational rank mobility by maternal education, 1963-66 and 1982-85 birth cohorts

Source: Authors' calculations based on the IID+
Note: Each point in this graph represents the mean child percentile rank for a given parental income rank, where child income is measured at ages 30 to 36 and parental income is average annual family income when the child is aged 15 to 19. The markers are weighed using the number of children. The slopes are from linear rank-rank regressions.

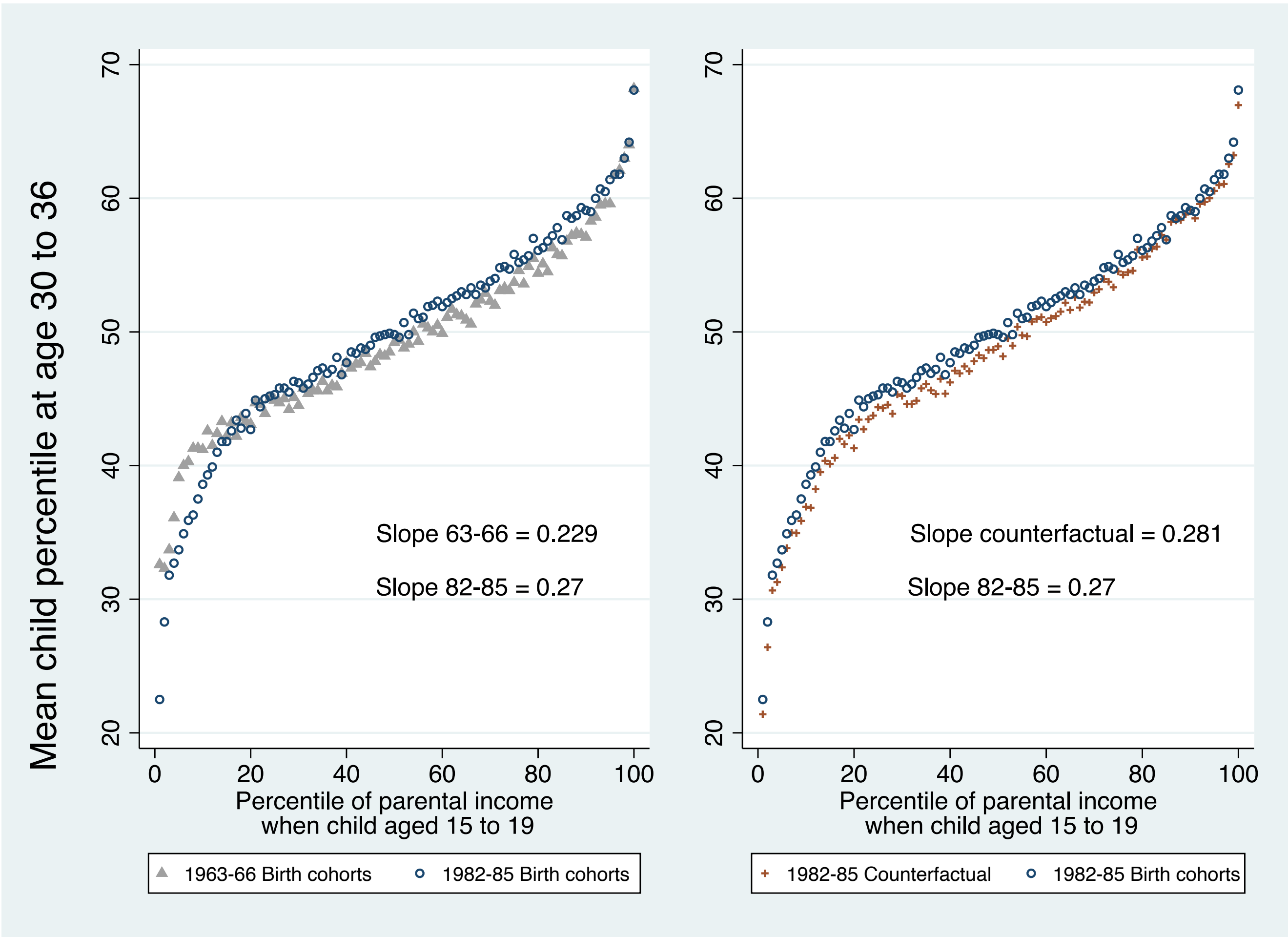

Figure 5: Intergenerational rank mobility, 1963-66 and 1982-85 birth cohorts and counterfactual

Source: Authors' calculations based on the IID+
Note: Each point in this graph represents the mean child percentile rank for a given parental income rank, where child income is measured at ages 30 to 36 and parental income is average annual family income when the child is aged 15 to 19. The slopes are from linear rank-rank regressions. The counterfactual is applying 1963-66 maternal education weights to compute the overall mean child percentiles using means by maternal education at 1982-85 levels.

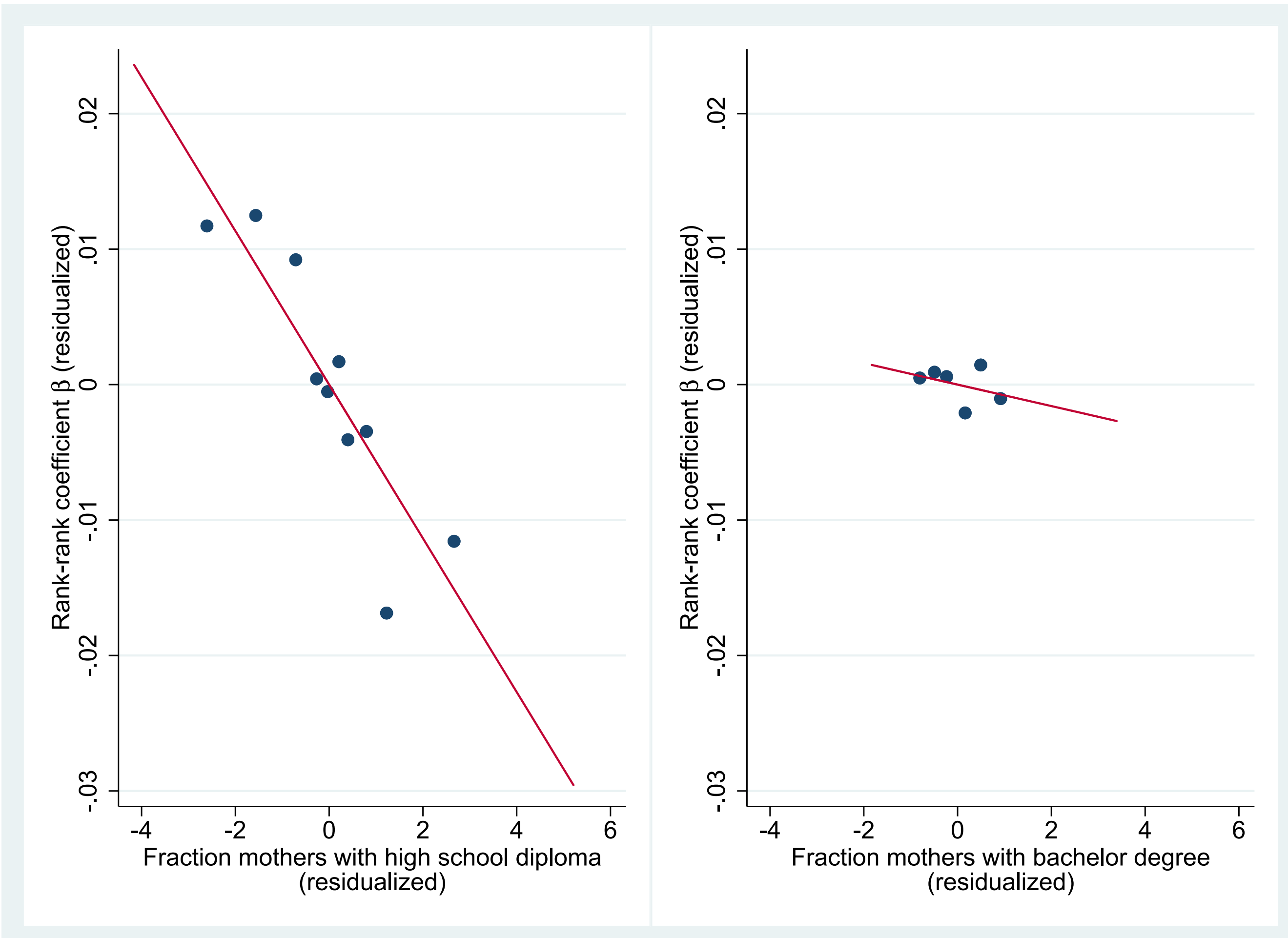

Figure 6: Intergenerational rank mobility and maternal education across time and space

Source: Authors' calculations based on the IID+
Note: This figure shows a binned scatter plot of a relative income mobility (β) at the province-by-birth cohort level, against the average education of mothers in each cell. Variables on both axes are first residualized from province and birth-cohort fixed effects. Bins are selected using the procedure proposed by Cattaneo et al. (2019) and implemented using the associated binsreg Stata command.

8 Tables

Table 1: Intergenerational Income Database Cohorts

IID cohort	Birth years	IID count	IID weighted count
1982-84	1963 to 1966	1,219,470	1,566,240
1984-86	1967 to 1970	1,158,900	1,555,280
1991	1972 to 1975	1,095,160	1,474,140
1996	1977 to 1980	1,166,440	1,557,800
2001	1982 to 1985	1,349,190	1,633,270

Source: Authors' calculations based on the IID
Note: This table shows the unweighted and weighted counts of children by IID cohort, as well as the years of birth. The IID cohorts are referred to using the year of the parent-child match in the tax files. The weighted count use the IID weights.

Table 2: Descriptive Statistics

Variable	Mean	Std. Dev.
Child is male	0.513	0.500
Child is female	0.487	0.500
Child total income (constant 2016 $)		
Ages 25 to 29	36,800	28,620
Ages 27 to 31	41,800	36,290
Ages 30 to 34	48,000	79,060
Ages 30 to 36	49,600	80,020
Parental total income (constant 2016 $)		
When child aged 15 to 19	89,500	119,880
When child aged 10 to 19	85,700	92,500
When mother aged 40 to 49	90,500	96,150
When mother aged 45 to 49	97,400	121,020
Single mother at time of IID link	0.157	0.363
Mother's age at birth	26.6	5.240
Mother's educational attainment		
Mother has a high school diploma	0.745	0.436
Mother has a bachelor degree	0.106	0.308

Source: Authors' calculations based on the IID+

Note: These statistics are computed using the IID weights. Weighted number of observations is 3,051,485. Some variables are based on a slightly smaller number of observations due to missing values.

Table 3: Maternal Education and Mother's Age at Birth by Child Birth Cohort

	Maternal educational attainment			
Birth cohort	No high school (%)	High school (%)	Bachelor (%)	Mother's age at birth
1963	40	54	6	26.5
1964	40	54	6	26.6
1965	39	55	6	26.5
1966	37	56	6	26.4
1967	35	58	7	26.2
1968	33	59	8	26.1
1969	32	60	8	26.2
1970	30	62	9	26.1
1972	26	64	10	26.1
1973	25	65	10	26.1
1974	24	66	10	26.1
1975	22	67	11	26.2
1977	20	68	12	26.6
1978	19	68	12	26.7
1979	19	69	13	26.8
1980	18	69	13	26.8
1982	16	69	15	27.2
1983	16	69	14	27.3
1984	16	70	15	27.4
1985	15	70	15	27.7
Variation 1963 to 1985	−25	+16	+9	+1.2

Source: Authors' calculations based on the IID+
Note: These statistics are computed using the IID weights. Weighted number of observations is 3,051,485.

Table 4: Transition Matrices, 1963 to 1985 Birth Cohorts

	Parental Income Quintile (when child aged 16 to 19)														
Child	1963 Birth Cohort					1974 Birth Cohort					1985 Birth Cohort				
quintile	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
Mother has no high school diploma and no bachelor degree															
% of cohort			40.4%					23.8%					15.1%		
1	0.33	0.25	0.22	0.20	0.16	0.39	0.26	0.22	0.19	0.18	0.42	0.25	0.21	0.19	0.15
2	0.25	0.25	0.23	0.20	0.19	0.26	0.27	0.24	0.20	0.17	0.25	0.27	0.25	0.23	0.16
3	0.20	0.22	0.22	0.21	0.18	0.16	0.21	0.23	0.23	0.19	0.15	0.22	0.21	0.21	0.20
4	0.14	0.17	0.19	0.21	0.22	0.11	0.15	0.18	0.20	0.20	0.10	0.15	0.19	0.19	0.21
5	0.08	0.11	0.14	0.18	0.25	0.08	0.10	0.14	0.18	0.26	0.07	0.11	0.14	0.17	0.28
Mother has a high school diploma but no bachelor degree															
% of cohort			53.6%					66.1%					70.3%		
1	0.26	0.22	0.19	0.17	0.14	0.31	0.21	0.19	0.15	0.13	0.32	0.21	0.17	0.15	0.12
2	0.23	0.22	0.21	0.18	0.15	0.23	0.24	0.21	0.18	0.15	0.24	0.23	0.22	0.19	0.15
3	0.21	0.21	0.21	0.20	0.18	0.19	0.21	0.22	0.21	0.19	0.17	0.21	0.23	0.22	0.19
4	0.17	0.20	0.20	0.22	0.22	0.15	0.19	0.21	0.24	0.23	0.14	0.19	0.21	0.23	0.24
5	0.13	0.16	0.19	0.22	0.30	0.12	0.15	0.17	0.21	0.29	0.12	0.15	0.17	0.21	0.29
Mother has a high school diploma and a bachelor degree															
% of cohort			6.1%					10.1%					14.7%		
1	0.27	0.19	0.15	0.17	0.13	0.38	0.18	0.18	0.15	0.12	0.37	0.21	0.18	0.17	0.13
2	0.18	0.18	0.20	0.17	0.14	0.17	0.21	0.18	0.17	0.14	0.20	0.22	0.19	0.16	0.14
3	0.16	0.19	0.16	0.19	0.16	0.19	0.21	0.21	0.18	0.16	0.14	0.18	0.20	0.20	0.17
4	0.19	0.25	0.26	0.20	0.21	0.12	0.20	0.22	0.25	0.23	0.15	0.20	0.22	0.23	0.24
5	0.20	0.20	0.22	0.27	0.36	0.14	0.20	0.22	0.25	0.35	0.14	0.19	0.21	0.23	0.32

Source: Authors' calculations based on the IID+

Note: The child income quintiles are based on average annual total income between the ages of 30 to 36 and are computed within a given birth cohort. Each cell shows the conditional probability for the child to be in a given income quintile given the income quintile of his or her parents. The percentages show the distribution of the educational attainment categories of the mother for a given birth cohort.

Table 5: Main Regression Estimates

Maternal education	OLS (1)	OLS (2)	IV (3)	IV (4)	IV (5)	IV (6)	IV (7)	IV (8)
Percent with high school diploma	-0.00584***	-0.00585***	-0.00829**	-0.00847**	-0.00768**	-0.0123***	-0.0124***	-0.0116***
	(0.00089)	(0.00090)	(0.00267)	(0.00287)	(0.00268)	(0.00337)	(0.00316)	(0.00279)
Percent with bachelor degree	-0.00272	-0.00273	-0.00790	-0.00777	-0.00756	-0.00766*	-0.00859*	-0.00705*
	(0.00365)	(0.00363)	(0.00634)	(0.00601)	(0.00661)	(0.00412)	(0.00395)	(0.00321)
Instruments								
Dummies legal instruction time	no	no	yes	yes	yes	no	no	no
Dummies legal dropout age	no	no	no	no	no	yes	yes	yes
Dummies legal entry age	no	no	no	no	no	yes	yes	yes
Two-way cluster								
Mother year of birth & mother province of birth	yes	yes	yes	yes	yes	yes	yes	yes
Fixed effects								
Child year of birth & province match	yes	yes	yes	yes	yes	yes	yes	yes
Mother age at birth & single family & child gender	no	yes	no	yes	yes	no	yes	yes
Robustness test of instruments								
Provincial linear time trend	no	no	no	no	yes	no	no	yes

Source: Authors' calculations based on the IID+

Note: The dependent variable is the rank-rank slope (β) estimated using child income at ages 30 to 36 and parental income when child is 15 to 19. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$. $N = 2,334,120$

Table 6: First Stage Estimates

Dependent variables: **percentage of mothers with high school diploma or bachelor degree**								
	High school	Bachelor	High school	Bachelor	High school	Bachelor	High school	Bachelor
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Legal entry age = 6	0.9525**	-0.1585	0.9279***	-0.313***				
	(0.4096)	(0.1219)	(0.3514)	(0.115)				
Legal entry age = 7	0.5032*	-0.2477	0.2326*	-0.2399				
	(0.289)	(0.1858)	(0.1327)	(0.1632)				
Legal entry age = 8	1.0604***	-0.6862***	0.7617	-0.9046***				
	(0.2778)	(0.108)	(0.4865)	(0.1821)				
Legal dropout age = 14	0.5877	0.0075	1.19812	0.0210				
	(0.447)	(0.0534)	(0.7642)	(0.1772)				
Legal dropout age = 15	1.8424***	-0.4583***	2.8768***	-0.5222**				
	(0.5335)	(0.1587)	(0.6474)	(0.2103)				
Legal dropout age = 16	0.7063	-0.3231	0.96301	-0.5583*				
	(0.655)	(0.217)	(0.8924)	(0.3204)				
Legal instruction time = 7					1.9242***	-0.5146***	2.6026***	-0.8175***
					(0.5951)	(0.1754)	(0.6138)	(0.2244)
Legal instruction time = 8					1.6332***	-0.3599***	2.3063***	-0.2732***
					(0.6354)	(0.1406)	(0.6804)	(0.0704)
Legal instruction time = 9					1.7561***	-0.7424***	2.3757**	-0.8718***
					(0.5335)	(0.2205)	(0.9402)	(0.1618)
Legal instruction time = 10					1.4969	-0.0265	2.1909*	0.2960
					(0.9471)	(0.2479)	(1.2788)	(0.1942)
Instruments								
Dummies legal dropout age	yes	yes	yes	yes	no	no	no	no
Dummies legal entry age	yes	yes	yes	yes	no	no	no	no
Dummies legal instruction time	no	no	no	no	yes	yes	yes	yes
Two-way cluster								
Mother YOB & mother POB	yes	yes	yes	yes	yes	yes	yes	yes
Fixed effects								
Child year of birth & province match	yes	yes	yes	yes	yes	yes	yes	yes
Mother age at birth & single family & child gender	no	no	yes	yes	no	no	yes	yes
F-stat: test of excluded instruments	233.05	.	.	41.88	159.35	15.2	16.02	35.55
F-stat: Sanderson-Windmeijer multivariate	50.51	8.42	13.93	24.23	31.92	3.57	15.11	.

Source: Authors' calculations based on the IID+

Note: YOB: year of birth. POB: province of birth. The dependent variables are either the percentage of mothers with high school diploma or with bachelor degree ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$. $N = 2,334,120$

Table 7: Decomposition Results

Dependent variable:	β_{pc}	λ_{pc}	$\pi_{pc,hs}R_{pc,hs}$	$\pi_{pc,bacc}R_{pc,bacc}$	β_{pc}	λ_{pc}	$\pi_{pc,hs}R_{pc,hs}$	$\pi_{pc,bacc}R_{pc,bacc}$
Maternal education	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Percent with high school diploma	-0.00847**	-0.00794**	-0.00146***	0.000928**	-0.0124***	-0.0117***	-0.00162***	0.000894*
	(0.00287)	(0.00274)	(0.000426)	(0.000348)	(0.00316)	(0.000479)	(0.00323)	(0.000487)
Percent with bachelor degree	-0.00777	-0.0120*	0.000883	0.00345***	-0.00859*	-0.0146***	0.00171*	0.00438***
	(0.00601)	(0.00575)	(0.00101)	(0.000775)	(0.00395)	(0.00400)	(0.000886)	(0.000964)
Instruments								
Dummies legal instruction time	yes	yes	yes	yes	no	no	no	no
Dummies legal dropout age	no	no	no	no	yes	yes	yes	yes
Dummies legal entry age	no	no	no	no	yes	yes	yes	yes
Two-way cluster								
Mother YOB & mother POB	yes	yes	yes	yes	yes	yes	yes	yes
Fixed effects								
Child year of birth & province match	yes	yes	yes	yes	yes	yes	yes	yes
Mother age at birth & single family & child gender	yes	yes	no	yes	yes	no	yes	yes

Source: Authors' calculations based on the IID+

Note: YOB: year of birth. POB: province of birth. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

A Appendix Figures

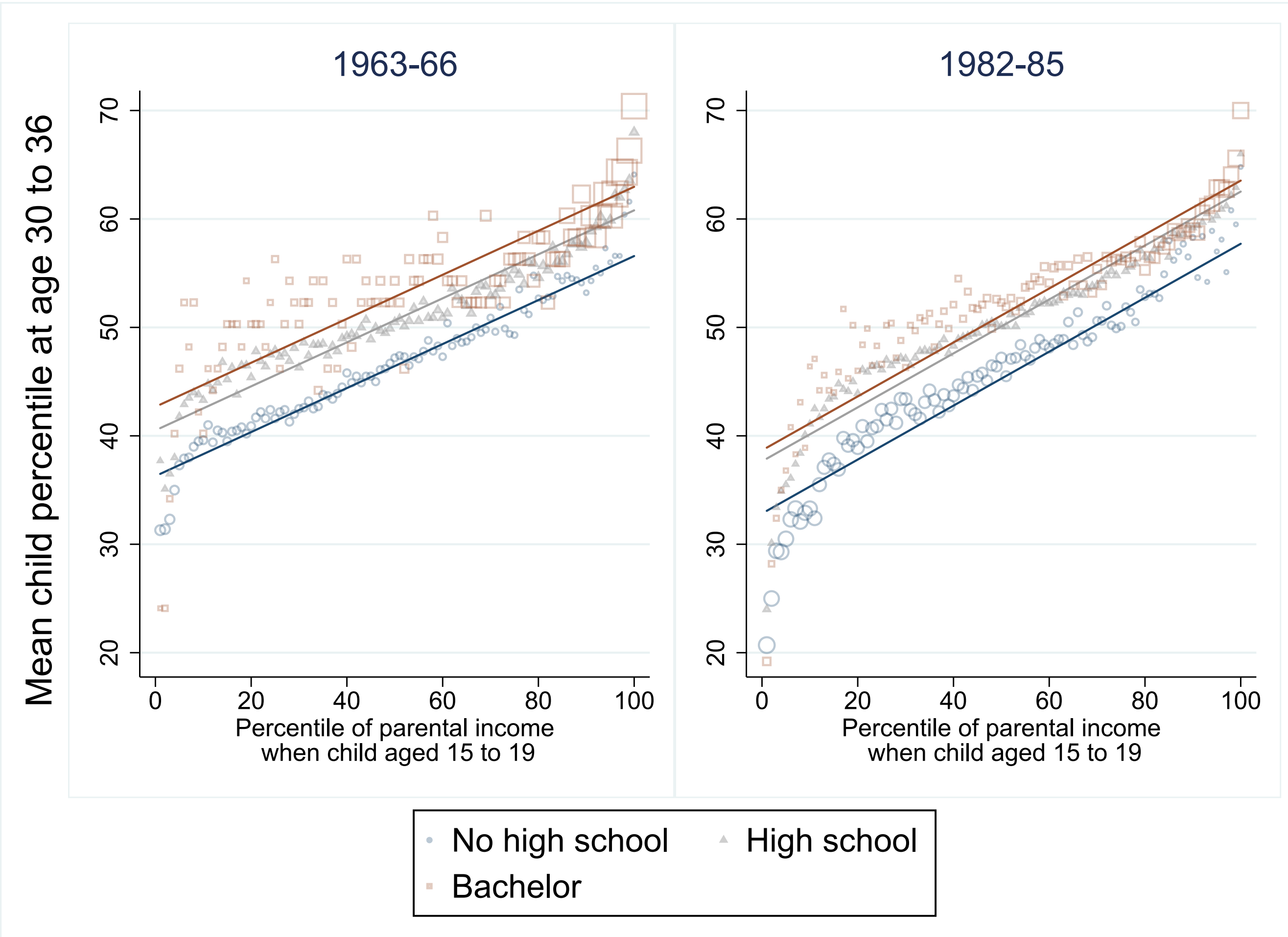

Figure A1: Intergenerational rank mobility within maternal education groups, 1963-66 and 1982-85 birth cohorts

Source: Authors' calculations based on the IID+

Note: Each point in this graph represents the mean child percentile rank for a given parental income rank, where child income is measured at ages 30 to 36 and parental income is average annual family income when the child is aged 15 to 19. The markers are weighed using the number of children. The slopes are from linear rank-rank regressions of child income rank on parent income rank that control for parental education dummies.

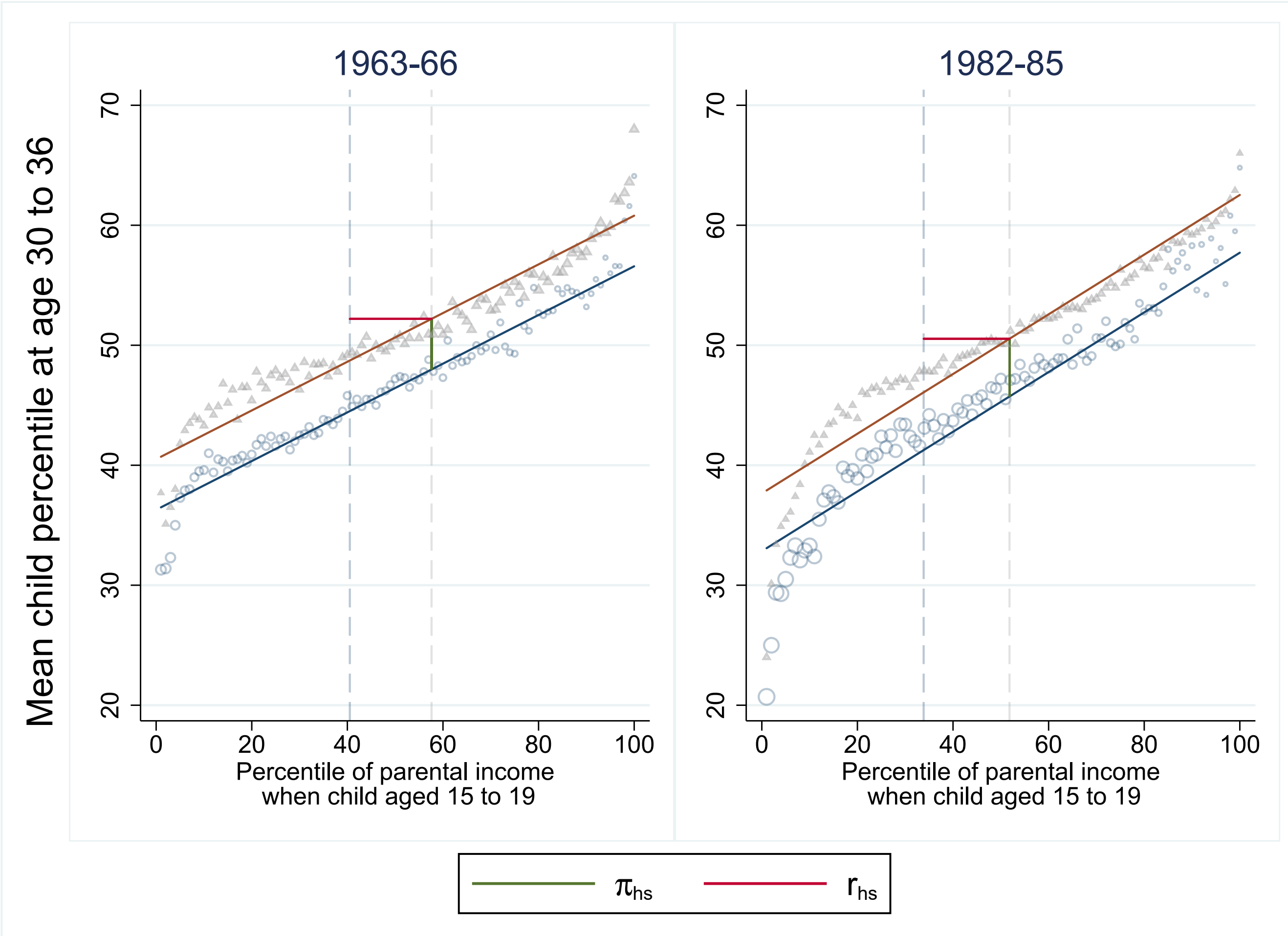

Figure A2: Intergenerational private return to high school graduation, 1963-66 and 1982-85 birth cohorts

Source: Authors' calculations based on the IID+

Note: Each point in this graph represents the mean child percentile rank for a given parental income rank, where child income is measured at ages 30 to 36 and parental income is average annual family income when the child is aged 15 to 19. The markers are weighed using the number of children. Vertical dashed lines indicate the average parental income rank separately by education group. The horizontal red line indicates the difference in average parental income rank between parents with a high school diploma and parents with no high school diploma. The vertical green line indicates the average intergenerational private return to parental human capital, conditional on parental income rank.

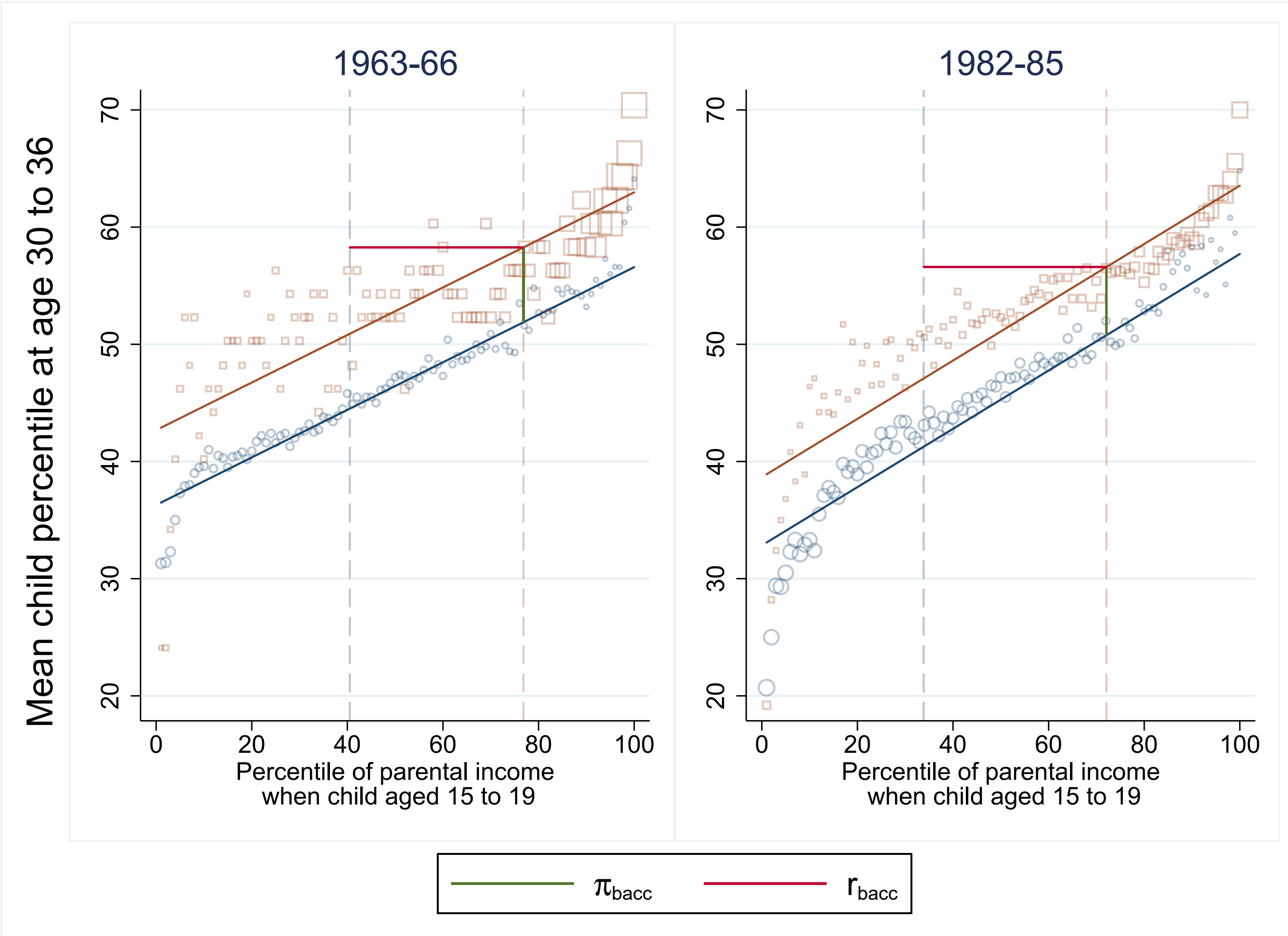

Figure A3: Intergenerational private return to college graduation, 1963-66 and 1982-85 birth cohorts

Source: Authors' calculations based on the IID+

Note: Each point in this graph represents the mean child percentile rank for a given parental income rank, where child income is measured at ages 30 to 36 and parental income is average annual family income when the child is aged 15 to 19. The markers are weighed using the number of children. Vertical dashed lines indicate the average parental income rank separately by education group. The horizontal red line indicates the difference in average parental income rank between parents with a high school diploma and parents with no high school diploma. The vertical green line indicates the average intergenerational private return to parental human capital, conditional on parental income rank.

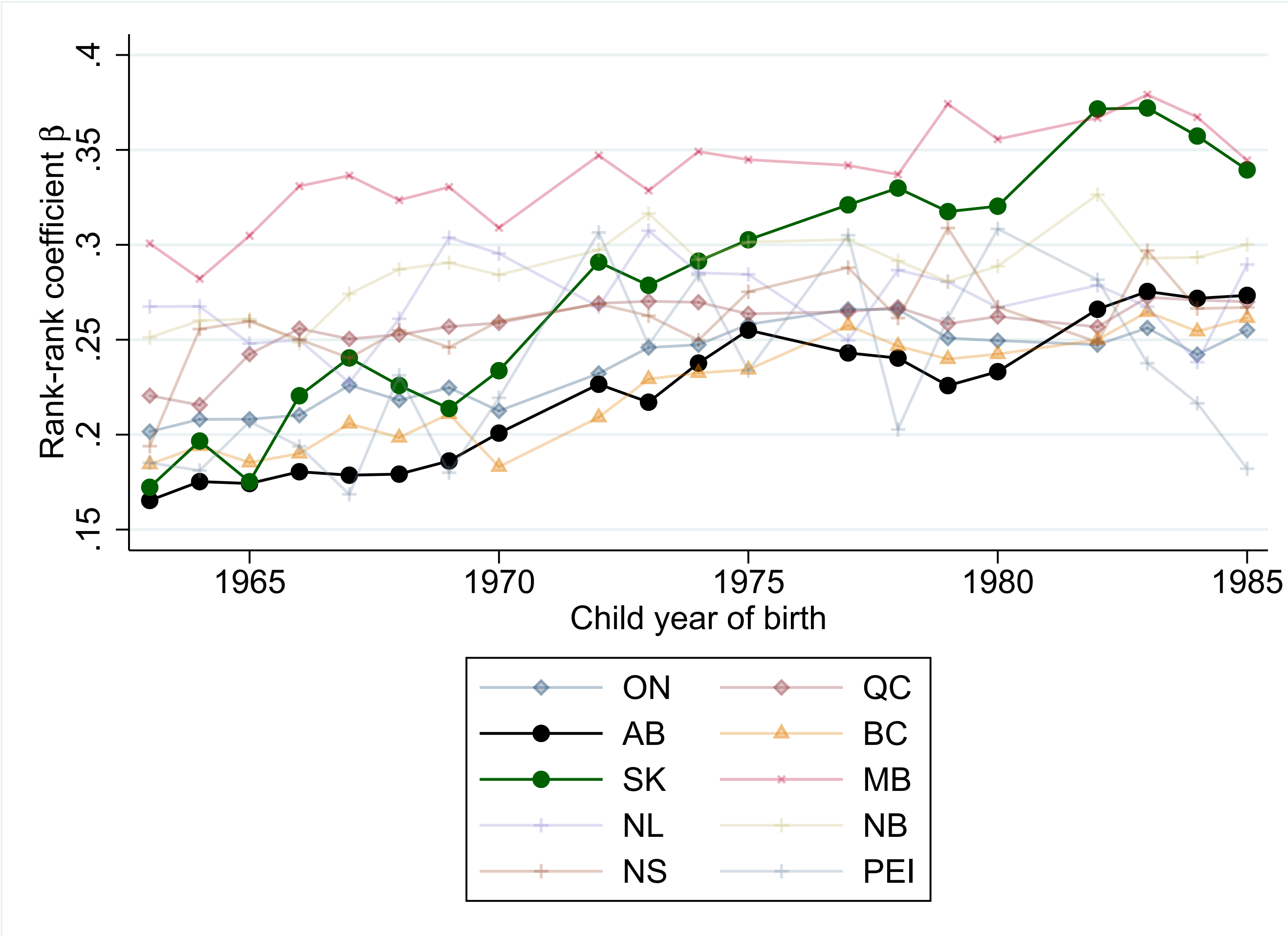

Figure A4: Intergenerational rank mobility by province over time

Source: Authors' calculations based on the IID+

Note: Each point in this graph represents the intergenerational rank mobility (β) estimated for a given child birth year and province, where child income is measured at ages 30 to 36 and parental income is average annual family income when the child is aged 15 to 19. The two provinces that have experienced the most dramatic changes in mobility (Alberta and Saskatchewan) are highlighted.

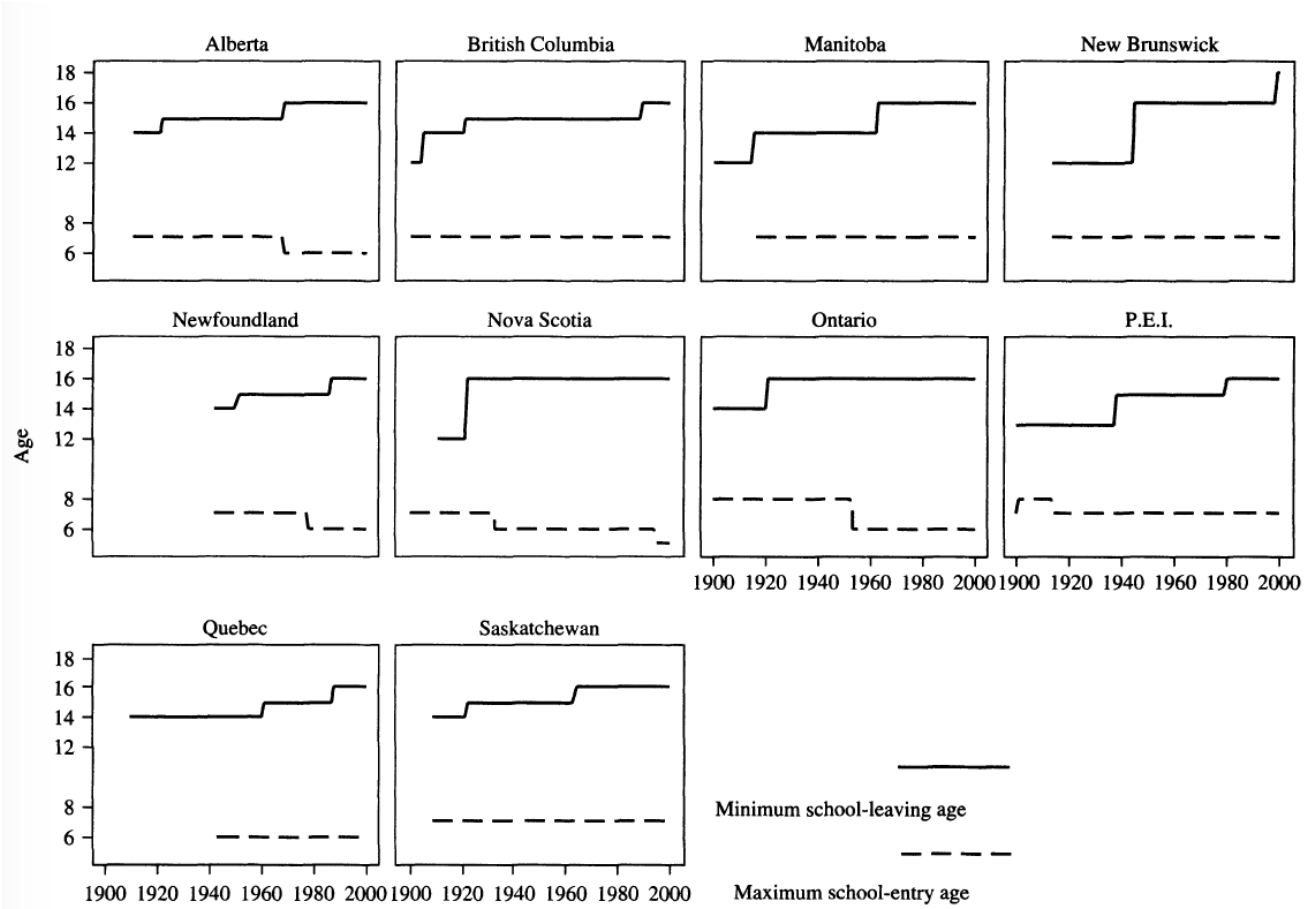

FIGURE 1 Minimum school-leaving ages and maximum school-entry ages by province, 1900–2000
NOTES: See data appendix for details.

Figure A5: Variation in compulsory schooling by province over time

Source: Figure 1 in Oreopoulos (2006)
Note:

B Appendix Tables

Table B1: Additional Descriptive Statistics

Child year of birth	Mean	Std. Dev.		
1963	0.035	0.184		
1964	0.042	0.199		
1965	0.045	0.207		
1966	0.048	0.214		
1967	0.045	0.208		
1968	0.049	0.215		
1969	0.050	0.207		
1970	0.048	0.214		
1972	0.047	0.211		
1973	0.048	0.214		
1974	0.049	0.216		
1975	0.052	0.222		
1977	0.049	0.216		
1978	0.052	0.221		
1979	0.054	0.226		
1980	0.056	0.230		
1982	0.055	0.227		
1983	0.057	0.232		
1984	0.059	0.236		
1985	0.060	0.237		
	Mother's place of birth		Residence when child aged 16 to 19	
Province	Mean	Std. Dev.	Mean	Std. Dev.
Newfoundland and Labrador	0.045	0.207	0.036	0.186
Prince Edward Island	0.009	0.093	0.007	0.084
Nova Scotia	0.050	0.218	0.043	0.202
New Brunswick	0.044	0.205	0.037	0.190
Quebec	0.287	0.452	0.271	0.445
Ontario	0.280	0.449	0.300	0.458
Manitoba	0.060	0.237	0.048	0.213
Saskatchewan	0.079	0.270	0.053	0.224
Alberta	0.080	0.272	0.104	0.306
British Columbia	0.066	0.248	0.101	0.301

Source: Authors' calculations based on the IID+

Note: These statistics are computed using the IID weights. Weighted number of observations is 3,051,485.

Table B2: IV using Various Specifications for the Dependent Variable

Maternal education	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: rank-rank slope, child income at ages 30 to 36, parental income when child is 15 to 19						
Percent with high school diploma	-0.00829**	-0.00847**	-0.00768**	-0.0123***	-0.0124***	-0.0116***
	(0.00267)	(0.00287)	(0.00268)	(0.00337)	(0.00316)	(0.00279)
Percent with bachelor degree	-0.00790	-0.00777	-0.00756	-0.00766*	-0.00859*	-0.00705*
	(0.00634)	(0.00601)	(0.00661)	(0.00412)	(0.00395)	(0.00321)
Dependent variable: rank-rank slope, child income at ages 27 to 31, parental income when child is 15 to 19						
Percent with high school diploma	-0.00817**	-0.00850**	-0.00784**	-0.0120***	-0.0121***	-0.0113***
	(0.00291)	(0.00309)	(0.00286)	(0.00356)	(0.00334)	(0.00296)
Percent with bachelor degree	-0.0110	-0.0109	-0.0112	-0.00980*	-0.0110**	-0.00920**
	(0.00661)	(0.00619)	(0.00656)	(0.00435)	(0.00431)	(0.00346)
Dependent variable: rank-rank slope, child income at ages 25 to 29, parental income when child is 15 to 19						
Percent with high school diploma	-0.00826**	-0.00866**	-0.00817**	-0.0119***	-0.0122***	-0.0113***
	(0.00324)	(0.00346)	(0.00320)	(0.00362)	(0.00335)	(0.00295)
Percent with bachelor degree	-0.0141*	-0.0139*	-0.0146*	-0.0119**	-0.0136**	-0.0119***
	(0.00684)	(0.00642)	(0.00646)	(0.00434)	(0.00443)	(0.00343)
Dependent variable: rank-rank slope, child income at ages 30 to 34, parental income when child is 15 to 19						
Percent with high school diploma	-0.00820**	-0.00833**	-0.00757**	-0.0121***	-0.0121***	-0.0113***
	(0.00267)	(0.00286)	(0.00264)	(0.00345)	(0.00325)	(0.00286)
Percent with bachelor degree	-0.00858	-0.00828	-0.00818	-0.00834*	-0.00927**	-0.00772**
	(0.00629)	(0.00594)	(0.00647)	(0.00417)	(0.00402)	(0.00320)
Dependent variable: rank-rank slope, child income at ages 27 to 31, parental income when child is 10 to 19						
Percent with high school diploma	-0.00944**	-0.00964**	-0.00908**	-0.0136***	-0.0138***	-0.0127***
	(0.00324)	(0.00344)	(0.00314)	(0.00394)	(0.00367)	(0.00325)
Percent with bachelor degree	-0.0136*	-0.0131*	-0.0138*	-0.0120**	-0.0137**	-0.0118***
	(0.00739)	(0.00690)	(0.00710)	(0.00467)	(0.00476)	(0.00358)
Dependent variable: rank-rank slope, child income at ages 27 to 31, parental income when mother is 40 to 49						
Percent with high school diploma	-0.00924***	-0.00952***	-0.00911***	-0.0120**	-0.0121***	-0.0113***
	(0.00265)	(0.00281)	(0.00254)	(0.00371)	(0.00348)	(0.00304)
Percent with bachelor degree	-0.00785	-0.00751	-0.00750	-0.00607	-0.00734	-0.00588
	(0.00612)	(0.00573)	(0.00578)	(0.00442)	(0.00449)	(0.00338)
Dependent variable: rank-rank slope, child income at ages 27 to 31, parental income when mother is 45 to 54						
Percent with high school diploma	-0.00783**	-0.00803**	-0.00747**	-0.0112***	-0.0113***	-0.0104***
	(0.00252)	(0.00267)	(0.00241)	(0.00312)	(0.00291)	(0.00259)
Percent with bachelor degree	-0.00756	-0.00727	-0.00772	-0.00668	-0.00777*	-0.00613*
	(0.00581)	(0.00543)	(0.00563)	(0.00379)	(0.00374)	(0.00287)
Instruments						
Dummies legal instruction time	yes	yes	yes	no	no	no
Dummies legal dropout age	no	no	no	yes	yes	yes
Dummies legal entry age	no	no	no	yes	yes	yes
Two-way cluster						
Mother YOB & mother POB	yes	yes	yes	yes	yes	yes
Fixed effects						
Child YOB & province match	yes	yes	yes	yes	yes	yes
Mother age at birth & single family & child gender	no	yes	yes	no	yes	yes
Robustness test of instruments						
Provincial linear time trend	no	no	yes	no	no	yes

Source: Authors' calculations based on the IID+

Note: YOB: year of birth. POB: province of birth. Standard errors in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$. $N = 2,334,120$

Table B3: IV using Various Instruments

Maternal education	(1)	(2)	(3)
Dependent variable: rank-rank slope, child income at ages 30 to 36, parental income when child is 15 to 19			
Percent with high school diploma	-0.00829**	-0.0123***	-0.00783**
	(0.00267)	(0.00337)	(0.00281)
Percent with bachelor degree	-0.00790	-0.00766*	-0.00868
	(0.00634)	(0.00412)	(0.00637)
Dependent variable: rank-rank slope, child income at ages 27 to 31, parental income when child is 15 to 19			
Percent with high school diploma	-0.00817**	-0.0120***	-0.00723**
	(0.00291)	(0.00356)	(0.00309)
Percent with bachelor degree	-0.0110	-0.00980*	-0.0112
	(0.00661)	(0.00435)	(0.00684)
Dependent variable: rank-rank slope, child income at ages 27 to 31, parental income when child is 10 to 19			
Percent with high school diploma	-0.00944**	-0.0136***	-0.00756*
	(0.00324)	(0.00394)	(0.00344)
Percent with bachelor degree	-0.0136*	-0.0120**	-0.0146
	(0.00739)	(0.00467)	(0.00858)
Dependent variable: rank-rank slope, child income at ages 27 to 31, parental income when mother is 40 to 49			
Percent with high school diploma	-0.00924***	-0.0120**	-0.00779**
	(0.00265)	(0.00371)	(0.00302)
Percent with bachelor degree	-0.00785	-0.00607	-0.00884
	(0.00612)	(0.00442)	(0.00709)
Instruments			
Dummies legal instruction time	yes	no	no
Dummies legal dropout age	no	yes	no
Dummies legal entry age	no	yes	no
Dropout age & legal entry age (linear)	no	no	yes
Dummy no law	no	no	yes
Two-way cluster			
Mother year of birth & mother province of birth	yes	yes	yes
Fixed effects			
Child year of birth & province match	yes	yes	yes

Source: Authors' calculations based on the IID+
Note: Standard errors in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$. $N = 2,334,120$

Table B4: IV using Various Types of Clustering of Standard Errors

Maternal education	(1)	(2)	(3)	(4)
Dependent variable: rank-rank slope, child income at ages 30 to 36, parental income when child is 15 to 19				
Percent with high school diploma	-0.00829**	-0.00829**	-0.00829***	-0.00829***
	(0.00267)	(0.00327)	(0.000826)	(0.00150)
Percent with bachelor degree	-0.00790	-0.00790	-0.00790***	-0.00790***
	(0.00634)	(0.00711)	(0.00154)	(0.00259)
Dependent variable: rank-rank slope, child income at ages 27 to 31, parental income when child is 15 to 19				
Percent with high school diploma	-0.00817**	-0.00817**	-0.00817***	-0.00817***
	(0.00291)	(0.00342)	(0.000851)	(0.00151)
Percent with bachelor degree	-0.0110	-0.0110	-0.0110***	-0.0110***
	(0.00661)	(0.00742)	(0.00169)	(0.00271)
Dependent variable: rank-rank slope, child income at ages 27 to 31, parental income when child is 10 to 19				
Percent with high school diploma	-0.00944**	-0.00944**	-0.00944***	-0.00944***
	(0.00324)	(0.00386)	(0.000970)	(0.00169)
Percent with bachelor degree	-0.0136*	-0.0136	-0.0136***	-0.0136***
	(0.00739)	(0.00826)	(0.00200)	(0.00304)
Dependent variable: rank-rank slope, child income at ages 27 to 31, parental income when mother is 40 to 49				
Percent with high school diploma	-0.00924***	-0.00924**	-0.00924***	-0.00924***
	(0.00265)	(0.00336)	(0.000755)	(0.00132)
Percent with bachelor degree	-0.00785	-0.00785	-0.00785***	-0.00785***
	(0.00612)	(0.00710)	(0.00157)	(0.00256)
Instruments				
Dummies legal instruction time	yes	yes	yes	yes
Two-way cluster				
Mother year of birth & mother province of birth	yes	no	no	no
Child year of birth & province match	no	yes	no	no
Cluster group				
Mother year of birth & mother province of birth	no	no	yes	no
Child year of birth & province match	no	no	no	yes
Fixed effects				
Child year of birth & province match	yes	yes	yes	yes

Source: Authors' calculations based on the IID+
Note: Standard errors in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$. $N = 2,334,120$