Switzer-Land of Opportunity: Intergenerational Income Mobility in the Land of Vocational Education

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Abstract

This study documents intergenerational income mobility in Switzerland and analyzes the role of educational tracks, local policies, and socio-demographic characteristics. We match the universe of labor incomes over generations and add census and survey data. Using over 900,000 observations from 18 cohorts (1967-1984), we show that income mobility in terms of rank-rank slope (0.14) is higher than in the US and even higher than in Nordic countries. At the same time, educational mobility is low. This shows that low educational mobility does not need to translate into low income mobility. We find high income mobility for individuals with vocational education and training (VET), suggesting that the divergence between educational and income mobility is due to the prominent VET system. Further, children of immigrants show higher mobility rates than children of Swiss born parents. Besides, regions with higher public expenditures, lower tax rates, and higher income inequality exhibit greater income mobility.

Keywords: social mobility, inequality, vocational education and training;
JEL classification: H0, J0, R0

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1 Introduction

Inequality is one of society's primary concerns. While the desired amount of inequality differs along the political spectrum, the notion that «every child should have the same chance to succeed» is a common denominator among all parties. The American Dream is the moral foundation on which most Western societies are built. Equal opportunity is not only morally desirable, but it also matters for economic growth. Economic growth can suffer when children from poorer parents are impeded from living up to their economic potential—a phenomenon sometimes referred to as «Lost Einsteins» (Bell et al., 2019).

One important facet of equal opportunities is intergenerational income mobility. How much does children's income depend on their parents' income? Despite its importance, only a handful of studies have reliably estimated intergenerational mobility. This is because of the demanding data requirements. To minimize bias, longitudinal income data and information on parent-child relationships are required. In recent years, some notable exceptions succeeded in analyzing high-quality data, for example Chetty et al. (2014a), Heidrich (2017), Bratberg et al. (2017), Acciari et al. (2019), Deutscher and Mazumder (2020), Connolly et al. (2019), and Corak (2020).

Policies that boost upward mobility are urgently needed. Vocational education and training (VET) might be such an option. Rodrik and Stantcheva (2021) declare vocational training as a policy option to intervene at the pre-production stage, targeting bottom incomes. Theoretically, the persistence of income inequality across generations is caused by the socioeconomic gap in human capital investment, that is, poorer parents underinvesting in child education. This underinvestment can be explained by credit constraints or informational frictions on the return to education (Becker and Tomes, 1986; Cunha and Heckman, 2007; Heckman and Mosso, 2014; Barone et al., 2017; Stuhler et al., 2018; Black et al., 2020). With VET, credit constraints might cause less underinvestment in children's human capital because this kind of training comes at low costs for parents and still gives children ample options for further education after the apprenticeship. However, so far there are no empirical studies analyzing the role of VET in intergenerational mobility.

In this paper, we study intergenerational income and educational mobility in Switzerland. We use administrative high-quality data that cover the universe of labor incomes between 1982 and 2017, combined with administrative linkages between parents and children. We provide national mobility estimates for country benchmarking and we analyze variations across regions. A strong focus lies on the role of Switzerland's VET system. The country is an interesting case since most children opt for VET after compulsory school. In addition, we study how tax rates and public expenditures are related to upward mobility and which personal characteristics best predict upward mobility.

Our study contributes to the literature in several ways. We are first to provide reliable estimates for intergenerational income mobility in a country with a strong VET system. Importantly, our data allows us to link information on education, religion, and other characteristics at an individual level. Second, we add an interesting data point on intergenerational mobility for country comparison. This data point is significant because Switzerland considerably differs from countries for which recent high-quality estimates exist, such as Italy, the US, or Sweden. Third, we analyze how the substantial variation across tax rates and public expenditures is correlated to upward mobility.

We find that intergenerational income mobility is high in Switzerland. A child with parents in the highest income rank 100 can expect to achieve rank 57, whereas a child with parents from the lowest rank 1 can expect to achieve rank 43. This wedge of 14 ranks translates to approximately 11,000 CHF (≊ 11,000 USD) in the early thirties[1], which corresponds to roughly two median monthly salaries in Switzerland. This difference in ranks is lower than, for example, in Sweden (18 ranks), Italy (25 ranks), and the US (34 ranks) (Heidrich, 2017; Chetty et al., 2014b; Acciari et al., 2019).

These high income mobility estimates are surprising not only because Switzerland differs from egalitarian welfare states like Sweden, but also, and primarily, because educational mobility is low in the country. The educational track—whether a child opts for VET or high school after compulsory school—highly depends on parental income. Only a little over 10 percent of children with parents below the median income opt for high school. In the top decile, this share amounts to over 40 percent. Also, children's odds of frequenting a high school are five times higher if one of their parents did so. These results are quite fascinating. They show that low educational mobility does not need to translate into low income mobility. However, we also see

[1] 12,300 CHF in the early forties.

that regions with high educational mobility have also high income mobility. This suggests that high educational mobility does lead to high income mobility, although in Switzerland to a lesser degree.

To test whether the country's prominent VET system can explain this divergence between educational and income mobility at a national level, we analyze upward mobility for educational tracks that start either with VET or high school. For each track, we calculate the share of children from poorer backgrounds and the share of those who move up the income ladder. This analysis shows that there is a trade-off: tracks with a higher probability of moving up the income ladder provide little access to children from poorer backgrounds. However, there are also tracks with better trade-offs. Those are the ones that start with VET and lead to further education after the apprenticeship. They provide relatively ample access to children from poorer backgrounds and still give them a high probability of climbing up the income ladder.

There are good theoretical reasons that support the thesis that VET can boost upward mobility. Theory informs us that a major factor for the persistence of income inequality across generations is that parents are financially constrained and therefore invest too little in their children's education, which consequently lowers their earnings (Becker and Tomes, 1986; Solon, 1992; Solon, 1999). With VET, this financial constraint might be less important. VET comes at low costs for parents since children even earn a small salary during the apprenticeship. At the same time, VET provides ample options for further education after the apprenticeship. Many of these options take place complementary to the job. This facilitates financing human capital investment.

We further find that mobility differs between regions in Switzerland. Income mobility is more heterogeneous than in Sweden but less heterogeneous than in the US. We do not find any clear and significant trend in income or educational mobility over time, while we see that inequality (GINI index) increased slightly over the child cohorts 1967 to 1984[2].

At a regional level, we see that higher expenditures and lower tax rates are correlated with higher mobility. Relating the income mobility estimates to inequality, we do not find evidence for a «Great Gatsby» curve, which states that higher inequality leads to lower income mobility. In contrast, we see that regions with higher inequality also have higher income mobility. There

[2]For family income: From around 30 to 31

are, however, two exceptions. When looking at the «cycle of poverty» and «cycle of privileges» measures , we see that inequality is negatively related to mobility.

The strongest individual predictor of upward mobility is gender. Men are almost three times as likely as women to climb the ladder from the bottom to the top quintile. Also, children of immigrants show higher upward mobility than children of parents born in Switzerland. In terms of religion, protestants show the lowest probability to achieve the American Dream—-even though the origins of the American Dream date back to the Protestant Revolution.

We structure this paper as follows. First, we summarize the literature on intergenerational mobility. Then, we outline the different measures to estimate income and educational mobility and describe our sample. Next, we present the mobility estimates at the national level and compare them to other countries. We also show how mobility estimates are correlated to each other. Then, we look at variations across time and space. We study the drivers of mobility: education, inequality, and initial conditions. In the robustness section, we show that our results are robust to several specifications. The last section concludes the discussion.

2 Literature

Since the pioneer contribution of Solon (1992), several scholars have analyzed income transmission across generations (see Solon (1992) and Black and Devereux (2011) for a review). Virtually all of those former studies rely on small-scale survey data and are therefore prone to several biases (e.g. sample selection, attenuation, or life-cycle bias). With the increasing access to large databases in the last decades, research on intergenerational income mobility has experienced a revival.

Our study adds to the current literature on intergenerational income mobility that uses administrative data to analyze income mobility in and within a country. In their innovative study, Chetty et al. (2014a) use tax data and provide a set of measures of relative and absolute income-mobility not just in the United States but also within the United States. They document sizeable geographical variation in mobility across commuting zones. For example, the probability that a child from a family in the bottom quintile reaches the top quintile is 4.5 percent in Atlanta, while it is over two times higher in Washington. Among others, the research stands out by its systematic within-country investigation to shed light on drivers of mobility and the use of directional measures.

Similar in and within-country analyses have been performed for Sweden, Denmark, Italy, Canada, and Australia. Heidrich (2017) shows that income persistence in Sweden is lower than in the United States and that relative mobility is quite homogeneous across regions, while absolute mobility differs more. Income mobility is also quite evenly distributed across the Danish municipalities (Eriksen, 2018). In contrast, Italian provinces exhibit substantial variation in income mobility (Güell et al., 2018; Acciari et al., 2019). Corak (2020) and Connolly et al. (2019) analyze mobility in and within Canada and find sizeable variation in mobility across regions. More recently, Deutscher and Mazumder (2020) analyze intergenerational income mobility in and within Australia. They conclude that there is high mobility in Australia but also substantial dispersion across regions.

For Switzerland, no study has analyzed intergenerational income mobility with administrative data. Bauer (2006) looks at intergenerational income mobility in Switzerland. He estimates an intergenerational income elasticity (IGE) of 0.35, suggesting that an increase of 1 percent in the parent's income is associated with an increase of 0.35 percent in the child's income. The results from this study have to be interpreted with caution, as they are based on predicted incomes from a small-scale survey. Several studies analyze the broader concept of social mobility. Favre et al. (2018) uses historical data from the City of Zurich to examine the extent of occupational persistence during the 1780s and 1870s. Unexpectedly, their results show a decrease in occupational mobility. A more recent study by Häner and Schaltegger (2020) investigates education persistence across 15 generations in the Swiss canton of Basel using a surname-based approach.

We aim to fill the gap in the literature by providing the first estimate of intergenerational mobility for Switzerland based on administrative data. Thus, we add a further data point to the small set of reliable country estimates for international comparison.

Despite being interesting per se, national and regional measures of income mobility alone are not enough for understanding the process of income transmission. In other words, the ultimate goal is to understand what shapes intergenerational income mobility and to inform policymakers on which policies to implement.

Since the seminal contribution of Becker and Tomes (1986), the theoretical literature on intergenerational income transmission has long emphasized the idea that institutions significantly affect economic opportunities (see Ichino et al. (2011) for a review). However, empirical evidence is rare.

The lack of past information about local conditions and socio-demographic characteristics probably contributes to the scarcity of descriptive evidence. Indeed, current information about local conditions, such as current local tax rates, does not necessarily reflect the local conditions when children were growing.

Findings of previous literature show that income mobility positively correlates with education, social capital, and economic activity, and negatively with inequality. The role of local tax policies is, however, less clear (Chetty et al., 2014a; Güell et al., 2018; Acciari et al., 2019). Chetty et al. (2014a) find a positive, while not robust, correlation between local taxes and upward mobility. Characterized by high decentralization, Switzerland is an ideal setting to analyze the role of local policies. Despite our purpose being purely descriptive, we aim to advance the understanding of mobility drivers by exploiting rich socio-demographic information and historical local public finance data. Our data has the advantage that we can directly link individual characteristics, such as education, religion, or family characteristics, which are arguably fixed after a certain age. Most important, municipal-level variables are available since the eighties.

To sum up, we add to the literature not only by providing a country estimate but also by describing determinants of mobility.

3 Measuring Intergenerational Mobility

3.1 Income Mobility

Income mobility aims to describe how a child's income depends on the parent's income. In this section, we describe the measures of income mobility. We largely follow the previous literature, specifically Chetty et al. (2014a) and Corak (2020). This is to ensure that we can compare our estimates to those of other countries.

It is important to distinguish between two concepts of intergenerational income mobility: *relative mobility* and *absolute mobility*. Relative mobility captures the idea that all children should have equal opportunities to succeed—independent of the economic status of their parents. Absolute mobility measures where children end up in the income distribution, when they come from a specific parent rank. Usually, one is interested in the economic outcome of children coming from low-income parents. Absolute mobility captures the idea that parents want their children to do better than themselves—independent of where they rank in the distribution.

Relative mobility has been the focus of most prior work. It aims to answer the following question: «To which extent does my income depend on my parent's position in the income distribution?» In a society with perfect equality of opportunities, the relative ranking of parent's and children's income should be uncorrelated—assuming that genetic dispositions in ability are uncorrelated to a parent's income.

Relative upward mobility occurs when children increase their position in the income distribution compared to their parents. However, if someone moves up in relative terms, someone has to move down. When comparing relative mobility between units, higher relative mobility could also happen if children from rich parents do worse. Similarly, if all children increase their income compared to their parents in such a way that the income ranking stays constant, relative income mobility does not increase. Thus, the impact of changes in relative mobility on welfare is ambiguous.

Absolute mobility might thus be more important from a normative perspective. Relative mobility is not necessarily informative to capture the opportunities of poor children. Relative mobility can also be high when all children have the same low income or if rich children do worse. From a normative perspective, absolute mobility might therefore be more meaningful than relative mobility.

3.1.1 Logarithmized Income Mobility Measures

Intergenerational Income Elasticity (IGE) has been the most used measure for income mobility, probably because of its intuitive appeal. The IGE is estimated by regressing the logarithm of child income $log(Y_c)$ on the logarithm of parent (usually father or family) income $log(Y_f)$:

$$log(Y_c) = \alpha + \beta log(Y_f) + \epsilon \tag{1}$$

The IGE results from Equation 1 as the estimated coefficient $\hat{\beta}$:

$$IGE = \hat{\beta} = \rho_{Y_c Y_f} \frac{SD(logY_c)}{SD(logY_f)} \tag{2}$$

where $\rho_{Y_c Y_f}$ is the correlation between the logarithm of child income and the logarithm of parent income. SD is the standard deviation.

The IGE measure the differences in income between children from high-income families versus children from low-income families. Thus, it captures the rate of regression to the mean. An IGE of 0.4 means that if parents earn 10 percent more, the income of their children is 4 percent higher.

The intuitive approach of the IGE comes with some drawbacks. The IGE does not only capture the parent child relationship. Equation 2 shows that higher inequality in parent's income can lead to higher $SD(logY_f)$ and thus to a lower IGE. The most important drawback is that the relationship between log incomes of parents and log incomes of children is not well approximated by a linear regression. As a result the elasticity might not reflect income mobility at all points of the distribution. A further problem when estimating the IGE is the handling of zeros because the logarithm of zero is not defined. Dropping zeros can lead to overestimated mobility if observations with zeros are more prevalent within children of low-income parents.

3.1.2 Rank transformed Income Mobility Measures

Despite the shortcomings of the IGE, a parsimonious statistic facilitates the comparison of intergenerational mobility estimates between units (Black and Devereux, 2011). Another parsimonious statistic is the *rank-rank slope (RRS)*. It gained attention in recent years because it overcomes several drawbacks of the IGE. The rank-rank slope is a positional measure: Income of parents and children are transformed into their percentile ranks. Then, child income rank is regressed on parent income rank. The estimated slope of the linear regression is called the rank-rank slope (RRS). Formally,

$$R_c = \zeta + \omega R_f + \varepsilon \tag{3}$$

where R_c is the rank of the child in the child cohort specific income distribution, and R_f is the parent's rank in the child cohort specific parent income distribution. The estimated coefficient $\hat{\omega}$ yields the rank-rank slope (RRS). The estimated constant $\hat{\zeta}$ is then the absolute rank mobility (Corak, 2020). It indicates which rank children from the lowest parental income rank can expect to achieve.

The rank-rank slope measures the correlation between a child's position and its parent's position in the income distribution. Values close to one indicate a society in which chance of succeeding depends highly on parent's rank and thus with low mobility. Values close to zero denote a society with high mobility. The $RRS \times 100$ equals the child rank difference, also called wedge, between children from the richest and lowest parent income percentile.

Compared to the IGE, the RRS has several advantages. First, zero incomes are preserved. Second, previous studies using rank-rank measures have discovered a strikingly linear functional form (Chetty et al., 2014a; Dahl and DeLeire, 2008; Heidrich, 2017; Acciari et al., 2019; Corak, 2020; Deutscher and Mazumder, 2020). This makes it a parsimonious statistics across the whole parental income distribution. The IGE in contrast shows non-linearities (compare Figure 2). Furthermore, the transformation leads to the same standard deviation for parent and child income (both have a uniform distribution). Thus, the RRS is independent of changes in inequality between parents and children.

Equation 3 can also be estimated for subgroups, such as geographic entities. When keeping the national income ranks, the estimates can be interpreted as *absolute mobility* estimates (Chetty et al., 2014a). This is because the ranks on small geographic entities are only weakly related to the ranks on a national level. For example, one might ask: «What is the income that children from poor parents can expect?» This is called *absolute upward mobility (AUM25)*. Following Chetty et al. (2014a), we define AUM25 as the mean adult rank of children whose parents were located at a the 25th percentile in the parent income distribution. Thus, we also refer to it as AUM25.

When looking at large sample, AUM25 can inferred non-parametrically by simply calculating the mean rank of children with parents at rank 25. However, for smaller samples, e.g. at the regional level, noise might distort the measure and this estimate at precisely that point. Therefore, we use a statistical model to increase stability of the estimate. This statistical model is again the linear rank-rank regression stated in Equation 3. Instead of using the observed rank at parents rank 25, we use the rank that our linear model predicts at $R_f = 25$. Because the relationship is linear, the mean child outcome at the 25th percentile of parent's income, is the same as the mean outcome for parent's below the median. That is, the AUM25 measures the mean outcome of children born in the poorer half of the society.

3.1.3 Directional Mobility

Following Corak (2020), we use three statistics to indicate directional mobility. Those measures look at specific parts of the quintile transition matrix. The *American Dream (Q1Q5)* measure (sometimes also called the *rags to riches* measure) describes the probability of a child born to parents in the bottom quintile to move up to the top quintile (Corak and Heisz, 1999; Hertz, 2006; Chetty et al., 2014a).

$$Q1Q5 = Pr[R_c > 80 | R_f \leq 20] \tag{4}$$

The *cycle of poverty measure (Q1Q1)* indicates the share of children from parents in the bottom quintile that stay in the bottom quintile.

$$Q1Q1 = Pr[R_c > 20 | R_f > 20] \tag{5}$$

Likewise, the *cycle of privileges (Q5Q5)* measures the share of children from parents in the top quintile that stay in the top quintile themselves.

$$Q5Q5 = Pr[R_c \geq 80 | R_f \geq 80] \tag{6}$$

3.1.4 Rate of Absolute Mobility (RAM)

The *rate of absolute mobility (RAM)* measures the fraction of children who earn more than their parents at the same age in real monetary units.

$$RAM = \frac{1}{N}\sum_{i}^{N} 1[Y_{ci} > Y_{fi}] \tag{7}$$

N is the number of children in the respective cohort. Incomes of parents Y_{fi} and children Y_{ci} have to be adjusted for inflation. Besides, income is usually measured around mid-life with the intention to minimize life-cycle bias.

3.2 Educational Mobility

3.2.1 Switzerland's Education System

Switzerland is well known for its vocational education and training (VET) system. In contrast to other countries, where vocational education is seen as the «last resort», the VET system in Switzerland is highly regarded and the «standard» track for the majority of adolescents after the lower-secondary level. Almost 70 percent of the children earn a vocational degree after compulsory school. Only around 20 percent opt for a high school, also called gymnasium or baccalaureate schools.[3] A high school degree allows children to take up studies at the university level in almost all fields. (Educa, 2021)

The education system differs from most foreign systems of vocational and professional education and training. VET is usually based on a dual system: It comprises practical training (apprenticeship) on three to four days at a company and is supplemented by formal classes on one to two days at a VET school. Currently, there are around 250 VET programs for different occupations. Therefore, many children obtain professional qualifications already at an upper secondary level, while in other countries the same qualifications are received on a tertiary level. (Educa, 2021)

After lower-secondary level, children can apply for apprenticeship at a training company. The training company can decide which children to employ. Usually, the firm's selection is based on the student's performance in school, the application documents, and on an interview—similar to «adults labor market procedures». Depending on the VET program, the duration ranges from two to four years. (Educa, 2021)

[3]Smaller tracks include specialized schools. They provide students with preparation for tertiary level professional education in specific occupational fields at colleges of higher education.

3.2.2 Educational Mobility Measures

We use three different measures for educational mobility. The correlation in years of schooling between parents and children, the share of children from the bottom quintile that visit a high school, and the change in likelihood to visit a high school when one of the parents visited a high school.

The *correlation in years of schooling* measures how the years of schooling between parents and children correlate. To do so, we use the highest education from any of the parents and approximate this with years of education.[4] Since vocational education is highly common in Switzerland, this measure might not capture the full persistence of educational inequality over generations. The reason is that a large share of time in the vocational apprenticeship is spent on hands-on training in a firm and not necessarily in a school. Thus, children in VET have far less formal education than children in a high school, even though the difference might not be large in terms of years of schooling if one approximates three years of VET to three years of schooling.

Therefore, we specifically look at the persistence in educational tracks over generations. First, we do so by measuring the share of children in the high school track by parental income. We refer to this measure as *Share Bottom 20 in HS* . We estimate the share of children in high school in the bottom quintile of the parental income distribution. Second, we look at how much more likely children are to visit a high school, if one of their parents visited high school. We call this measure *Child in HS if parent was.* To keep things simple, we run a linear regression model with the binary outcome variable of child high school on parental high school. The slope then indicates how much more likely children from parents with a high school degree are to also visit a high school.

[4] The conversion table from highest completed education into years of schooling can be found in the appendix in Table A1

4 Data and Variable Construction

4.1 Data sources

We use several data sources for our analysis. We combine individual-level demographic information and official (mandatory) survey records, both provided by the Federal Statistical Office (FSO), with social security earnings records (SSER) from the Central Compensation Office (CCO).

We derive data on demographic characteristics, family ties, and citizenship from the «Population and Households Statistics» (STATPOP), a collection of several registers.[5] To establish the intergenerational connection, we use information from the INFOSTAR register. This register contains around 85 percent of all parent-child relationships of the Swiss population. Family ties for non-natives are less likely to be identified since births occurring in foreign countries are not recorded. We will take this into account by excluding non-natives.[6]

We match individual information to the longitudinal «social security earnings records» (SSER). The register includes every legal labor income in Switzerland. It provides complete earnings information for employed and self-employed in Switzerland since 1982. Its purpose is to calculate public old-age insurance. Earning records are not top-coded, allowing us to depict the labor income distribution accurately.

We complement the matched STATPOP-SSER with information from the structural survey (SE). This data set is available since 2010 and surveys roughly 200,000 persons per year (2 percent of the population). Participation is mandatory and non-participation is sanctioned. As we have nine years available, we have a sample size of over 1,600,000 unique observations (some individuals are surveyed multiple times). The survey includes, for example, information on education, religion, and occupation. Although this data is only available since 2010, this is not a drawback for us. Most variables we use, such as educational attainment or religion, can be assumed to stay constant after the age of 30.

[5] This data is also known as the «New Population Census» or the «Register Survey».

[6] Excluding immigrants might be seen as a limitation. However, regarding comparability, we are in line with other studies, which exclude immigrants from the sample (Chetty et al., 2014a) or (Heidrich, 2017). One could also argue that intergenerational mobility, which is also a measure for opportunities during childhood, should focus only on children that spent their entire childhood in a country. Children of immigrants are included in our sample if they are born in Switzerland.

4.2 Sample Selection

The core sample comprises native child cohorts from 1967 to 1984. Conditional on being born in Switzerland, we link 72 percent of children to their father. The share varies between 88 percent for the 1984 cohort and 56 percent for the 1967 cohort. As we observe the universe of Swiss residents between the years 2010 and 2017, non-identified intergenerational links are because of death, emigration, or missing register updates in the IT system. Following the previous literature, we measure child income between the age of 30 and 33, while we measure lifetime family income when the child is between 15 and 20 years old. Therefore, our sample includes cohorts aged at least 15 years in 1982 and at least 33 years in 2017. Virtually every individual in our sample has at least one income record. For over 97 percent of children born between 1967 and 1984, we observe at least one non-negative income record between the age of 30 and 33. [7]

The core sample comprises individuals born between 1967 and 1984, for whom we can at least identify the father, whose mean income is non-negative between the age of 30 and 33, and whose mean parent income is non-negative between child age 15 to 20. The justification for requiring the father to be identified lies in the relatively strong gender difference in labor income. Using children for which only the mother needs to be identified, leads to higher income mobility estimates. A concern might then be that if the father passed away before 2010, we cannot accurately capture the persistence in income inequality and introduce attenuation bias. In a robustness sections, we also use different samples. For example, for those for whom we can identify either father or mother or for whom we can identify both father and mother. In a robustness check, we also use different samples.

Although we have an extensive coverage of child-parent relationships, we still check whether it represents Switzerland accurately. Table A2 shows sample means for the full population (1967 to 1984 cohorts) and the core sample and alternative samples. In the population, we have 1,266,376 individuals born in Switzerland between 1967 to 1984 (Column 1). For almost 90 percent of those individuals, we have been able to identify either the mother or the father (Column 2). Conditioning on observations for whom we can identify at least the father, which

[7] Negative income records occur because of accounting techniques. When the income has to be corrected, the correction is recorded with a minus, and the amount has to be subtracted. Less than 0.03 percent of observations have either negative mean parent income or negative mean income.

is our core sample, the share declines to 72 percent (Column 3). The last column restricts to individuals for which we can identify the father and the mother (Column 4). Panel (A) shows the summary statistics for the income sample. Our core sample (Column 3) is slightly younger than the full sample, as parents of older cohorts are more likely to be dead relative to parents of younger cohorts. The lower Part of the Table, Panel (B), reports descriptive statistics for the education sample. We do not observe the education level for everybody in the core sample since information on education stems from the structural survey (SE). However, the size of the education sample is still large. Overall, sample differences are minimal or explainable and our core sample represents the total population of children born in Switzerland.

4.3 Income Definition

Income is the sum of wage earnings (employment and self-employment income), unemployment benefits, military compensation, maternity leave payments, and disability benefits. We deflate all incomes with the consumer price index (Swiss CPI) to 2017 CHF.

Child Income. In the core specification of rank mobility, we measure child income during the ages 30 to 33. The principal reason for this choice is to compare our estimates to other countries, specifically to the US. To smooth out transitory income shocks, we average income over four years. We set income equal to zero if we do not observe any income during those four years. In Section 8, we test the robustness of our baseline estimates using alternative age definitions. In Table A3, we assess the sensitivity to alternative income definitions.

Family Income: In the core specification, family income is the average of father and mother income when the child is between 15 and 20 years old. The reason for this choice is threefold: First, we aim to capture a child's opportunities while it is growing. The age between 15 to 20 is decisive in Switzerland because children decide which educational track they will follow. Second, parents are on average in their mid-forties, making their rank in the income distribution stable and the life-cycle bias negligible. Third, to ensure comparability to the US (Chetty et al., 2014a). In Table A3, we evaluate the sensitivity of this choice by varying child age at which parent income is measured.

4.4 Summary Statistics

Table 1 provides summary statistics for the core sample. In the main specification, we use 923,107 observations for the income and 308,622 observations for the education analysis. Panel (B) and Panel (C) also show child and parent income at different points of the distribution. More detailed description of the child and parent income distribution can be found in the Appendix in Table A4.

We base the geographic assignment of a child on the mother's municipality in 2010. If the mother is missing, we use the father's municipality in 2010. We do not have longitudinal information on geographic location of individuals before 2010. Data allows, however, to figure out since when an individual lives in a municipality. Geographic mobility is low in Switzerland. Over 70 percent of mothers live in the same municipality as they used to live in 1995. In addition, we also know the place of birth of individuals, which is usually in a hospital close to their municipality. Thus, we use the municipality of birth in a robustness check.

Table 1: Summary Statistics of Core Sample

	(1) mean	(2) sd	(3) min	(4) max
Panel A: General				
Personal Characteristics				
Year of birth	1975.65	5.27	1967	1984
Father age at childbirth	30.26	5.20	13	68
Mother age at childbirth	27.47	4.62	13	57
Female	0.49	0.50	0	1
Married	0.45	0.50	0	1
Non-Native Father[a]	0.11	0.31	0	1
Geograpy				
Same municipality as in 1995[b]	0.71	0.46	0	1
Lake Geneva Region	0.15	0.36	0	1
Espace Mittelland	0.25	0.43	0	1
Northwestern Switzerland	0.13	0.34	0	1
Zürich	0.18	0.38	0	1
Eastern Switzerland	0.14	0.35	0	1
Central Switzerland	0.11	0.32	0	1
Ticino	0.04	0.18	0	1
Language Region				
German	0.76	0.43	0	1
French	0.20	0.40	0	1
Latin	0.04	0.20	0	1
Education[c]				
High-school	0.21	0.41	0	1
VET	0.66	0.47	0	1
Master	0.16	0.37	0	1
Income				
Child: at least one income record	0.96	0.21	0	1
Family: at least one income record	1.00	0.06	0	1
Child income at age 30-33	60,598.21	39,451.96	0	7,385,721
Child income at age 40-43[d]	75,358.69	80,547.33	0	12,711,202
Family income at child age 15-20	64,214.18	65,426.26	0	13,654,888
Panel B: Child Income at Age 30-33				
Bottom 20	10,970	9,041		
At Rank 25	34,426	3,476		
At Rank 50	61,857	2,690		
Top 20%	109,995	42,932		
Top 10%	126,510	54,118		
Top 1%	186,735	105,673		
Panel C: Family Income at Child Age 15-20				
Bottom 20	26,042	9,282		
At Rank 25	40,901	1,517		
At Rank 50	55,049	2,332		
Top 20%	123,132	122,051		
Top 10%	155,176	162,008		
Top 1%	291,319	345,799		
Obs.	923,107			

[a]Father not born in Switzerland

[b]Mother

[c]Observations: 308,622

[d]Observations: 365,573

Notes: Table 1 provide a description of the core sample. Panel A reports general characteristics. Panel B and Panel C show the average income and the standard deviation of children's income between 30 and 33 and family income (measured when the child is between 15 and 20). The number of observations refers to the " Income sample". All amounts are in 2017 CHF.

5 National Mobility Estimates

5.1 Income

5.1.1 Income Mobility Estimates

Figure 1 presents the *rank-mobility estimates*. The points show the expected income rank of children for every parent income rank. The relationship is almost linear. This justifies the use of a linear regression to summarize the rank-rank relationship and the rank-rank slope is an insightful and parsimonious statistic across the parental income distribution.

The line in Figure 1 is the prediction of a linear regression of child rank on parent rank. A higher slope (RRS) means lower intergenerational mobility. Here, the slope is 0.14. Since there are 100 ranks, the difference between the lowest and the highest income rank is 14 (0.14×100), which is sometimes referred to as the wedge between rich and poor children. We can also translate the rank back into monetary units to increase the interpretability. This difference of 14 ranks translates to approximately 11,000 CHF ($\approxeq$ 11,000 USD) in the early thirties, which corresponds to roughly two median monthly salaries in Switzerland.[8] The constant in the regression in Figure 1 is 44. This is the rank which a child with parents in the lowest rank can expect to achieve. The R^2 of the regression is only 0.02. While there is clearly a positive relationship between parent and child rank, parental income rank is only a weak predictor of the child's income rank. The *AUM25* can be calculated by the slope and the constant and is 46. Thus children from the bottom half of the income distribution can expect to achieve income rank 46.[9]

The *directional mobility* estimates are shown in the quintile transition matrix in Table 2. It describes in which quintile children end up conditional on their parent quintile. If child and parent income were, one would expect to see 20 percent in each cell. This would be the case with perfect mobility.[10]

The *American Dream (Q1Q5)* measure is presented in column 1 and row 5. It reveals the share

[8] Mean income for parent and child rank can be found in Table A4 in the appendix.
[9] In the national sample, due to its large size, the AUM25 can also be retrieved by simply looking at the mean rank of children with parents at rank 25.
[10] Table A6 shows the same for the distribution with both parents identified

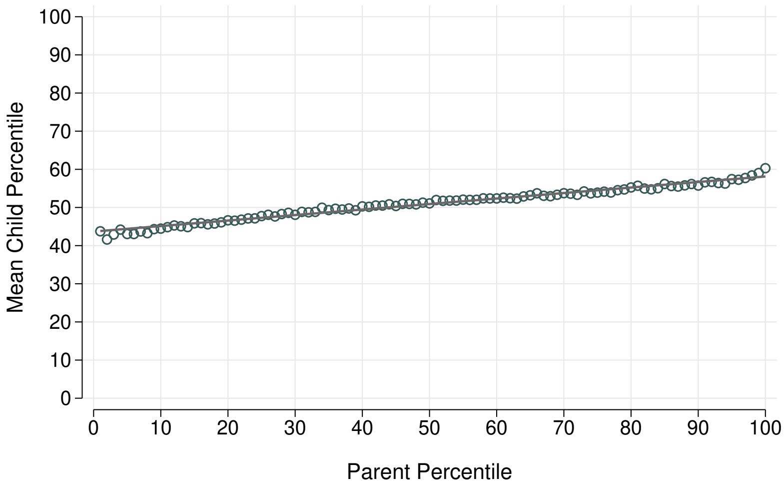
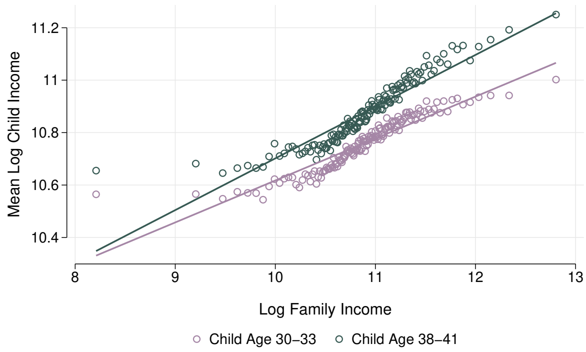


Figure 1: Child and Family Rank Relationship

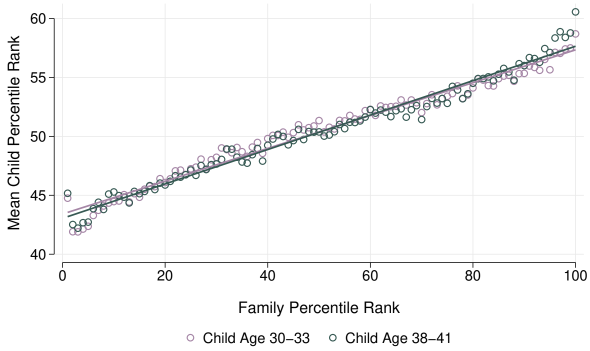
Notes: The points show the mean child rank for each parent rank. Ranks are in percentiles. The pink line is the prediction of an OLS regression of child rank on parent rank based on 923,262 observations. The OLS regression yields a constant of 43.7 and a (rank-rank) slope of 0.14 (RRS). The R^2 is 0.02. The estimated rank-rank slope of 0.14 is a measure of relative income mobility. The higher this slope, the more child income depends on parent income, hence the lower income mobility. The rank difference between children from the poorest and the richest parents equals the slope $\times 100$, and is 14 in this case. This is sometimes also called the «wedge» between children from the highest and lowest parent percentile.

of children with parents at the bottom quintile that make it to the top quintile. In Switzerland, this share is around 12 percent. The *cycle of poverty measure (Q1Q1)* is shown in row 1 and column 1. It indicates the share of children from the bottom quintile, which stay in the bottom quintile. In Switzerland, this share is around 24 percent. The *cycle of privileges measure (Q5Q5)* is shown in row 5 and column 5. This share is around 30 percent. Thus, around 30 percent of children from the top quintile stick in the top quintile.

Figure 2 compares the parent-child income relationship in logs to the relationship in ranks for different ages at which child income is measured. The slope of the line in Panel (a) is the *intergenerational income elasticity (IGE)*. The figure reveals two insights: First, the log relationship is not linear. Thus, the IGE differs along the parental income distribution. It is lower at the bottom and at the top of the parental income distribution. While those non-linearities are interesting per se, they make it difficult to use the IGE as a parsimonious statistic and compare it to other countries. Second, the slope is higher if child income is measured at



(a) Intergenerational Income Elasticity (IGE)



(b) Rank-Rank Slope

Figure 2: Log-Log and Rank-Rank Relationship by Child Age

Notes: This figure shows how the IGE and the rank-rank slope depend on the age at which child income is measured. The estimated IGE in Panel (a), represented by the lines, is higher when measured at later ages. Thus, the IGE is subject to severe life-cycle bias when child income is measured too early. The relationship between log-child and log-parent income is not linear. The rank-rank slope in Panel (b) is almost similar when child income is measured at later ages.

Table 2: Quintile Transition Matrix

	Family quintile				
Child quintile	1	2	3	4	5
1	23.66	21.55	19.43	17.93	17.43
2	21.46	20.26	19.48	19.26	19.54
3	20.94	21.92	20.37	19.02	17.75
4	17.66	21.07	21.38	20.56	19.33
5	11.87	15.49	19.35	22.98	30.30

Notes: Each cell describes in which quintile (row) children end up conditional on the parent quintile (column). Parent quintile is based on mother and father income conditional that father income is identified. For example, 17.44% of children from parents in the top quintile of the income distribution will end up in the bottom quintile of the income distribution. 11.8% of children from parents of the bottom quintile of the income distribution end up in the top quintile («American Dream measure»). The table includes children born in Switzerland from 1967 to 1984 for which at least the father can be identified. It is based on 923,262 observations.

later ages (life-cycle bias). Therefore, the IGE should be interpreted with caution.[11]

The *IGE* is 0.16 when child income is measured between 30 and 33, and 0.21 if child income is measured between 38 and 41 (see Table A7). Nybom and Stuhler (2016) show that life-cycle bias is lowest when income is measured around mid-life. Thus, 0.21 would be our baseline estimate. Furthermore, the IGE varies along the parental income distribution. It is around 0.09 in the lowest parent tertile, 0.42 in the middle tertile, and 0.22 in the highest tertile. Around half of the size of the IGE is driven by changes in inequality over generations. This can be seen in Column (2) and (7) in Table A7. When log income is standardized, thus divided by the standard deviation, the IGE becomes 0.10 for income at age 30 to 33 and 0.12 for age 38 to 41 (also see Equation 2. Thus the IGE is not only smaller, but also less prone to life-cycle bias.

Finally, we move to the *rate of absolute mobility (RAM)*. Table 3 shows the share of children earning more than their parents at the same age. Income is averaged between the ages 40 and 45. This reduces the number of included cohorts and the sample size (n=451,491). The results show that 39 percent of children earn more than their father did, at the same time, 83 percent of children earn more than their mother. Due to the gender specific labor market participation over time, comparing sons to fathers might be most sensible. Here, we see that almost 58 percent of sons earn more than their father.

[11]Estimates for different samples are shown in Table A5 in the Appendix

Table 3: RAM: Rate of Absolute Mobility

Child Sex	Share Child Income > Father Income	Share Child Income > Mother Income	Observations
All	0.386 (0.0007)	0.834 (0.0005)	451,491
Female	0.183 (0.0008)	0.739 (0.0009)	230,931
Male	0.579 (0.0010)	0.925 (0.0005)	220,560

Notes: This figures shows the share of children earning more in real terms than their mother or father at the same age. Income of children and parents is measured at the same ages between 40 to 45 (child cohorts: 1967 to 1977). For example, 18.3% of women earn more between 40 and 45 than their father did between 40 and 45. Income is deflated with the consumer price index 2017. Standard errors are shown in parentheses.

5.1.2 International Comparison

How can these national estimates be interpreted? Table 4 puts the mobility estimates of Switzerland in context to other countries. As always, one has to be careful when comparing estimates across countries since data processing might differ for example with respect to the analyzed cohorts or the definition of income. To enhance comparability, we have only chosen studies that use large and/or administrative data and were conducted in the last 10 years.

Looking at the rank-based mobility results shows that Switzerland has very high income mobility estimates. One exception is the «American Dream (Q1Q5)» measure: In Sweden, for example, children from the bottom quintile are more likely to reach the top quintile than in Switzerland. Also, Switzerland is doing a little worse in terms of IGE. However, as shown above, this measure is highly susceptible to the location in the parental income distribution, to changes in inequality over time, and to the age at which child income is measured. This makes comparison between countries very unreliable. Thus, we argue that in the most comprehensive measure, the rank-rank slope (RRS), Switzerland is doing better than any other country.

5.2 Educational Mobility

Despite the high income mobility estimates in the previous section, we find that educational mobility is low in several dimensions. Figure 3 shows how the educational track depends on the parental income rank. In the bottom quintile, only around ten percent of children visit a high school. In the top decile, however, more children opt for a high school than VET.

Table 4: International Comparison

Country	Mobility Measure						Source	Observations
	RRS	IGE	Q1Q5	Q1Q1	Q5Q5	AUM25		
Switzerland	0.14	0.22	11.87	23.67	30.3	46	Chuard-Keller and Grassi (2021)	923,262
US	0.34	0.45	7.50	33.7	36.5	41.4	Chetty et al. (2014a)	40,000,000
Sweden	0.18	0.29	15.7	26.3	34.5	43.6	Heidrich (2017)	927,008
	0.22	0.231	-	-	-	-	Bratberg et al. (2017)	252,745
Italy	0.25	0.25	9.9	28.66	35.6	44	Acciari et al. (2019)	647,662
Canada	0.24	0.20	11.4	30.1	32.3	44.35	Corak (2020)	3,002,950
Australia	0.21	0.19	12.3	31	30.7	45.1	Deutscher and Mazumder (2020)	1,025,800
Norway	0.22	0.19	-	-	-	-	Bratberg et al. (2017)	324,870
Denmark	0.20	0.17	-	-	-	-	Helsø (2021)	151,360
	-	-	11	31	35	-	Eriksen (2018)	205,625

Notes: This table compares results of recent studies on intergenerational income mobility that use high quality data and are thus likely to provide reliable results. *RRS* stands for rank-rank slope. The higher the RRS, the lower income mobility. *IGE* stands for intergenerational elasticity. For Switzerland, IGE is measured at age 38 to 41. The higher the IGE, the lower mobility. *Q1Q5* is the «American Dream» measure. It reports the share of children from the bottom quintile that make it to the top quintile. The higher this measure, the higher mobility. *Q1Q1* is the «cycle of poverty» measures. It reports the share of children from the bottom quintile that stay in the bottom quintile. The higher this measure, the lower mobility. *Q5Q5* is the «cycle of privileges» measures. It reports the share of children from the top quintile that stay in the bottom quintile. The higher this measure, the lower mobility. *AUM25* stands for absolute upward mobility at percentile 25. It shows where children with parents at the 25th percentile of the income distribution can expect to end up. This follows from the prediction of the rank-rank slope regression. It also shows where children with parents below the median can expect to end up.

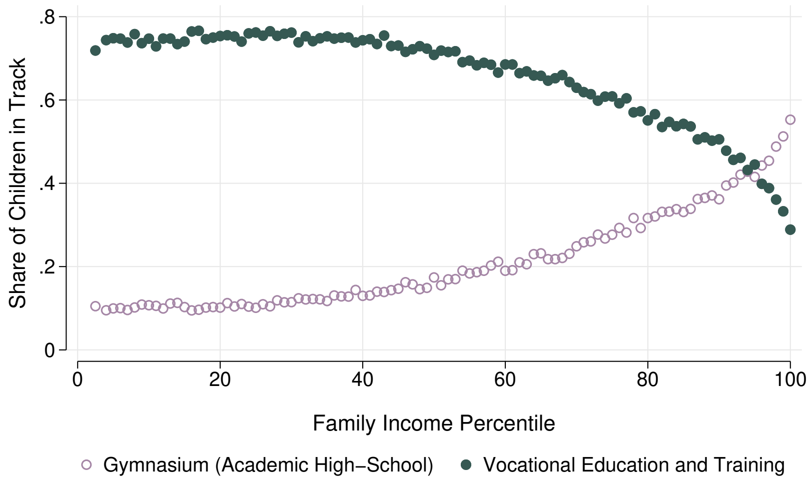


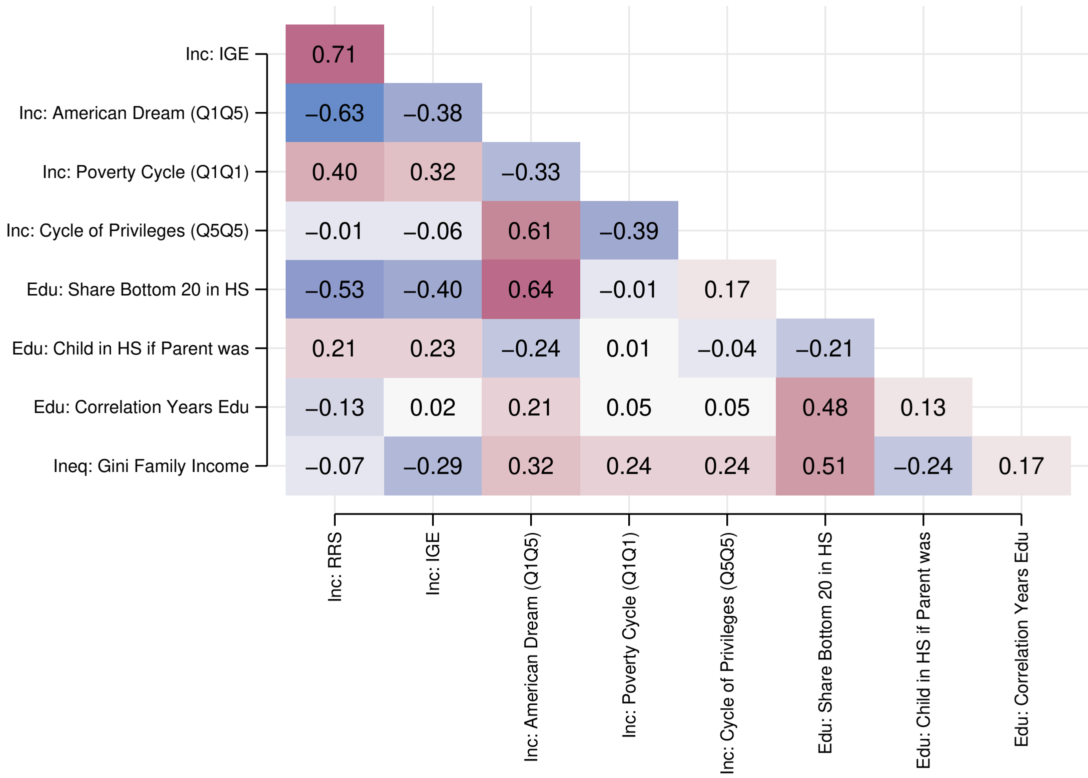
Figure 3: Educational Track by Parent Income

Notes: This figure shows the share of children by family income rank in the high school (gymnasium) and the vocational education and training track (VET).

Table 5 provides further evidence of low intergenerational educational mobility. Column (1) shows the slope coefficient of a linear regression of years of schooling of the child on years of schooling of the parents. We associate one year of schooling more of the parents with 0.33 years more schooling of the child. This is a relatively high-estimate compared to other countries, and especially considering the high income mobility estimates (Hertz et al., 2008). Column (2) shows that children with at least one parent with a high school degree are around 5 times more likely to visit a high school themselves. Similarly to Figure 3, columns (3) and (4) show how much more likely children are to visit a high school when parents are in the top quintile or the top percentile of the income distribution.

The results of low educational mobility are in line with previous research. For example, Bauer and Riphahn (2007) find high intergenerational persistence in terms of educational track. Also, Hertz et al. (2008) rank Switzerland's educational mobility similar to the ones of the US or Pakistan.

Figure 4: Correlation Mobility Measures (Unit: LM Region)



Notes: This graph shows the correlation of different mobility and inequality measures on a labor market units (n=106). *RRS* is the rank-rank slope, *IGE* is the intergenerational income elasticity, *Share Bottom 20 in HS* measures the share of children from parents in the bottom quintile that go to high school, *Child in HS if Parent was* is the slope coefficient of a linear provability model that regresses high school attendance of the child on high school attendance of the parents, *correlation Years Edu* measures the correlation in years of education between parents and children, *Gini Family Income* measures the GINI index for family income at child age 15 to 20.

Table 5: Educational Mobility

	OLS	Logit		
	(1)	(2)	(3)	(4)
	Child Yrs. Schooling	Child HS	Child HS	Child HS
Yrs. School Parent	0.334***			
	(0.0029)			
Parents HS		5.237***		
		(0.0793)		
Parents > Rank 80			3.436***	
			(0.0337)	
Parents > Rank 99				4.753***
				(0.1707)
Observations	152,334	182,501	308,673	308,673
Mean Dep. Var.	14.233	0.219	0.210	0.210

Exponentiated coefficients in Col (2) to (4); Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table shows different measures of educational mobility. Column (1) shows how years of schooling of parents and children are correlated (yrs of schooling are standardized). Column (2) shows how much more likely children are to visit a high-school if one of their children visited a high-school. Column (3) shows how much more likely children are to visit a high-school if their parents are in the top quintile of the income distribution compared if they are below. Column (4) shows the same as column (3) but does so for the top percentile of the parent income distribution.

5.3 Correlation of Mobility Measures

Figure 4 shows how mobility measures correlate with each other on a labor market regions level.[12] When looking at the rank-rank slope (RRS), we find high correlations with most income mobility measures. One exception is the cycle of privileges measure (Q5Q5): The persistence in the top quintile of the income distribution seems to be only weakly correlated to the rank-rank slope. Interestingly, the cycle of privileges measure is strongly correlated with the American Dream measure. This result is somewhat counter-intuitive. It is telling us that regions with high top income persistence over generations also provide good opportunities to children from the bottom quintile to climb to the top quintile.

Moving further to educational mobility, we see that there is a fairly strong correlation of most income mobility measures with educational mobility. For example, a higher rank-rank slope (lower income mobility) is associated with a lower share of children from the bottom quintile in high schools and also with a higher persistence in the educational track («Child in HS if

[12] Figure A9 in the Appendix shows the same on a cantonal level.

Parent was»). The educational mobility measure of «correlation in years of education» is only weakly related to most other measures. As mentioned before, this measure might not capture the full persistence in educational inequality because of the idiosyncratic education system in Switzerland.

The finding that intergenerational educational mobility is correlated with income mobility is important. It implies that our previous (national) finding of high income mobility but low educational mobility does not mean that education does not matter. Although this is not a causal estimate, it is in line with predictions of theoretical models (e.g. Becker and Tomes (1986)) which state that educational mobility is the main pathway to income mobility. The crucial point is that in Switzerland, educational inequality translates only weakly into income inequality over generations. One can argue that this is due to its VET system, which provides good wage outcomes with comparably little (formal) education. We further elaborate this point in Section 7.1

6 Mobility Across Time and Space

6.1 Mobility over Time

Figure 5 shows how *income mobility* developed. It does so for three measures of relative mobility: The American Dream measure (Q1Q5), the poverty cycle measure (Q1Q1), and the rank-rank slope (RRS). In general, there is no clear and significant trend in any of the income mobility measures. If anything, one can discern a small upward trend in the poverty cycle measure, which would suggest lower mobility. However, the same can be said about the American Dream measure, which would then suggest higher mobility.

The rank-rank slope increases slightly since cohort 1975, but decreased before. One interpretation for the peak around the cohort 1972 might be the boom before the financial crisis in 2008. For Children born in 1972, their income is measured between 2002 and 2005. It is conceivable that children from high income parents profited more of this upswing. This would then mechanically lead to lower mobility. It is also interesting that the increase in the rank-rank slope around this time did not affect children from the bottom quintile—since the Q1Q1 and Q1Q5 measure stay almost constant.

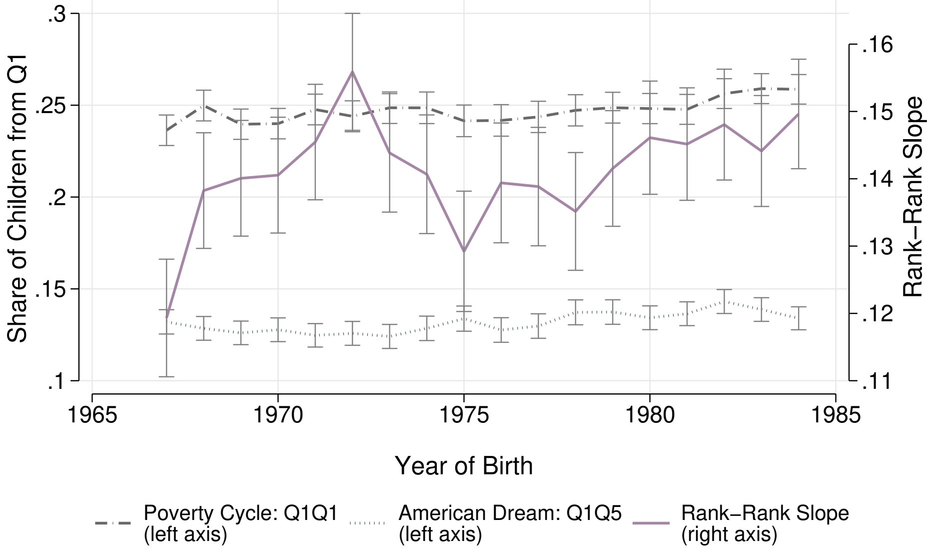


Figure 5: Income Mobility over Time

Notes: This figure shows how income mobility varies across cohorts. The *poverty cycle (Q1Q1)* measure shows the share of children from the bottom quintile staying in the bottom quintile. An increase means lower mobility. The *American Dream (Q1Q5)* measure shows the share of children from the bottom quintile moving to the top quintile. A decrease shows lower mobility. The *rank-rank slope (RRS)* on the right axis shows the rank-rank slope. An increase shows lower mobility. The bars represent 95% confidence intervals.

Figure 6 shows how educational mobility developed. There is a trend towards higher educational mobility in terms of educational tracks: The share of children from the bottom quintile that visit a high school increases from around 8 percent in the late 60s cohort to around 12 percent for the 80s cohort. Also, whether a child visits a high school depends less on whether parents visited a high school since cohort 1975. At the same time, the correlation in years of schooling between parents and children increases slightly. However, as mentioned before, the years of schooling measure should be interpreted with caution.

6.2 Geographical Variation

In this section, we analyse if Switzerland is a land of opportunity overall, or whether there are some regions with a high intergenerational (income) mobility driving the result. This is to say, that the national mobility estimates in the previous section could mask differences in mobility across regions. Regional analysis can be important to guide further research in finding policies that promote upward mobility. We will look more deeply at regional covariates in Section 7.

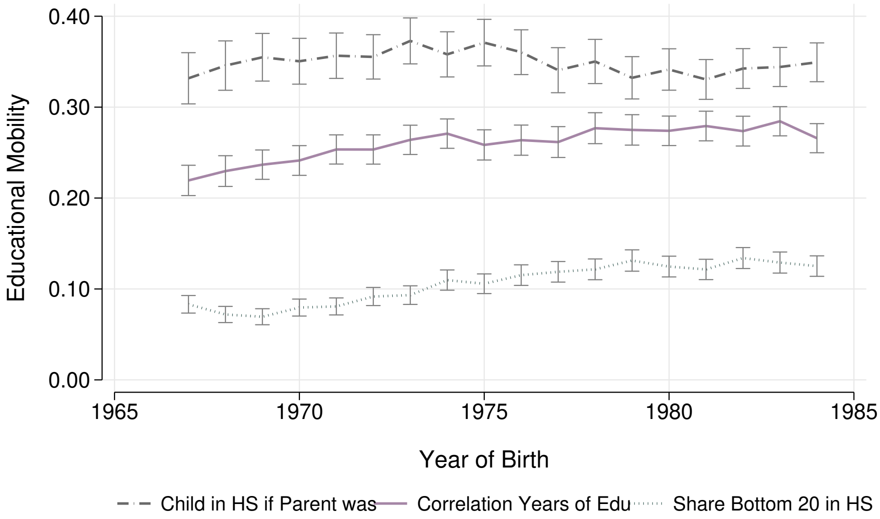


Figure 6: Educational Mobility over Time

Notes: This figure shows how educational mobility varies across cohorts. «Child in HS if Parent was» shows how much more likely children are to be in high school if one of their parents was in high school. «Correlation Years Edu» shows the correlation between years of education of parents and children. «Share Bottom 20 in HS» shows the share of children from the bottom quintile of the income distribution that visit a high school.

We analyze mobility on two geographical entities: labor market regions (n=106) and cantons (n=26). Cantons are the main political entities with substantial authority in policy setting. Labor market regions depict commuting patterns and are constructed by the Swiss Federal Office of Statistics, similarly to commuting zones in the US.[13]

Figure 7 shows heat-maps of the different income mobility measures on a labor market level. The precise estimates can be found in Table A8 in the Appendix. Figure A1 and Table A9 in the Appendix do the same on a cantonal level. The darker the colors, the higher the mobility estimates. One can see that there is spatial correlation: Regions with higher mobility are more likely close to regions with high mobility. In general, there is a pattern with higher mobility in urban regions and lower mobility in the mountains. Again, the cycle of privileges (Q5Q5) measure seems to be less related to the other measures. In urban regions, we also see that children from rich parents are also more likely to stay rich.

[13]In the main specification, we use the mother's municipality in 2010 to approximate childhood location because we do not have panel information on the exact location until 2010. In the robustness section we show that the results of our maps are robust to several location specifications, such as place of birth or place of residence of the child (see Section 8.3).

Figure 8 shows the same for educational mobility on a labor market level.[14] Here, brighter colors highlight regions with higher educational mobility. The patterns is similar to the on from income mobility before: Urban regions show higher mobility than regions in the mountains.

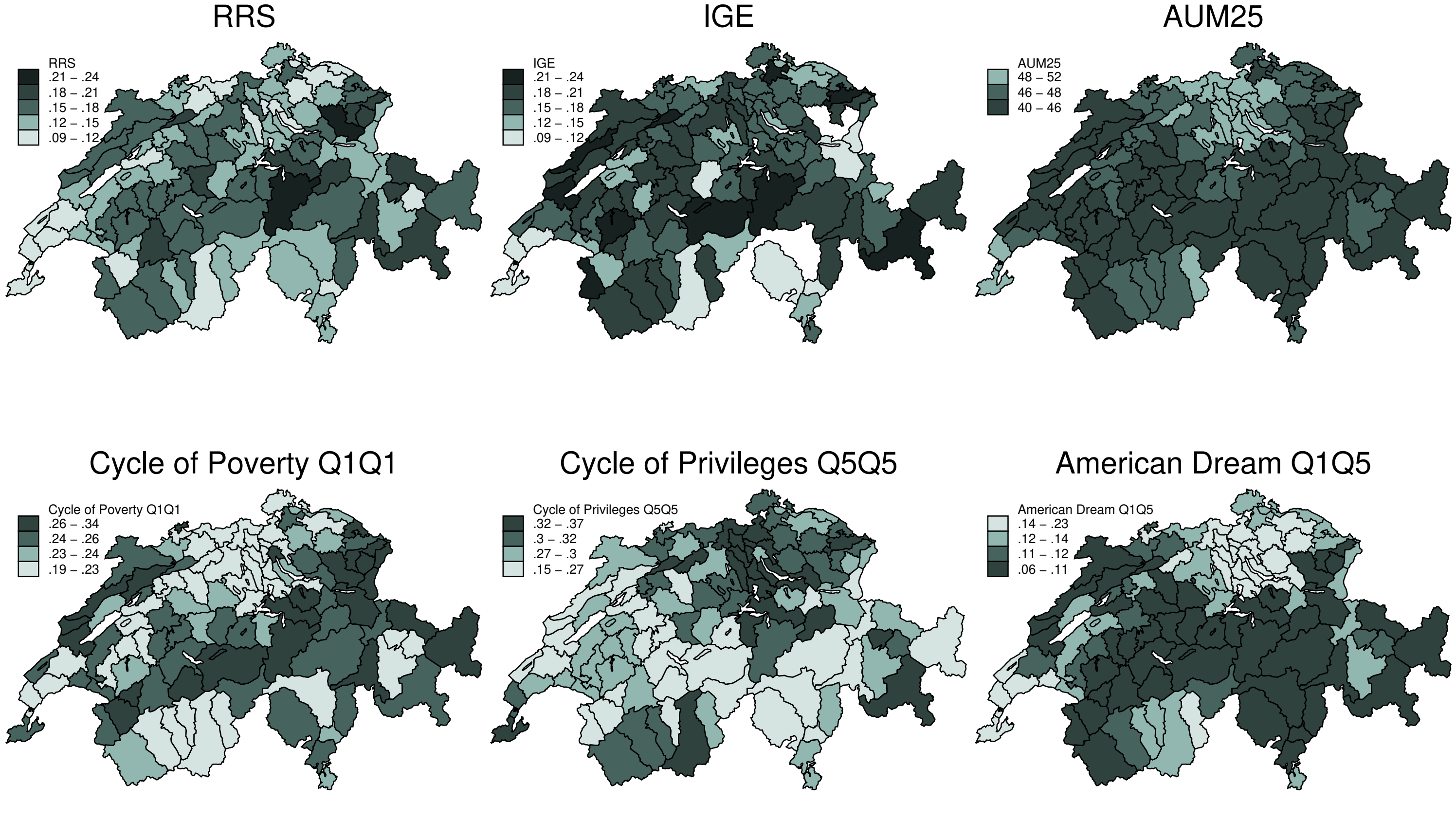
Table 6 summarizes how the mobility estimates vary across labor market regions. Looking at the variation coefficient, we see the highest variation in the educational mobility measure «Share Bottom 20 in HS». This varies between 2.6 percent in Schanfigg and 27.4 percent in Geneva. The cycle of privileges (Q5Q5) and the cycle of poverty (Q1Q1) estimates show a small variation coefficient (CV) and seem to be more homogeneous across Switzerland.

The highest absolute mobility at $p = 25$ (AUM25) can be found in Limmattal (close to the city of Zurich) with 56, the lowest in Kandertal (in the mountains) with 41. This means children from the bottom half of the income distribution will on average reach rank 56 in the national income distribution in Limmattal, while children from Kandertal reach 41. When we calculate this difference back to income levels, this amounts to around 12,500 Swiss Francs[15], which is around twice the median monthly salary. The standard deviation in absolute mobility is 2.3 (and 1.8 when using cantonal units). This is slightly higher than the standard deviation in Sweden (1.6) (Heidrich, 2017). Also, the range in Sweden is smaller: Absolute mobility at $p = 25$ varies from 41 in Arjäng to 49 in Värnoma. In terms of income, this difference mounts to 90 percent of a monthly salary in Sweden. The variation in Switzerland is however smaller than in the US, where absolute mobility at $p = 25$ varies between 36 ($\approxeq$ \$26,300) in Charlotte and 46 ($\approxeq$ \$37,900) in Salt Lake City (Chetty et al., 2014a).

[14] Again, the precise estimates can be found in the Appendix in Table A11

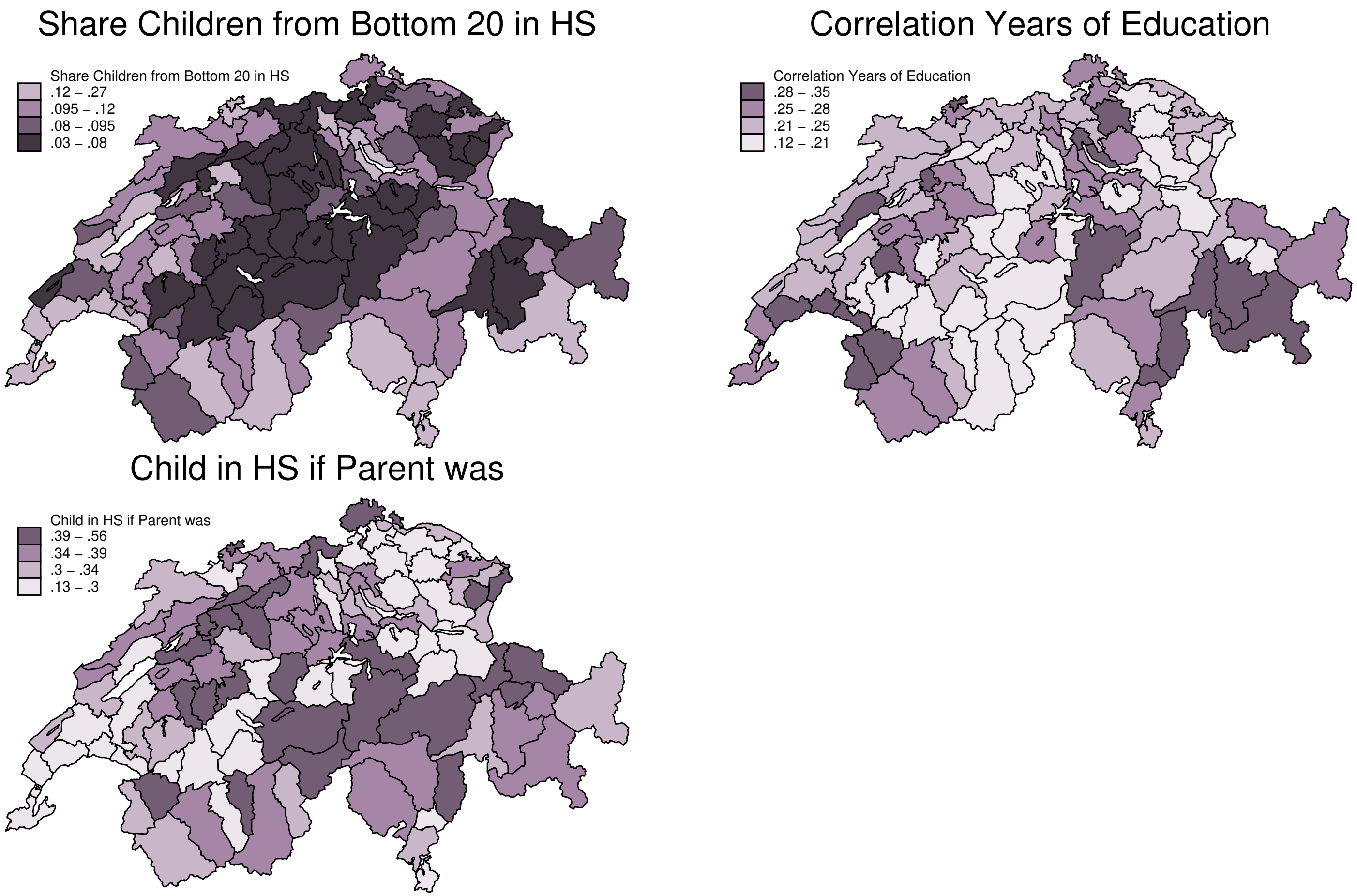
[15] 12,572 Francs at age 30-33 and 14,271 at age 39 to 42

Figure 7: Income Mobility Estimates Labor Market Regions



Notes: This figures shows how income mobility estimates vary across labor market regions. Brighter colors indicate higher mobility.

Figure 8: Educational Mobility Estimates Labor Market Regions



Notes: This figures shows how educational mobility varies across labor market regions. Brighter colors indicate higher mobility.

Table 6: Variation in Mobility on Labor Market Level

Variable	Mean	Std.	Min	Max	CV
Income Mobility					
RRS	0.145	0.026	0.099	0.233	0.181
IGE	0.170	0.037	0.081	0.257	0.215
AUM25	46.794	2.279	40.815	51.731	0.049
Q1Q1	0.245	0.028	0.188	0.336	0.114
Q5Q5	0.296	0.038	0.145	0.368	0.127
Q1Q5	0.126	0.032	0.064	0.232	0.255
Educational Mobility					
Years Education	0.243	0.046	0.121	0.350	0.189
Share Bottom 20 in HS	0.104	0.044	0.026	0.274	0.427
Child in HS if Parent was	0.348	0.074	0.130	0.560	0.214

Notes: This table shows summary statistics for the labor market regions (n=106) for different income and educational mobility estimates. CV is the variation coefficient. The mean represents the unweighted mean and therefore differs from the national mean.

7 Drivers of Mobility

7.1 Educational Tracks

In the previous paragraphs, we were looking at income and educational mobility separately. Now we are interested in how upward income mobility depends on the educational track. This might help in understanding the puzzle, why income mobility is high, even though educational mobility is low. We take up the approach by Chetty et al. (2020). In their paper, they analyze the background of children and the probability to move up the income ladder for different colleges in the US. Instead of colleges, we are looking at educational tracks.

If there are a lot of children that move up the income ladder in a specific educational track, this might be (a) because of high probability for poor children to move up the income ladder or (b) because there are many children from poor families in this track. The product of (a) and (b) yields the mobility rate—the share of children from poor backgrounds that reach the top. Say differently, we can decompose the mobility rate into the *probability of moving up* and into *access* it provides to children from low-income families.

We define educational tracks as a two element decision to simplify the analysis. The first element is the education after compulsory school: the upper secondary track. This can be: VET, gymnasium (high school), specialised middle school, or none (only mandatory). VET is the most common track, gymnasium—which is like a high school— the second most common.[16] The second element is the highest education on the tertiary or post-secondary level, if children decide to take up such an education. It comprises Bachelor, Master, PhD, HF, HFP, and vocational matura[17]. Bachelor's and Master's degrees can be obtained at a university or at an University of Applied Sciences. PhD can only be obtained at universities. HF and HFP are specialized, vocational specific, further educations that require a VET diploma.

In the first step, we are looking at the American Dream measure. Thus, access is defined as the share of children from the bottom quintile of the income distribution. Upmover rate is defined as the share of children from the bottom quintile that make it to the top quintile. The same with «medium upward mobility», the probability that children from the bottom half make it to the top half, is shown in the Appendix in Figure A3.

Figure 9 shows the up-mover rate on the vertical and the access rate on the horizontal for the specified tracks. It sticks out that most tracks lie on a curve and that there is a trade-off: Tracks providing a high probability of moving up, give only little access to poor children, for example «Gym+Master». There are only around 10 percent of children with parents from the bottom quintile in this track. However, if a child from the bottom quintile is in this track, it has a high likelihood of 37 percent of moving to the top quintile. This could either be by selection, e.g. more able children from poor families select into this track (selection effect) or because the track really adds some value to those children (causal effect).

The most interesting part is that there are some tracks that lie off this curve and provide a better trade-off. Those are the tracks on the upper-right. They provide relatively high access *and* relatively high chances to move up the ladder. It is striking that all those tracks start with VET and add some higher education. Thus, one can conclude that tracks that start with *VET and add some other higher education* inhabit lot of children that move up, because they provide relatively high access and relatively good wage outcomes. Interestingly, children that have a vocational degree «only» have relatively low mobility rate. Thus, the high mobility in Switzerland is not necessarily because of the VET system, but because there is a high

[16] Since there are very few children in specialised middle school, we refrain from showing their further paths

[17] Strictly speaking, the vocational matura (baccalaureate) is also part of the upper-secondary level.

permeability to further education when children start with VET.

The numbers are shown in Panel (a) in Table 7. More importantly, it also shows that the mobility rate—the product of the up-mover rate and the access rate—is highest for those tracks that start with VET and add some further education. Panel (b) in Table 7 shows the same results but defines access as the share of children from the bottom half of the parent income distribution, and the upmover rate as making it to the top half of the income distribution. Again, tracks starting with VET and add some further education show the highest mobility rate. It is interesting that with this measure also «VET only» shows a relatively high mobility rate. When looking at medium upward mobility, «VET only» might still drive upward mobility. Children are, however, less likely to make it to the top quintile with VET only.

Taken together, the low educational mobility in terms of educational tracks does not matter too much for income and therefore only weakly translates into low income mobility. «Medium upward mobility» is high, even when children «only» conduct vocational education. Even more promising for policy advice are the tracks that start with VET and add some further education. There are many children in those tracks that achieve the American Dream. This is likely because children can opt for this kind of education even if parents are credit constraint. Children of poorer parents can opt for VET, which comes at very little costs for parents and even gives the children a small wage. After the children received their VET diploma they can opt for further education. A large share of this further education can be done parallel to a job, which further facilitates financing this human capital investment. This finding is in line with recent and seminal evidence on the importance of credit constraints in human capital accumulation (e.g. Black et al. (2020), Card and Solis (2020), Bettinger et al. (2019), Chu and Cuffe (2020), Denning and Jones (2019), Brown et al. (2012), and Carneiro and Heckman (2002)).

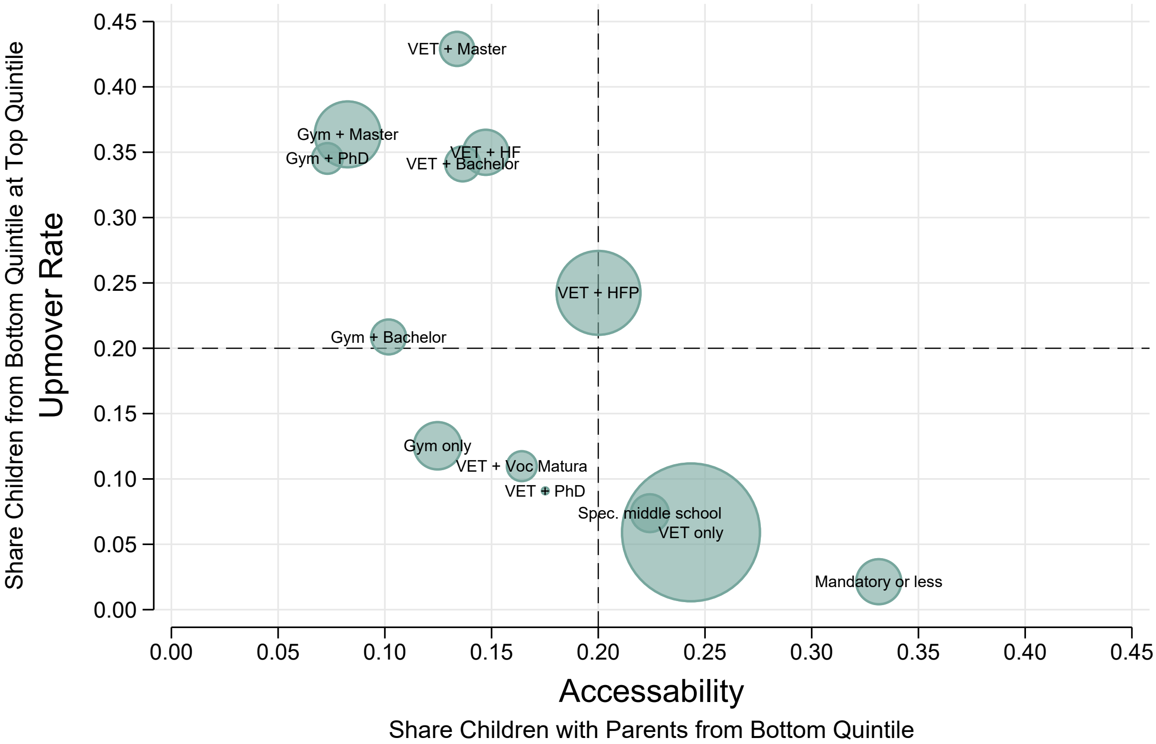


Figure 9: Access and Upward Mobility Rate by Educational Track (Q1Q5)

Notes: This graph shows how upward mobility (upmover rate) and access differ between educational tracks. Upmover rate is defined as the share of children with parents in the bottom quintile that move to the top quintile (Q1Q5). Accessibility is defined as the share of children from the bottom quintile relative to the total number of children in the educational track. The size of the points is proportional to the number of children in that track. The syntax of the educational tracks is defined as follows: [Upper Secondary Education] + [Highest Post Secondary Education]. *Gym* refers to gymnasium (academic high school), *VET* to vocational education and training. *HF* and *HFP* are occupation specific higher educations. *Voc Matura* refers to "vocational matura", which is VET with more formal education, *spec. middle school* refers to specialized middle schools, which is like a professional high school and not as selective as the gymnasium.
The upmover rate multiplied with the access rate equals the mobility rate, which is the share of children that climb from the bottom to the top quintile *relative to all children in that track.* In contrast, the upmover rate is the share of children that climb to the top quintile *relative to children from parents in the bottom quintile.*

Table 7: Access and Upmover Rate by Educational Track

(a) American Dream

Educational Track	Upmover Rate $P[R_C > 80 \mid R_P \leq 20]$		Access Rate $P[R_P \leq 20]$		Mobility Rate $P[R_C > 80 \wedge R_P \leq 20]$		N
VET only	0.059	(0.001)	0.243	(0.001)	0.014	(0.000)	31,936
Gym only	0.125	(0.008)	0.125	(0.003)	0.016	(0.001)	1,922
Gym + Bachelor	0.209	(0.014)	0.102	(0.003)	0.021	(0.002)	853
Gym + Master	0.364	(0.010)	0.083	(0.002)	0.030	(0.001)	2,472
Gym + PhD	0.345	(0.022)	0.073	(0.003)	0.025	(0.002)	475
VET + Bachelor	0.341	(0.014)	0.136	(0.004)	0.047	(0.002)	1,155
VET + HF	0.350	(0.010)	0.147	(0.003)	0.052	(0.002)	2,066
VET + HFP	0.242	(0.004)	0.200	(0.002)	0.049	(0.001)	9,723
VET + PhD	0.091	(0.039)	0.175	(0.021)	0.016	(0.007)	55
VET + Voc Matura	0.110	(0.010)	0.164	(0.005)	0.018	(0.002)	1,011
Mandatory or less	0.021	(0.002)	0.331	(0.004)	0.007	(0.001)	4,627
Spec. middle school	0.074	(0.006)	0.224	(0.004)	0.017	(0.001)	2,208

(b) Medium Upward Mobility

Educational Track	Upmover Rate $P[R_C > 50 \mid R_P \leq 50]$		Access Rate $P[R_P \leq 50]$		Mobility Rate $P[R_C > 50 \wedge R_P \leq 50]$		N
VET only	0.399	(0.002)	0.599	(0.001)	0.239	(0.001)	78,550
Gym only	0.419	(0.007)	0.346	(0.004)	0.145	(0.003)	5,329
Gym + Bachelor	0.481	(0.010)	0.289	(0.005)	0.139	(0.004)	2,421
Gym + Master	0.649	(0.006)	0.240	(0.002)	0.155	(0.002)	7,170
Gym + PhD	0.653	(0.013)	0.218	(0.005)	0.142	(0.004)	1,414
VET + Bachelor	0.660	(0.008)	0.404	(0.005)	0.267	(0.005)	3,416
VET + HF	0.680	(0.006)	0.435	(0.004)	0.295	(0.004)	6,100
VET + HFP	0.703	(0.003)	0.514	(0.002)	0.361	(0.002)	24,949
VET + PhD	0.416	(0.044)	0.398	(0.028)	0.166	(0.021)	125
VET + Voc Matura	0.491	(0.009)	0.473	(0.006)	0.232	(0.005)	2,910
Mandatory or less	0.178	(0.004)	0.657	(0.004)	0.117	(0.003)	9,175
Spec. middle school	0.332	(0.007)	0.529	(0.005)	0.176	(0.004)	5,210

Notes: This table shows how the upward mobility (upmover rate) and access differs between educational tracks as shown in Figure 9. For panel (a), the upmover rate is defined as the share of children with parents in the bottom quintile that move to the top quintile (Q1Q5). Accessibility is defined as the share of children from the bottom quintile relative to the total number of children in the educational track. The mobility rate shows the share of children who move from the bottom to the top quintile relative to all children. For panel (b), the upmover rate is defined as the share of children with parents in the bottom half that move to the top half. Access is defined as the share of children from the bottom half relative to the total number of children in the educational track. The mobility rate shows the share of children to move from the bottom to the top half relative to all children.
Standard errors of the mean (se) are shown in parentheses. N refers to the observations in either the bottom quintile for Panel (a) or the bottom half Panel(b).

7.2 Regional characteristics

7.2.1 Public Goods and Fiscal Policies

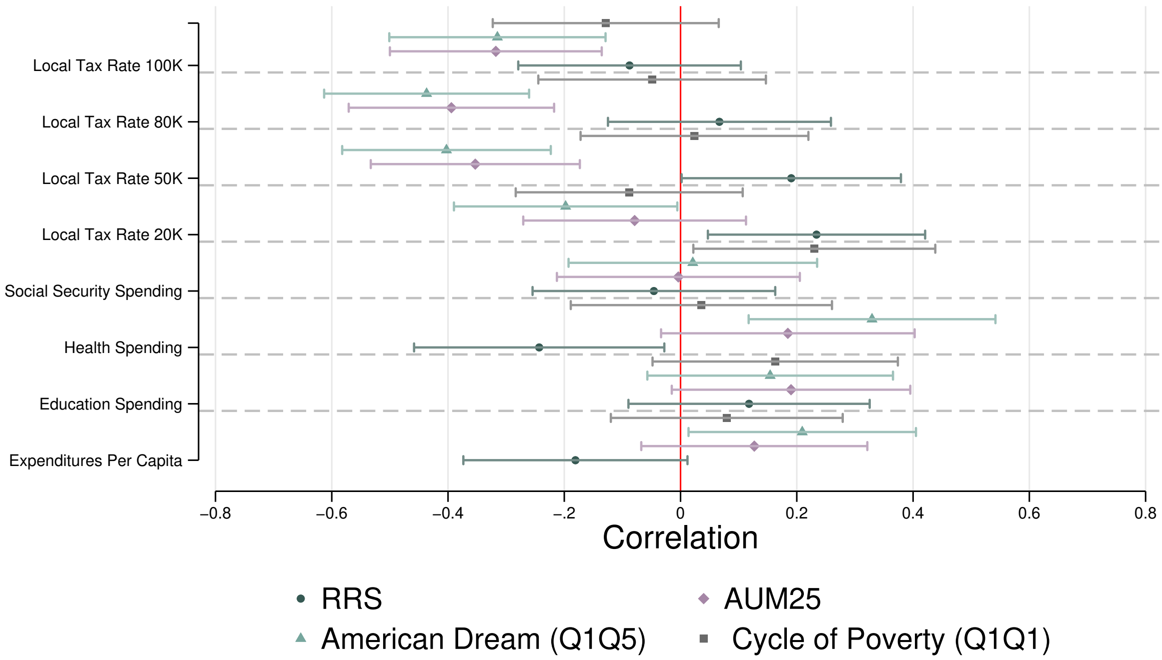
For policymakers, it is important to understand how public policy can increase upward mobility. To shed first light on a broad level, we analyse how income mobility is related to tax rates and public expenditures. In Switzerland, there is considerable variation in tax rates and public expenditures since it is organized federally.

To capture tax policies, we rely on local personal income tax rates from Parchet (2019). The author computes the consolidated (cantonal, municipal and, church) tax rates for all municipalities in Switzerland between 1983 and 2012. We define the local tax rate for four income brackets in each labor market (LM) region as the (unweighted) average consolidated tax rate across the LM region's municipalities. To proxy local public goods provision, we use data on local public finances from Fontana-Casellini (2020). The author has collected information on local (municipal and cantonal) expenditures (by functional category) since 1950. The coverage rate ranges between 2 percent in 1982 to 74 percent in 2004, with an average of 50 percent. We define local government spending as the (unweighted) mean of (per capita) municipal and cantonal spending in the municipalities in each LM region. Ideally, we aspire to capture local conditions when children grow up. Therefore, we take the mean local tax rate and government spending between 1982 and 2004, when our children are between 15 and 20 years old.

Figure 10 shows how tax rates at different income levels and different expenditures are related to income mobility. Symbols display the value of the correlation of our mobility measures with regional characteristics, while the lines show the 95% confidence interval based on standard errors clustered at the LM region level.

The figure reveals some interesting patterns. First, there is a negative correlation between tax rates and the share of children achieving the American Dream (Q1Q5) and between absolute upward mobility (AUM25). Thus, the lower tax rates, the higher income mobility. Interestingly, in terms of Q1Q5 and AUM25, mobility is also higher for total per capita expenditures, health and education spending. It is also interesting that the higher social security spending, the higher the number of children trapped in the poverty cycle. Of course, causality could go in both directions. Overall, we find that regions that invest more in health and education exhibit

Figure 10: Public Expenditures and Taxes



Notes: This figure displays how income mobility estimates are related to public expenditures and tax rates. On the y-axis, we list the local Labor Market (LM) characteristics. Each symbol represents a different intergenerational income mobility measure (RRS, AUM25, Q1Q5, Q1Q1) and plots the unweighted correlation of intergenerational income mobility with local conditions across LM regions. The lines represent 95% confidence intervals, calculated using standard errors clustered at LM region level. We evaluate the tax rate of four income levels: 20,000 CHF, 50,000 CHF, between 80,000 CHF and 100,000 CHF. Regarding local spending, we consider per capita expenditures and three (per capita) spending categories: Education, health, and social security.

higher levels of upward mobility. In contrast, regions with higher tax rates tend to have lower levels of upward mobility.

7.2.2 Income Inequality («Great Gatbsy Curves»)

There is currently concern that increasing income inequality could also lead to lower income mobility. The relationship between inequality and income mobility has been named the «Great-Gatsby Curve» (Corak, 2013). It is based on the empirical finding that countries with higher inequality also show lower mobility. Here, we test whether we can also observe this relationship on a within-country level.

We find mixed evidence for the existence of a Great Gatsby curve in Switzerland. Figure 11 plots income mobility against income inequality on a cantonal level. The linearly fitted line shows the relationship weighted by the population size of the canton. Income inequality is measured on family income level with the Gini Index. This index ranges from 0 to 1. The higher the index, the higher inequality. Figure A4 in the Appendix shows the results are similar when using labor market regions instead of cantons.

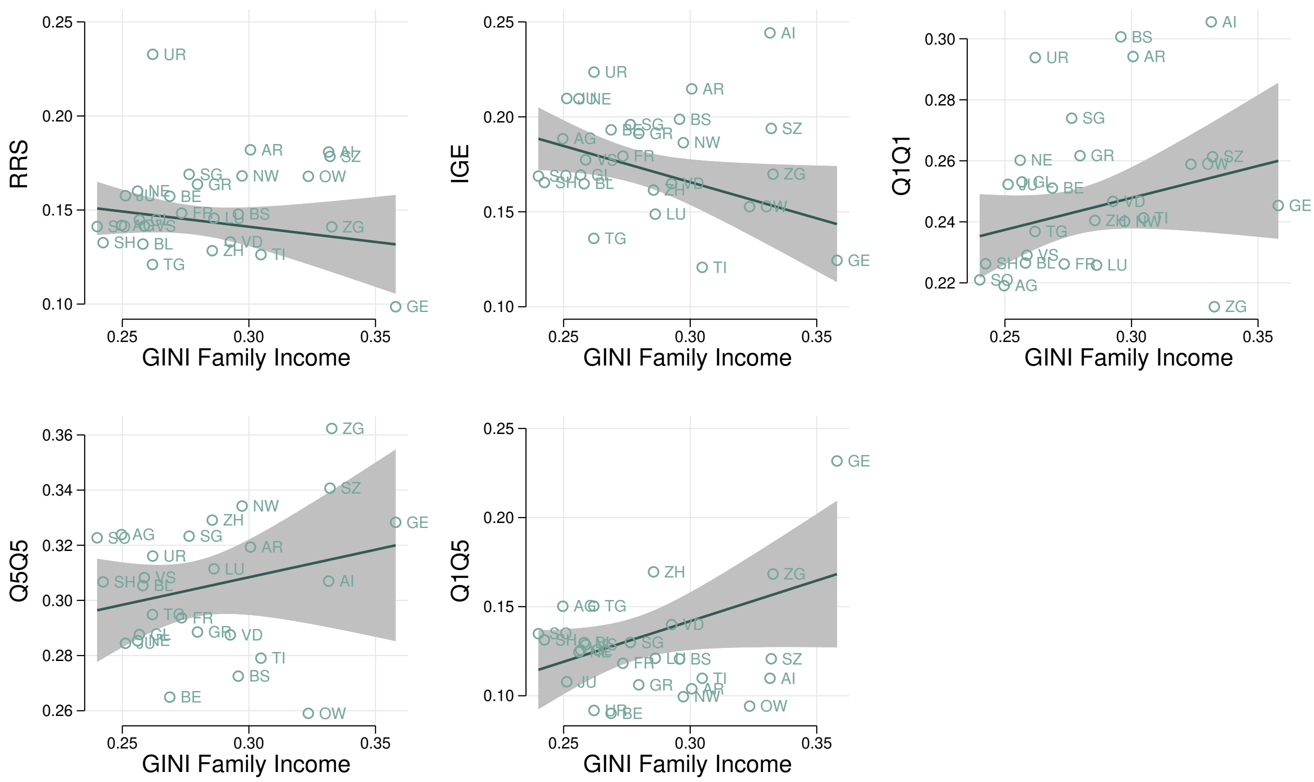
The rank-rank slope (RRS) and the IGE show a negative correlation: The higher inequality, the higher mobility. The results of the American Dream (Q1Q5) go in the same direction. If inequality is higher, children from the bottom quintile are also more likely to reach the top quintile. Thus, when looking at the above mentioned measure, there is no support for the Great Gatsby curve. There is, however, evidence for a Great-Gatsby curve when looking the directional mobility measures Q5Q5 and Q1Q1. In cantons with higher inequality, there seems to be higher persistence at the top and at the bottom of the parental income distribution. How can this counter-intuitive finding on Q1Q5 and Q1Q1 be interpreted? Maybe more inequality leads to more polarized outcomes. It could inspire children to a «all or nothing» mentality. Some children are really incentivized to make it to the top, while others do not even try to do so.

7.3 Individual Socio Demographic Characteristics

For policymakers, it is also important to know which individual characteristics are associated with low income mobility, for example, to create programs targeting specific groups. Column (1) in Table 8 shows how the American Dream (Q1Q5) measure varies for different personal characteristics. Column (2) shows how large the share is of children in the bottom quintile for this characteristic. Column (3), the mobility rate, shows the share of children achieving the American dream with a certain characteristic.

The most striking difference occurs between women and men. While almost 19 percent of men from the bottom quintile end up in the top quintile of the income distribution—in the distribution with men and women— this share is only around 6 percent for women. Men are, thus, around three times more likely to achieve the American Dream. Of course, this number reflects individual labor income and not household income and is subject to within-household

Figure 11: Great Gatsby Curves (cantonal level)



Notes: This graph shows how income mobility is relates to income inequality on a cantonal level. It does so for different income mobility measures. Income inequality is measured on a family level when children are between 15 and 20 years old. The grey line shows the fitted slope between the values weighted by the size of observations in each canton.

labor division within a household. Thus, gender specific consumption inequality is most likely lower.

Looking at different religions reveals other interesting insights: Jewish children (although small in sample size), show the highest likelihood to climb up the ladder. Also, the point estimate for Muslim children is high. Protestant children have to lowest likelihood to achieve the American Dream—which is noteworthy since the origins of the American Dream trace back to the Protestant Reformation in Europe.

The next interesting finding is that children with parents born abroad have a higher likelihood to achieve the American Dream. This is not only true if parents were born in high-income countries, like the Germany, the UK, or France, but also for low or middle-income countries, such as Turkey, Poland, or Bosnia. Thus, Switzerland provides good opportunities for second-generation immigrants.[18]

Many variables in Table 8 are correlated. Therefore, it is hard to figure out which variable indeed predict upward mobility. To further understand which personal variables drive upward mobility, we conduct a LASSO regression (Tibshirani, 1996).

Table 9 shows the «post-selection OLS coefficients». Also in this multivariate regression for which the variables were selected by LASSO, gender is the strongest predictor of the American Dream measure. Similarly, children of immigrated parents show a higher upward probability and Protestants the lower mobility. Also, regions and language regions are predictive of upward mobility.

[18] Switzerland experienced strong immigration during the Yugoslav Wars 1991 to 2001. Since we are looking at cohorts born until 1984 in Switzerland, those children are not yet in the sample.

Table 8: American Dream by Personal Characteristics

		(1) AD (Q1Q5)		(2) Share Bottom 20		(3) Mobility Rate		(4) N (Q1)	(5) N
Sex	Male	0.188	(0.001)	0.200	(0.001)	0.038	(0.000)	94,273	472,072
	Female	0.057	(0.001)	0.200	(0.001)	0.011	(0.000)	90,368	451,190
Parents Divorced	no	0.127	(0.001)	0.208	(0.000)	0.026	(0.000)	158,891	765,513
	yes	0.108	(0.002)	0.163	(0.001)	0.018	(0.000)	25,750	157,749
Religion	Catholic	0.134	(0.002)	0.232	(0.001)	0.031	(0.001)	22,523	97,047
	Protestant	0.117	(0.003)	0.183	(0.001)	0.021	(0.001)	14,857	81,402
	Other Christian	0.132	(0.007)	0.241	(0.004)	0.032	(0.002)	2,370	9,854
	Jewish	0.333	(0.066)	0.106	(0.014)	0.035	(0.008)	51	481
	Islamic	0.150	(0.020)	0.354	(0.016)	0.053	(0.008)	307	867
	Other	0.133	(0.027)	0.166	(0.012)	0.022	(0.005)	158	951
	No confession	0.160	(0.004)	0.148	(0.001)	0.024	(0.001)	9,378	63,257
Language Region	German	0.124	(0.001)	0.196	(0.000)	0.024	(0.000)	137,178	699,709
	French	0.133	(0.002)	0.197	(0.001)	0.026	(0.000)	36,643	186,126
	Italian	0.097	(0.003)	0.282	(0.002)	0.027	(0.001)	9,549	33,903
	Romanian	0.062	(0.007)	0.355	(0.009)	0.022	(0.003)	1,103	3,111
Any Parent born abroad	no	0.119	(0.001)	0.212	(0.000)	0.025	(0.000)	148,169	698,614
	yes	0.145	(0.002)	0.162	(0.001)	0.023	(0.000)	35,345	218,416
Boths Parents born abroad	no	0.121	(0.001)	0.200	(0.000)	0.024	(0.000)	175,425	877,655
	yes	0.181	(0.004)	0.205	(0.002)	0.037	(0.001)	8,089	39,375
Country of Birth Father	Switzerland	0.120	(0.001)	0.201	(0.000)	0.024	(0.000)	164,750	820,572
	Italy	0.141	(0.004)	0.248	(0.002)	0.035	(0.001)	8,865	35,798
	Germany	0.177	(0.009)	0.118	(0.002)	0.021	(0.001)	2,002	16,939
	France	0.162	(0.010)	0.164	(0.004)	0.027	(0.002)	1,330	8,133
	Austria	0.164	(0.013)	0.140	(0.004)	0.023	(0.002)	837	5,995
	Spain	0.191	(0.015)	0.176	(0.006)	0.034	(0.003)	686	3,904
	Turkey	0.147	(0.010)	0.391	(0.009)	0.058	(0.004)	1,201	3,068
	Cechia	0.149	(0.032)	0.081	(0.007)	0.012	(0.003)	121	1,489
	UK	0.178	(0.028)	0.132	(0.009)	0.024	(0.004)	185	1,404
	Netherlands	0.134	(0.029)	0.125	(0.010)	0.017	(0.004)	142	1,136
	Croatia	0.197	(0.035)	0.119	(0.010)	0.024	(0.005)	127	1,063
	Poland	0.159	(0.034)	0.120	(0.011)	0.019	(0.004)	113	943
	Greece	0.196	(0.033)	0.158	(0.012)	0.031	(0.006)	148	934
	Algeria	0.162	(0.024)	0.272	(0.015)	0.044	(0.007)	228	838
	Serbia	0.138	(0.027)	0.199	(0.014)	0.027	(0.006)	160	803
	Portugal	0.194	(0.034)	0.179	(0.014)	0.035	(0.007)	139	777
	Bosnia	0.208	(0.034)	0.190	(0.014)	0.040	(0.007)	144	759
Country of Birth Mother	Switzerland	0.121	(0.001)	0.210	(0.000)	0.025	(0.000)	159,385	758,597
	Italy	0.145	(0.005)	0.252	(0.003)	0.036	(0.001)	4,524	17,953
	Germany	0.157	(0.007)	0.129	(0.002)	0.020	(0.001)	2,673	20,722
	France	0.140	(0.008)	0.161	(0.004)	0.023	(0.001)	1,746	10,838
	Austria	0.153	(0.009)	0.177	(0.004)	0.027	(0.002)	1,445	8,179
	Spain	0.208	(0.016)	0.165	(0.006)	0.034	(0.003)	665	4,035
	Turkey	0.167	(0.012)	0.404	(0.010)	0.067	(0.005)	1,014	2,512
	Cechia	0.203	(0.034)	0.099	(0.008)	0.020	(0.004)	138	1,401
	UK	0.230	(0.023)	0.127	(0.007)	0.029	(0.003)	322	2,539
	Netherlands	0.119	(0.018)	0.121	(0.006)	0.014	(0.002)	312	2,572
	Croatia	0.179	(0.029)	0.125	(0.009)	0.022	(0.004)	173	1,388
	Poland	0.190	(0.031)	0.138	(0.010)	0.026	(0.005)	163	1,183
	Greece	0.117	(0.031)	0.152	(0.013)	0.018	(0.005)	111	730
	Algeria	0.171	(0.037)	0.222	(0.019)	0.038	(0.009)	105	474
	Serbia	0.119	(0.026)	0.181	(0.013)	0.022	(0.005)	151	835
	Portugal	0.149	(0.044)	0.135	(0.015)	0.020	(0.006)	67	498
	Bosnia	0.172	(0.030)	0.203	(0.014)	0.035	(0.006)	163	804

Notes: This table shows how upward mobility varies for different personal characteristics. *AD (Q1Q5)* shows the share of children from the bottom quintile that move to the top quintile for a given characteristics, *Share Bottom 20* indicates the share of children in the bottom quintile in this group, *Mobility Rate* shows the share of children achieving the American Dream overall in this group, *N (Q1)* shows the number of observations in the bottom quintile, *N* shows the number of observations for all parent income groups. Standard errors of the mean are shown in parentheses.

Table 9: Post LASSO Regression Results

Dep.Var.:		American Dream (Q1Q5) (Post LASSO Coefficient)
Sex	Male	0.149
Any Parent born abroad	No	-0.019
Both Parents born abroad	No	-0.033
Religion	Protestant	-0.020
NUTS-2 Region	Lake Geneva	0.035
	Mittelland	-0.013
	NW	0.036
	Zurich	0.098
Language Region	Italian	-0.031
Intercept		0.102

Notes: This table shows the results of an OLS regression where the coefficients are select using LASSO. The set of potential (factor) variables includes sex, religion of child parents immigration, country of father, country of mother, language region, NUTS-2 region, maritial status of mother, maritial status of father. Year of birth fixed effects included everywhere. Total number of covariates: 85. Number of observations included: 46,158. Implemented in Stata with *rlasso* by Ahrens et al. (2019). λ is determined by the with heteroskedastic plugin method.

8 Robustness

8.1 Attenuation Bias

Attenuation bias arises when transitory income shocks are not filtered out. This will attenuate the correlation between child and parents' earnings, leading to upward biased estimates of mobility. It is easy to see when using a single point in time. If transitory fluctuations are not serially correlated, averaging income across more years of observations eases the attenuation bias (Solon, 1992; Mazumder, 2005).

To understand whether our estimates suffer from such attenuation bias, we vary the number of years to calculate the average parental income. Figure A5 Panel (a) shows the results from an OLS regression of child rank on parent rank varying the number of years over which we aggregate parent mean income. We start with one year, the year when the child is 15, up to fourteen years, the years when the child is between 15 and 28. In our baseline estimates, we measure parent mean income when the child is between 15 and 20. Thus income is averaged across six years. In the graph, the baseline estimate corresponds to the vertical line. The rank-rank slope based on one year of income data is 0.132, which is lower than the rank-rank slope based on six years (0.141).

This attenuation bias is much smaller than the one encountered by Solon (1992). His IGE estimates were 0.3 for a single year and 0.4 when using a five-year average. Mazumder (2005) reports that even five-year averages suffer from attenuation bias. However, we find that the rank-rank slope is virtually unaffected by adding more years of observations beyond six years: The rank-rank slope is 0.144 when we use 12 years of observations and 0.144 when we use 16 years. The quality of our data and the rank-rank specification lead to stable estimates. The magnitude of the attenuation bias is comparable to the one found by Chetty et al. (2014a). They noticed an increase of 6.6 percent in the rank-rank slope, when five years of observations were used instead of a single year and nearly no changes in estimates when adding more years beyond five years.

Panel (b) tests how robust our estimates are to the number of years used to average child's income. The first point uses only the year when the child is 30 years old. This yields a rank-rank slope of 0.125. The vertical line corresponds to the baseline specification with a rank-rank slope of 0.141. Beyond this point, the number of cohorts is decreasing in the number of years. This is because in the core sample we can observe income for every cohort up to the age of 33. The rank-rank slope in the last point is 0.151, the sample includes only the 1967 and 1970 cohorts, and uses mean child income between the age of 30 and 47 (17 year average). The rank-rank slope increases when we aggregate child income over a larger time span. Thus, this bias is of small magnitude. Moreover, the bias includes also part of the life-cycle bias, as children are on average older. Even with this «upper-bound» estimate, Switzerland would rank among the countries with the highest relative mobility in terms of rank-rank slope.

8.2 Life-Cycle Bias

Life-cycle bias arises when income measured at the life-cycle stage systematically deviates from lifetime income. This might be the case when child income is measured earlier than their parent's income or when only a short snapshot of lifetime income is used. Life-cycle bias imposes a danger to understate income for those with steeper income profiles, like the more educated children. This can lead to an overestimation of mobility.

Figure A6 evaluates the sensitivity of our baseline estimates to changes in age at which child income is measured. We plot the coefficients of separate rank-rank slopes by varying the age at which a child incomes are measured for three samples. Parents' income is measured when the child is between the age of 15 and 20. Parents are ranked relative to other parents of children in the same birth cohorts. Child incomes are averaged across four years, at different ages up to the age 47. In the first point, the mean income is averaged over the age of 21 and 24. The straight line plots the coefficient of the core sample, the vertical line shows the baseline estimates. As before, beyond that point the number of cohorts decreases in child age. Around the age of 33—which is defined as the mean of age 30 to 33—, the rank-rank slope is reasonably stable. Life-cycle bias should not be an issue for our rank-rank estimates estimates.

When varying the age at which a child incomes are measured, we implicitly vary the number of cohorts and the calendar years at which child income is measured. However, we get similar results if we keep calendar year 2017 fixed and vary the cohorts, and if we restrict the sample to the 1967 to 1970 cohorts. The dashed line shows the RRS for the 1967 and 1970 cohorts, for which we observe income up to age of 47. The dotted line reports the coefficients when keeping calendar year fixed from 2014 to 2017 and varying the cohorts.

There is, however, substantial life-cycle bias when looking at the IGE. We have shown this in Panel (b) of Figure 2 and in Table A7. Focusing on the rank-rank slope therefore allows us to look at more cohorts since we can measure child income at earlier ages.

A similar bias emerges if parents' income is measured too early or too late. In Table A3, we evaluate the robustness of our estimates to the age at which parents' income is measured. To simplify the analysis, we focus on father's age. We also report the coefficient of the rank-rank slope when parents' income is measured at father's age 45. For a subset of cohorts, our data allows us to measure parents' income when the child is very young. We also want to test whether financial resources during early childhood matter more for child outcomes than resources at later ages of the childhood. Therefore, we restrict our sample to the cohorts from 1979 to 1981. Then, we measure parents' income when the child is between three and eight, and between nine and fourteen years old. The estimates reveal virtually no variation with father's age between 30 and 50 years old.

8.3 Location Choice

In the main specification, we use the mother's municipality in 2010 to approximate childhood location. This is because we do not have panel information on the exact location until 2010. However, we know when a person arrived in a specific municipality in 2010 and in which municipality a person was born. The municipality of birth is usually the location of the hospital in which the mother gave birth.

Table A12 shows how robust the regional mobility estimates are for different location assignment rules. We use three alternative specifications and compare its correlation with our base specification. «Mother Location 16» restricts the sample to children for which we know for sure that the mother lived in this place when the child was 16 75 percent of mother's still living in the same municipality where they lived when their child was 16. «Child Place of Birth» is the place where the child was born. 77 percent of mothers still live in the same canton where their child was born. Finally, we use child location in 2010 used the location where the child lives when adult. This assignment rule should be taken with caution, as children are more mobile and this location does not present the place where they grew up.

There is a very high correlation between the main specification and the alternative mobility measures. Interestingly, the IGE is also the less robust to income mobility estimate when looking at geographic assignment rules. The correlation is lowest when looking at the location of the child in 2010. However, this is most likely not a good approximation for the place where the child grew up.[19]

8.4 Regional Deflator

Our regional mobility estimates could be affected by differences in purchasing power. Purchasing power is likely to vary between regions in Switzerland. Regional deflation might therefore affect the ranks of the parents and children in the national income distribution. In mountainous regions, prices might be lower and a nominal income might be valued higher than in urban areas.

[19] We provide the precise income and educational mobility estimates, including standard errors for all geographic assignment rules here: Zip

Although no general regional price indices are available, we can draw from price indices for housing. Table A13 shows how the rank-rank slope varies when using different regional price indices. Column(1) reports our baseline; we adjust income using the national consumer price index. Column (2) uses the Residential Property Privately Owned Apartments Price Index, column(3) the Residential Property Regional Housing Price Index and column(4) the Rented properties, rental housing units price index.

The rank-rank slope decreases when we account for regional real estate price differences, which means a lower correlation between a child's position and family position in the income distribution. The drop is in line with previous studies (Acciari et al., 2019; Chetty et al., 2014a) and does not substantially affect the estimates. Indeed, one can expect regional price differences to have only a minor effect on intergenerational correlation when most children live close to their parent's place, and regional differences do not significantly change over time.[20]

8.5 Capital Income

How susceptible are our estimates to the definition of income? Since our data only used labor income, a natural concern is that our estimates would be different when including capital income. We argue that this is unlikely the case when using rank transformed income measures—which are our main estimates of interest (RRS, Q1Q5, Q1Q1, Q5Q5, AUM25). Accordingly, our rank based mobility measures are well suited to be compared to other countries. We base our argument on two pillars: empirical findings of previous studies and and theoretical arguments.

For Australia, Deutscher and Mazumder (2020) show that the RRS changes only sightly when adding capital to labor income. They find the RRS of wages to be 0.19 and the rank-rank slope and only slightly smaller than the rank-rank slope based on total income 0.22. In contrast, the IGE is much more susceptible to changes in income definition. Based on wages, the IGE is 0.11, while based on total income, the IGE is 0.19. Assuming that capital income in Australia is similarly distributed as in Switzerland, this relative or absolute increase in the RRS would still leave the RRS small compared to other countries. We can also compare our RRS to the study by Heidrich (2017) for Sweden, which also only uses labor income. Here, we see that Switzerland (0.14) still has a lower RRS than the Sweden (0.18).

[20]E.g. 50 percent of children live closer than 10 miles from their mother's place in 2010

We can also draw from other empirical studies and analyzing the joint distribution of capital and labor income and combine them with theoretical arguments to infer how our results would change with capital income. For Switzerland, Martínez (2020) analyzes the joints distribution for capital and labor income using administrative data. Since we (and other studies) measure at relatively early ages (around 30 and 45), capital income is unlikely to play a major role since it is most prevalent in old ages. It is therefore unlikely that there are major changes when assigning children to their income rank. The same holds true for parents, since most parents are measured around father's age of 45. Rank based measures could also be biased if parents with high capital income have low labor income. We would wrongly classify rich parents as poor, which would then attenuate the RRS. Non-working capital income rich individual is a myth in Switzerland. Capital income is highly correlated with labor income and much more right-skewed than labor income. Therefore, such wrong rank assignments should be rare.

8.6 Comparisons with US-Distribution

When comparing the rank-rank slopes between different countries, one concern is that the distributions can differ. For example, inequality in the US is considerably larger than in Switzerland. Therefore, we convert the Swiss income into PPP adjusted US dollars and assign the ranks according to the US distribution according to Chetty et al. (2014a).[21]

Figure A8 shows rank mobility between the US and Switzerland which permits analysing absolute and relative mobility. For better comparison, we converted the Swiss incomes into the US income distribution. For Switzerland, the constant is higher and the rank-rank slope is considerably lower. A higher rank implies that absolute mobility is higher. Children from similarly poor parents can expect to have much higher wage outcomes in Switzerland than in the US. Only for the top income percentiles, children in the US have higher wage outcomes. The relatively good wage outcomes for Switzerland are at least partly because of the high valuation of the Swiss Franc since the financial crisis.

[21]PPP data is retrieved from https://stats.oecd.org/Index.aspx?DataSetCode=CPL. Data for the US from https://opportunityinsights.org/data/.

9 Discussion and Conclusion

In this paper, we use administrative income, census, and survey data to document intergenerational income and educational mobility in Switzerland. We analyze how upward mobility varies across regions and which personal and regional characteristics correlate with upward mobility. Most importantly, we analyze how income mobility varies between educational tracks.

We find that intergenerational mobility is high in Switzerland. Income mobility in terms of rank-rank slope (RRS) is 0.14 and higher than in all other countries for which high-quality estimates exist. We also see that, compared to other countries, children from the bottom quintile of the parental income distribution are less likely to stay in the bottom quintile themselves («cycle of poverty»). Also, children from the top quintile are less likely to stay in the top quintile themselves («cycle of privileges»). In terms of the «American Dream» measure, which indicates the share of children from the bottom quintile that makes it to the top quintile, only Sweden has a higher share than Switzerland. Taken together, almost all mobility estimates are higher in Switzerland than in the US, Italy, Canada, Denmark, Australia, or Sweden.

Despite the high income mobility estimates, we find that educational mobility is low. Children's educational track and years of education depend considerably on parental income and education. The socioeconomic gap is especially strong when looking at whether children frequent a high school or a VET program (educational track). Children from the top decile of the parental income distribution are almost five times more likely to frequent a high school than those below the top quintile.

We investigate the reasons behind this divergence of educational and income mobility. First, we find that in regions with high educational mobility, there is—in general—also high income mobility. This suggests that educational mobility is still related to income mobility, as seminal theoretical papers suggest (Becker and Tomes, 1986). However, in Switzerland, low educational mobility translates only weakly into low levels of income mobility. Second, the reason for this weak link might be the permeability of the VET system, not the system per se. We find that educational tracks that start with VET and add some further education account for a large share of upward mobility. Conceptually, this makes sense. VET comes at almost no costs for parents and, therefore, credit constraints are less binding for children's human capital accumulation—if there is ample scope for further education.

Intergenerational mobility varies across regions in Switzerland. This variation is slightly higher than in Sweden but lower than in the US or Italy (Chetty et al., 2014a; Heidrich, 2017). Looking at regional correlates, we find higher income mobility in regions with higher public spending but lower mobility in regions with higher tax rates. Looking at the relationship between mobility and inequality («Great Gatsby Curve»), we find a weak positive relationship with most measures but a negative one when using the cycle of poverty or the cycle of privileges measures.

Our results have potentially important policy implications. First, they show that low educational mobility does not necessarily translate into low income mobility. This is an important and maybe even comforting finding for countries that—by lack of administrative income data—try to infer income mobility from educational mobility. Second, although we currently lack causal evidence, there are good reasons to think of VET as a driver of upward mobility. This system could thus be an interesting policy option for countries with low intergenerational income mobility.

References

Acciari, Paolo, Alberto Polo, and Giovanni L. Violante (2019). *"And Yet It Moves": Intergenerational Mobility in Italy.* Working Paper 25732. National Bureau of Economic Research. DOI: 10.3386/w25732.

Ahrens, Achim, Christian B Hansen, and Mark Schaffer (2019). "LASSOPACK: Stata module for lasso, square-root lasso, elastic net, ridge, adaptive lasso estimation and cross-validation".

Barone, Carlo, Antonio Schizzerotto, Giovanni Abbiati, and Gianluca Argentin (2017). "Information barriers, social inequality, and plans for higher education: evidence from a field experiment". *European Sociological Review* 33.1, pp. 84–96.

Bauer, Philipp (2006). *The Intergenerational Transmission of Income in Switzerland A Comparison between Natives and Immigrants.* WWZ Discussion Paper 06/01.

Bauer, Philipp and Regina T. Riphahn (Feb. 2007). "Heterogeneity in the intergenerational transmission of educational attainment: evidence from Switzerland on natives and second-generation immigrants". *Journal of Population Economics* 20.1, pp. 121–148.

Becker, Gary S. and Nigel Tomes (1986). "Human Capital and the Rise and Fall of Families". *Journal of Labor Economics* 4.3, S1–S39.

Bell, Alex, Raj Chetty, Xavier Jaravel, Neviana Petkova, and John Van Reenen (2019). "Who becomes an inventor in America? The importance of exposure to innovation". *Quarterly Journal of Economics* 134.2, pp. 647–713. DOI: 10.1093/qje/qjy028.

Bettinger, Eric, Oded Gurantz, Laura Kawano, Bruce Sacerdote, and Michael Stevens (2019). "The Long-Run Impacts of Financial Aid: Evidence from California's Cal Grant". *American Economic Journal: Economic Policy* 11.1, pp. 64–94. DOI: 10.1257/pol.20170466.

Black, Sandra E, Jeffrey T Denning, Lisa J Dettling, Sarena Goodman, and Lesley J Turner (2020). *Taking it to the limit: Effects of increased student loan availability on attainment, earnings, and financial well-being.* Tech. rep. National Bureau of Economic Research.

Black, Sandra E. and Paul J. Devereux (2011). "Recent Developments in Intergenerational Mobility". In: ed. by David Card and Orley Ashenfelter. Vol. 4. Handbook of Labor Economics. Elsevier. Chap. 16, pp. 1487–1541. DOI: https://doi.org/10.1016/S0169-7218(11)02414-2.

Bratberg, Espen, Jonathan Davis, Bhashkar Mazumder, Martin Nybom, Daniel D Schnitzlein, and Kjell Vaage (2017). “A comparison of intergenerational mobility curves in Germany, Norway, Sweden, and the US”. *The Scandinavian Journal of Economics* 119.1, pp. 72–101.

Brown, Meta, John Karl Scholz, and Ananth Seshadri (2012). “A new test of borrowing constraints for education”. *The Review of Economic Studies* 79.2, pp. 511–538.

Card, David and Alex Solis (2020). *Measuring the Effect of Student Loans on College Persistence*. Tech. rep. National Bureau of Economic Research.

Carneiro, Pedro and James J Heckman (2002). “The evidence on credit constraints in post-secondary schooling”. *The Economic Journal* 112.482, pp. 705–734.

Chetty, Raj, John N Friedman, Emmanuel Saez, Nicholas Turner, and Danny Yagan (2020). “Income segregation and intergenerational mobility across colleges in the United States”. *The Quarterly Journal of Economics* 135.3, pp. 1567–1633.

Chetty, Raj, Nathaniel Hendre, Patrick Kline, and Emmanuel Saez (Sept. 2014a). “ Where is the land of Opportunity? The Geography of Intergenerational Mobility in the United States *”. *The Quarterly Journal of Economics* 129.4, pp. 1553–1623. DOI: 10.1093/qje/qju022.

Chetty, Raj, Nathaniel Hendren, Patrick Kline, Emmanuel Saez, and Nicholas Turner (2014b). “Is the United States Still a Land of Opportunity? Recent Trends in Intergenerational Mobility”. *The American Economic Review* 104.5, pp. 141–147.

Chu, Yu-Wei Luke and Harold E Cuffe (2020). “Do Struggling Students Benefit From Continued Student Loan Access? Evidence From University and Beyond”. *Evidence From University and Beyond (March 31, 2020)*.

Connolly, Marie, Miles Corak, and Catherine Haeck (2019). “Intergenerational Mobility Between and Within Canada and the United States”. *Journal of Labor Economics* 37.S2, S595–S641. DOI: 10.1086/703465.

Corak, Miles (2013). “Inequality from generation to generation: The United States in comparison”. *The economics of inequality, poverty, and discrimination in the 21st century* 1, pp. 107–126.

– (2020). “The Canadian geography of intergenerational income mobility”. *The Economic Journal* 130.631, pp. 2134–2174.

Corak, Miles and Andrew Heisz (1999). “The intergenerational earnings and income mobility of Canadian men: Evidence from longitudinal income tax data”. *Journal of Human Resources*, pp. 504–533.

Cunha, Flavio and James Heckman (2007). “The technology of skill formation”. *American Economic Review* 97.2, pp. 31–47.

Dahl, Molly W. and Thomas DeLeire (2008). “The Association between Children’s Earnings and Fathers’ Lifetime Earnings: Estimates Using Administrative Data”. University of Wisconsin–Madison.

Denning, Jeffrey T and Todd R Jones (2019). “Maxed out? The effect of larger student loan limits on borrowing and education outcomes”. *Journal of Human Resources*, 0419–10167R1.

Deutscher, Nathan and Bhashkar Mazumder (2020). “Intergenerational mobility across Australia and the stability of regional estimates”. *Labour Economics* 66, p. 101861. DOI: https://doi.org/10.1016/j.labeco.2020.101861.

Educa (2021). *Upper secondary level*.

Eriksen, Jesper (2018). *Finding the Land of Opportunity Intergenerational Mobility in Denmark*. Tech. rep. Mimeo.

Favre, Giacomin, Joël Floris, and Ulrich Woitek (2018). “Intergenerational Mobility in the 19th Century: Micro-Level Evidence from the City of Zurich Intergenerational Mobility in the 19 th Century Micro-Level Evidence from the City of Zurich”.

Fontana-Casellini, Laura (2020). “The effect of municipal budget balanace rules: the Swiss case”.

Güell, Maia, Michele Pellizzari, Giovanni Pica, and José V. Rodríguez Mora (2018). “Correlating Social Mobility and Economic Outcomes”. *The Economic Journal* 128.612, F353–F403. DOI: https://doi.org/10.1111/ecoj.12599.

Heckman, James J and Stefano Mosso (2014). “The economics of human development and social mobility”. *Annu. Rev. Econ.* 6.1, pp. 689–733.

Heidrich, Stefanie (Oct. 2017). “Intergenerational mobility in Sweden: a regional perspective”. *Journal of Population Economics* 30.4, pp. 1241–1280.

Helsø, Anne-Line (2021). “Intergenerational Income Mobility in Denmark and the United States*”. *The Scandinavian Journal of Economics* 123.2, pp. 508–531. DOI: https://doi.org/10.1111/sjoe.12420.

Hertz, Tom (2006). “Understanding mobility in America”. *Center for American Progress Discussion Paper*.

Hertz, Tom, Tamara Jayasundera, Patrizio Piraino, Sibel Selcuk, Nicole Smith, and Alina Verashchagina (2008). “The inheritance of educational inequality: International comparisons and fifty-year trends”. *The BE Journal of Economic Analysis & Policy* 7.2.

Häner, Melanie and Christoph A. Schaltegger (2020). “The Name Says It All. Multigenerational Social Mobility in Switzerland, 1550-2019”. IFF-HSG Working Papers.

Ichino, Andrea, Loukas Karabarbounis, and Enrico Moretti (2011). “The Political Economy Of Intergenerational Income Mobility”. *Economic Inquiry* 49.1, pp. 47–69. DOI: https://doi.org/10.1111/j.1465-7295.2010.00320.x.

Martínez, Isabel Z. (2020). “Evidence from Unique Swiss Tax Data on the Composition and Joint Distribution of Income and Wealth”. In: *Measuring and Understanding the Distribution and Intra/Inter-Generational Mobility of Income and Wealth*. University of Chicago Press.

Mazumder, Bhashkar (2005). “Fortunate Sons: New Estimates of Intergenerational Mobility in the United States Using Social Security Earnings Data”. *The Review of Economics and Statistics* 87(2), pp. 235–255.

Nybom, Martin and Jan Stuhler (2016). “Heterogeneous income profiles and lifecycle bias in intergenerational mobility estimation”. *Journal of Human Resources* 51.1, pp. 239–268.

Parchet, Raphaël (2019). “Are Local Tax Rates Strategic Complements or Strategic Substitutes?” *American Economic Journal: Economic Policy* 11.2, pp. 189–224. DOI: 10.1257/pol.20150206.

Rodrik, Dani and Stefanie Stantcheva (2021). *A Policy Matrix for Inclusive Prosperity*. Tech. rep. National Bureau of Economic Research.

Solon, Gary (1992). “Intergenerational Income Mobility in the United States”. *The American Economic Review* 82.3, pp. 393–408.

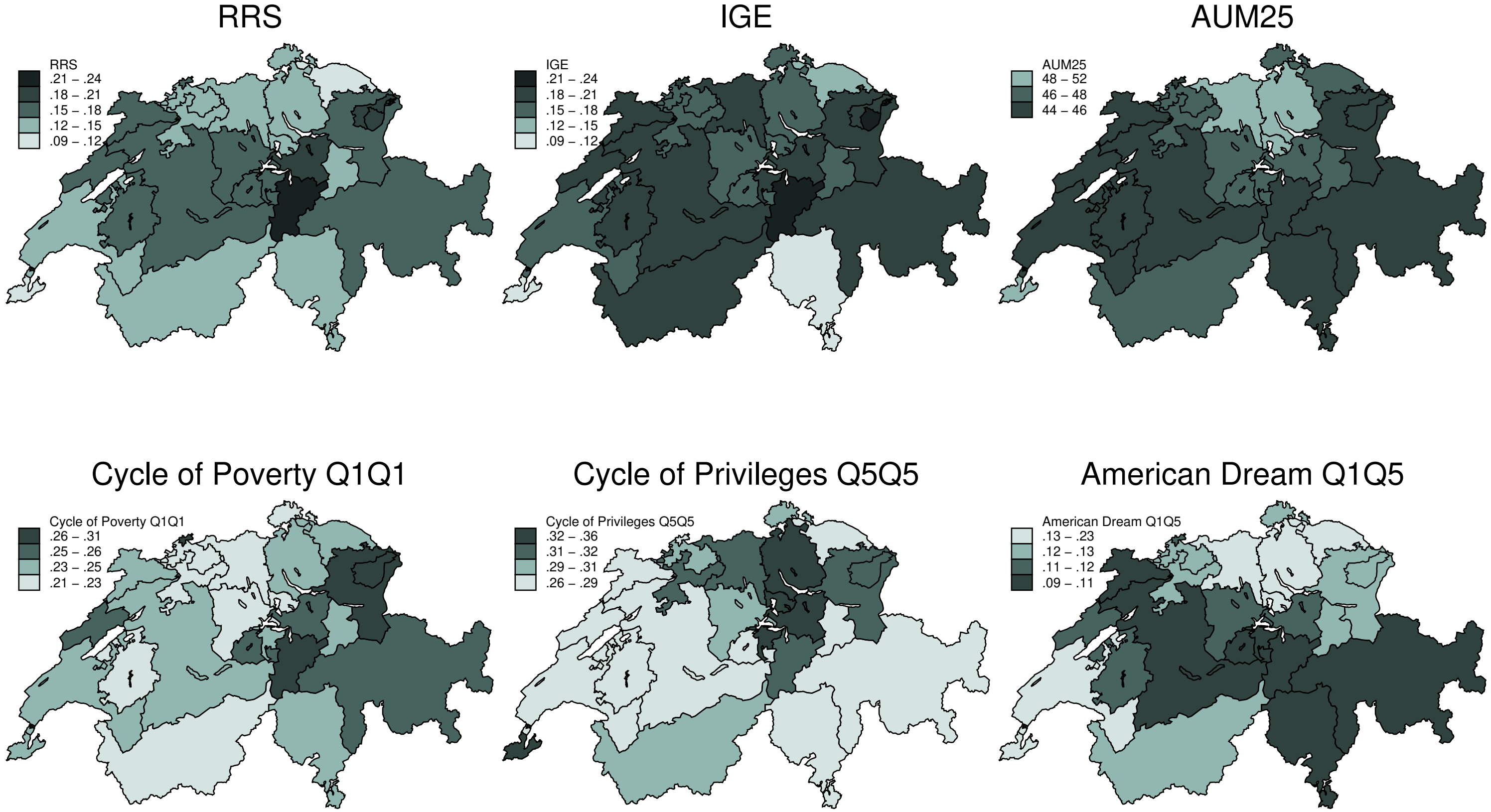
– (1999). “Intergenerational mobility in the labor market”. In: *Handbook of labor economics*. Vol. 3. Elsevier, pp. 1761–1800.

Stuhler, Jan et al. (2018). “A review of intergenerational mobility and its drivers”. *JRC Working Papers* JRC112247.

Tibshirani, Robert (1996). “Regression shrinkage and selection via the lasso”. *Journal of the Royal Statistical Society: Series B (Methodological)* 58.1, pp. 267–288.

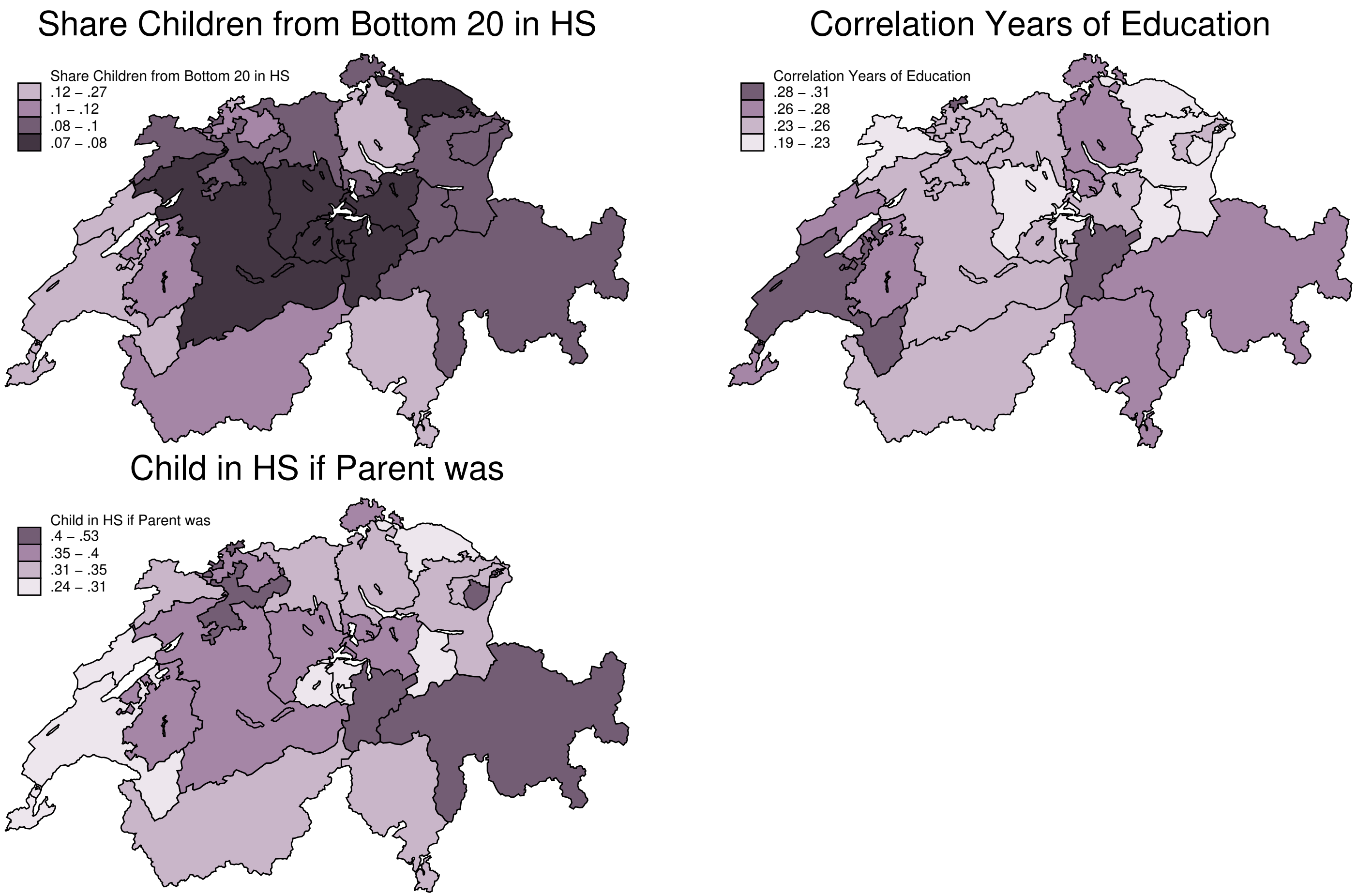
Appendix

Figure A1: Income Mobility Estimates by Cantons



Notes: This figure shows how educational mobility varies across cantons. Brighter colors indicate higher mobility.

Figure A2: Educational Mobility Estimates by Cantons



Notes: This figure shows how educational mobility varies across cantons. Brighter colors indicate lower mobility.

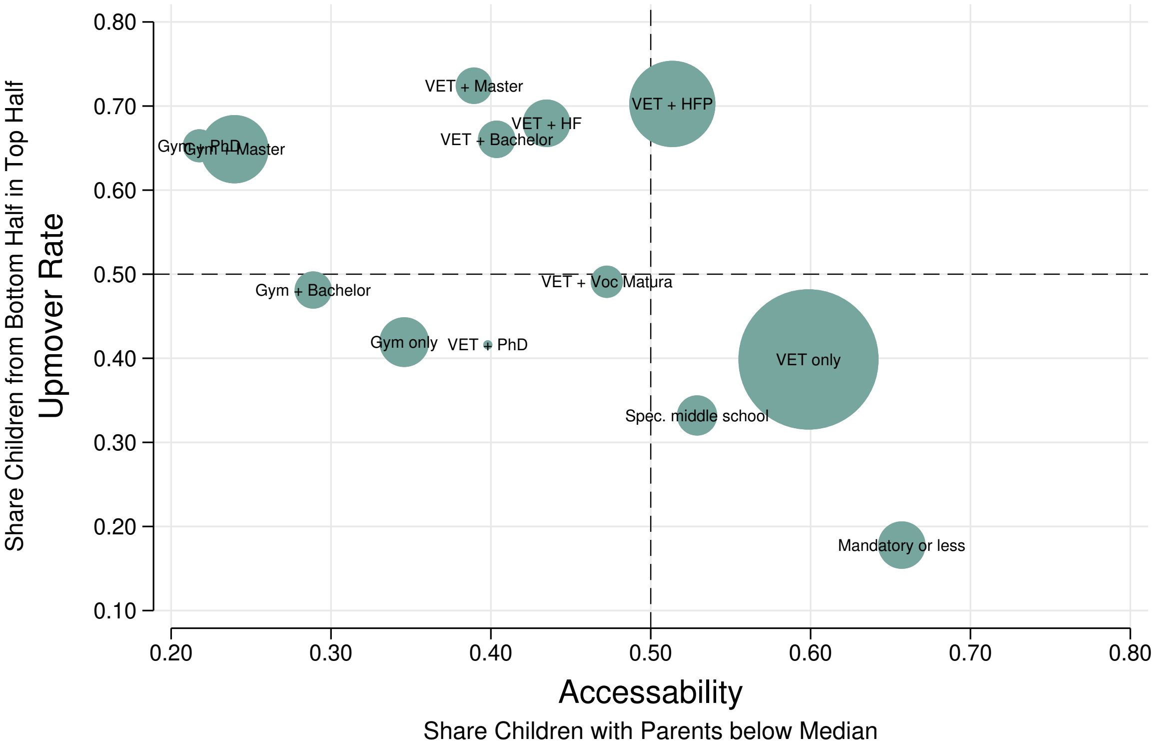
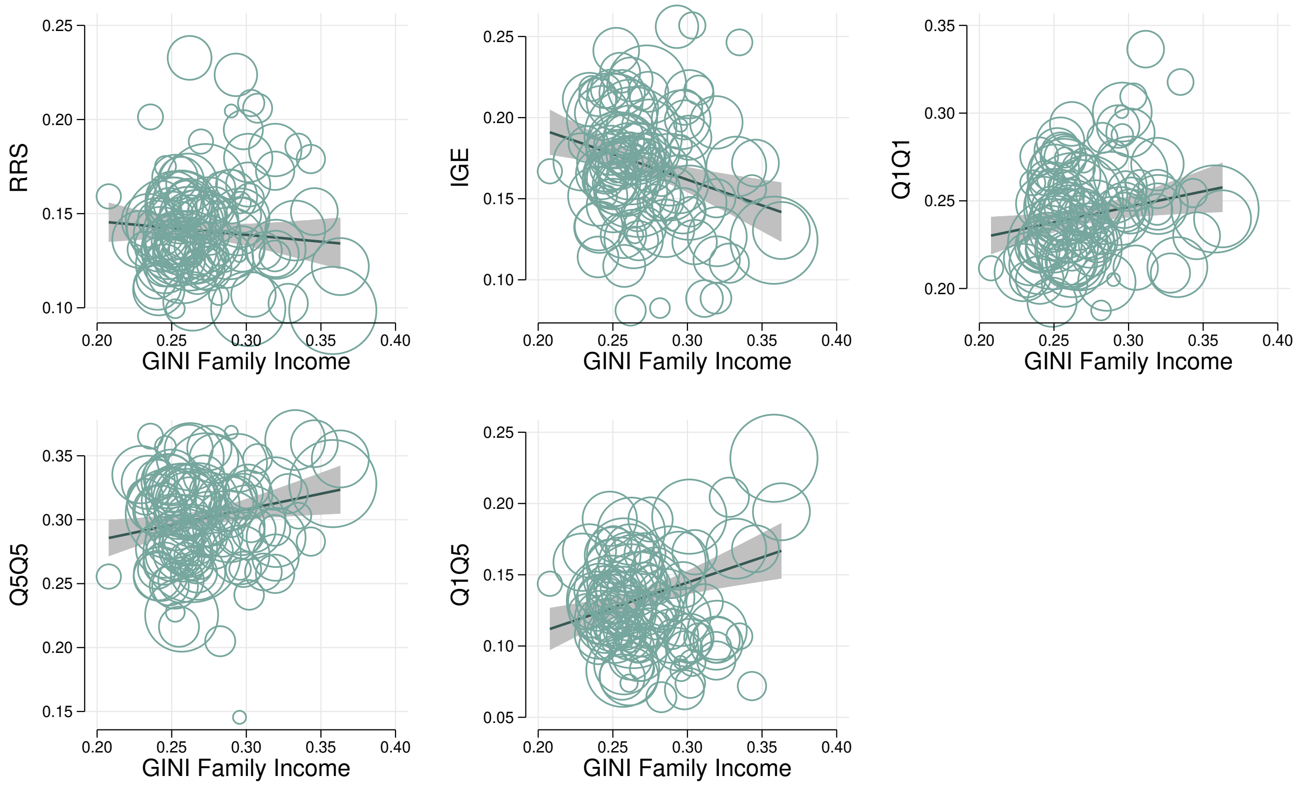


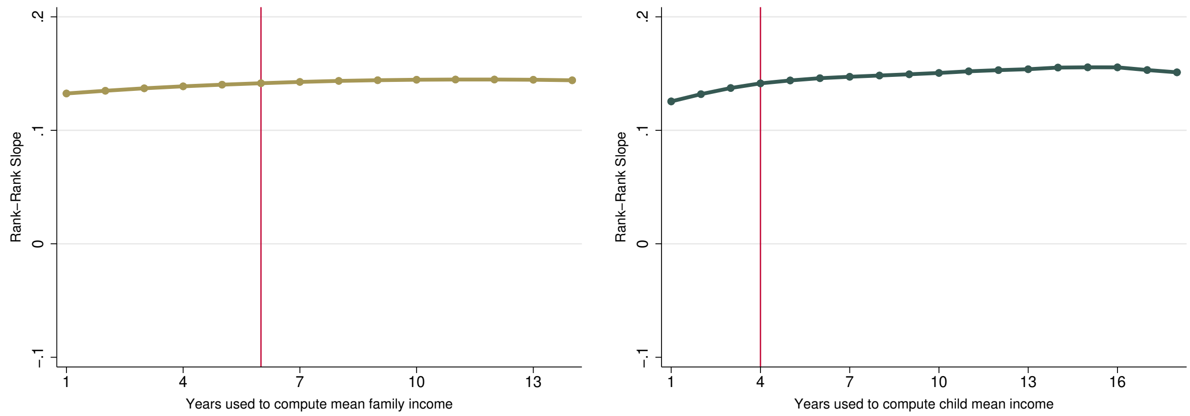
Figure A3: Access and Upward Mobility Rate by Educational Track (Medium Upward Mobility)

Notes: This graph shows how upward mobility (upmover rate) and access differ between educational tracks. Upmover rate is defined as the share of children with parents below the median moving above the median. Accessibility is defined as the share of children from the bottom half relative to the total number of children in the educational track. The size of the points is proportional to the number of children in that track. The syntax of the educational tracks is defined as follows: [Upper Secondary Education] + [Highest Post Secondary Education]. *Gym* refers to gymnasium (academic high school), *VET* to vocational education and training. *HF* and *HFP* are occupation specific higher educations. *Voc Matura* refers to "vocational matura", which is VET with more formal education, *spec. middle school* refers to specialized middle schools, which is like a professional high school and not as selective as the gymnasium.
The upmover rate multiplied with the access rate equals the mobility rate, which is the share of children that climb from the bottom to the top half *relative to all children in that track.* In contrast, the upmover rate is the share of children that climb to the top half *relative to children from parents in the bottom half.*

Figure A4: Great Gatsby Curves (Labor Market Level)



Notes: This graph shows how income mobility is relates to income inequality on a labor market regions level. It does so for different income mobility measures. Income inequality is measured on a family level when children are between 15 and 20 years old. The grey line shows the fitted slope between the values weighted by the size of observations in each canton.



(a) RRS by Number of Years of Father Income

(b) RRS by Number of Years of Child Income

Figure A5: Robustness of Rank-Rank Slope Estimates: Attenuation Bias

Notes: In this figure we asses the robustness of the rank-rank slope to changes in the number of years used to measure father income (Panel (a)) and child income (Panel (b)). Fathers are ranked relative to other fathers of children in the same birth cohort. Children are ranked relative to other children in the same birth cohort.

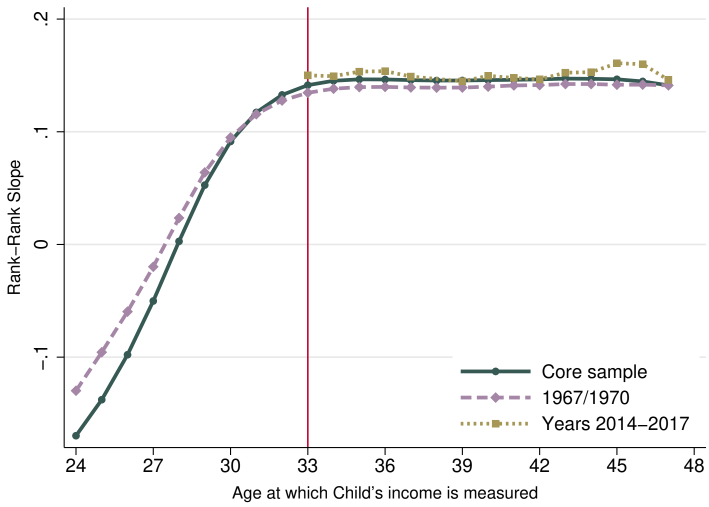
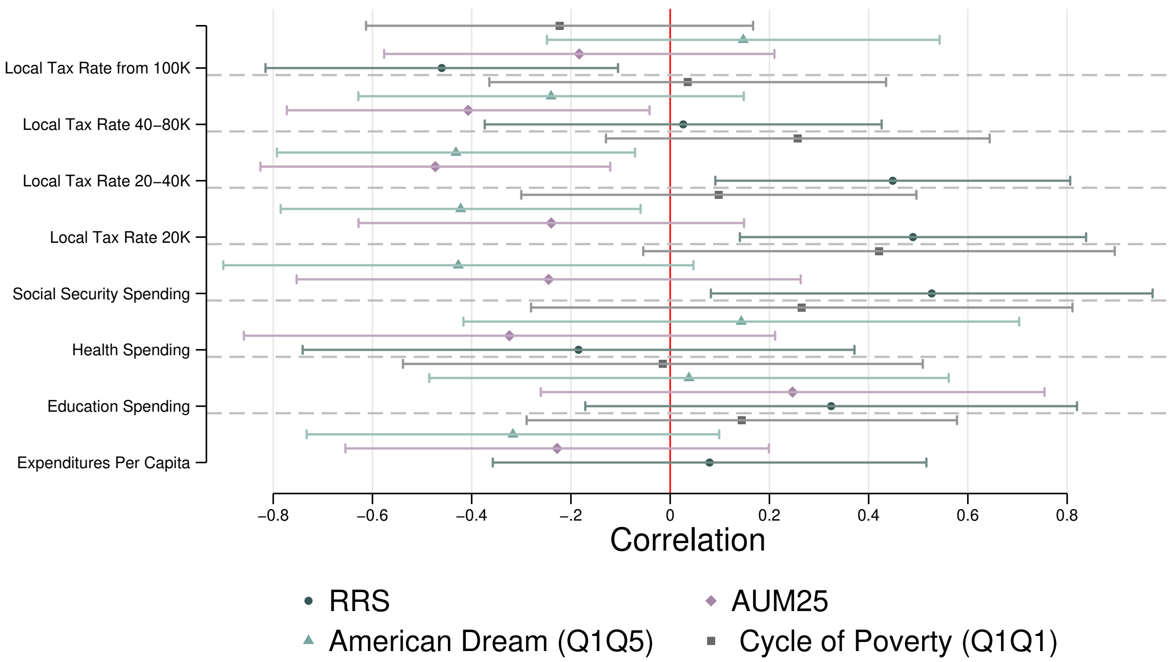


Figure A6: Life-Cycle Bias

Notes: This figure assesses the robustness of the rank-rank slopes estimates. For the baseline estimates, father income is averaged over the years when the child is between 15 and 20 years old. Father rank is defined relative to other fathers of children born between 1969 and 1984. Child mean income is the average income when the child is between the age 30 and 33. Child rank is defined relative to children in the same birth cohort. This corresponds to the point at age 33. The first point corresponds to the rank-rank slope when child mean income is averaged over the ages of 21 and 24. The last point uses average mean income between age 44 and 47 and is only observable for the 1969 and 1970 cohorts. Mean father rank is defined according to father income of children born in those cohorts. The dashed line plots the rank-rank slope coefficients by varying the age at which child income is measured only for the 1969 and 1970 cohorts. The dotted line plots the rank-rank slope coefficients when income is measured in the year 2014 to 2017.

Figure A7: Spatial Correlates: Canton



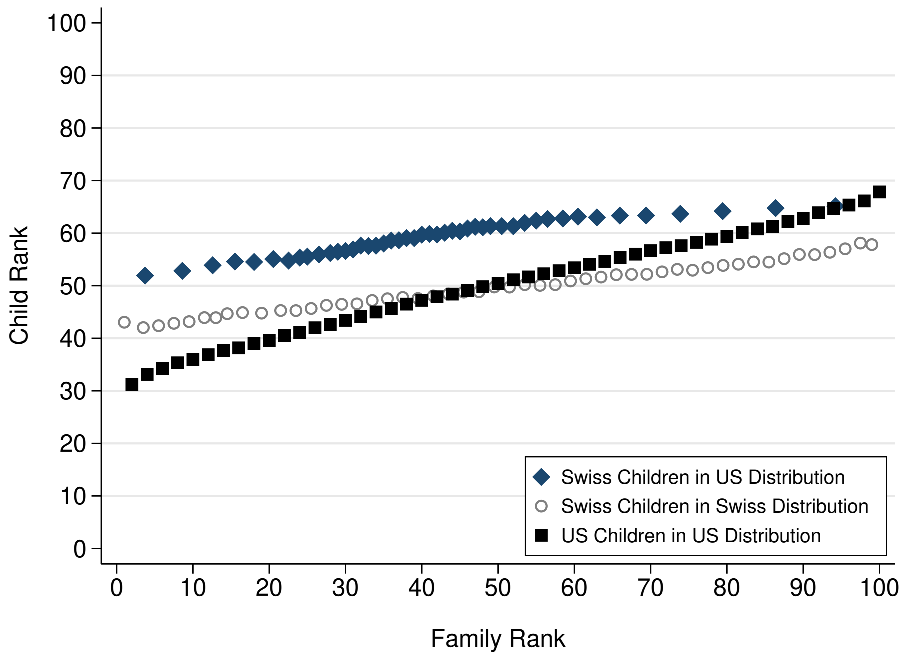


Figure A8: Comparison Switzerland - US

Notes: This graph shows the rank mobility for Switzerland and the US. The black squares correspond to the estimates of Chetty et al. (2014a). The circles correspond to the estimates in our study, where the ranks are assigned according to the Swiss distribution. For the blue diamonds, the income of parents and children is converted into US dollar PPP equivalents and then assigned to ranks according to the US distribution.

Figure A9: Correlation Mobility Measures (Units: Cantons)

Notes: This graph shows the correlation of different mobility and inequality measures on a cantonal unit (n=26). *RRS* is the rank-rank slope, *IGE* is the intergenerational income elasticity, *Share Bottom 20 in HS* measures the share of children from parents in the bottom quintile that go to high school, *Child in HS if Parent was* is the slope coefficient of a linear probability model that regresses high school attendance of the child on high school attendance of the parents, *correlation Years Edu* measures the correlation between years of education of parents and children, *Gini Family Income* shows the Gini index for family income at child age 15 to 20.

Table A1: Highest Education and Years of Schooling

Highest Education	Years of Schooling
No education	0
Max 7 years mandatory school	7
Mandatory school only	9
Vocational Training and Education	12
High school (gymnasium)	13
Higher professional degree	14
Bachelor degree	16
Master degree	18
PhD, habilitation	21

Table A2: Sample Selection

	Sample			
	(1)	(2)	(3)	(4)
	Full mean	Any Parent mean	Father (Core) mean	Both mean
Panel A: Income Sample				
Year of Birth	1975.10	1975.24	1975.65	1975.79
Female (%)	48.67	48.91	48.87	48.87
Married (%)	46.23	45.77	45.14	44.87
Lake Geneva Region (%)	15.80	15.12	14.84	14.65
Espace Mittelland (%)	24.23	25.07	25.25	25.31
Northwestern Switzerland (%)	13.33	13.05	13.12	13.09
Zürich (%)	17.83	17.57	17.75	17.78
Eastern Switzerland (%)	14.09	14.29	14.23	14.27
Central Switzerland (%)	10.72	11.26	11.28	11.38
Ticino (%)	4.00	3.64	3.53	3.52
German (%)	74.31	75.36	75.79	76.03
French (%)	21.18	20.47	20.16	19.92
Latin (%)	4.50	4.17	4.05	4.05
Child Income at Age 30-33				
Average Income	59,103	59,734	60,598	60,896
Top 10%	124,760	125,350	126,510	126,712
Top 5%	142,275	142,865	144,233	144,387
Top 1%	183,863	184,486	186,735	186,695
Obs.	1,266,376	1,114,543	923,107	859,286
Panel B: Education Sample				
High-School (%)	19.96	20.07	20.99	21.24
VET(%)	66.05	66.09	65.69	65.61
Master (%)	15.70	15.77	16.43	16.62
Obs.	380,018	371,269	308,622	287,848

Notes: The table provides summary statistics by sample. Panel (A) shows the summary statistics for the income sample. Column (1) reports the mean of all individuals born in Switzerland between 1967 and 1984. Column (2) to column (4) are sub-samples of column (1). Column (2) restricts to individuals that can be linked to the mother or the father. Column (3) is our core sample: individuals that can be linked to the father. Column (4) is the most conservative sample, it restricts to individuals matched to both parents. Panel (B) shows the summary statistics for the education sample. All amounts are in 2017 CHF.

Table A3: Relative Mobility Estimates for Different Samples

		Intergenrational correlation			
		Rank-Rank-Slope (1)		IGE (2)	
A. Varying Child Age					
Core Sample: 1967-1984	Child age 30-33	0.141	(0.0010)	0.166	(0.0017)
Birth cohorts 1967-1981	Child age 33-36	0.146	(0.0011)	0.191	(0.0021)
Birth cohorts 1967-1978	Child age 36-39	0.145	(0.0013)	0.205	(0.0025)
Birth cohorts 1967-1974	Child age 40-43	0.147	(0.0016)	0.219	(0.0030)
Birth cohorts 1967-1971	Child age 43-46	0.145	(0.0020)	0.212	(0.0037)
B. Varying Family Age					
Birth cohorts 1979-1984	Child age 3-8	0.136	(0.0017)	0.177	(0.0033)
Birth cohorts 1973-1984	Child age 9-14	0.138	(0.0013)	0.172	(0.0022)
C. Alternative Income Definitions					
Excl. Missing Incomes		0.096	(0.0174)	0.081	(0.0284)
Recoding non labor income to 0		0.137	(0.0010)	0.165	(0.0017)

Notes: This table reports the baseline estimates and the results of OLS regressions of a measure of child income on a measure of parents' income for several samples. Column (1) reports the coefficient of the rank-rank slope and standard errors in parentheses, column (2) reports the IGE coefficient and the standard error in parentheses. Panel (A) shows the value of the RRS and IGE when child income is measured later in life compared to the baseline specification. Family income is measured when the child is between 15 and 20. Panel (B) shows the value of the RRS and IGE when family income is measured earlier relative to the baseline specification, when the children are between 3 and 8 years old, or between 9 and 14. Panel (C) shows the value of the RRS and the IGE when we only include observations for which we observe every income record between the ages of 30 and 33 for children and between the ages of 15 and 20 for families.

Table A4: Mean Child and Family Income by Rank

Rank	Child Income	Family Income	Rank	Child Income	Family Income	Rank	Child Income	Family Income	Rank	Child Income	Family Income
1	0	3,719	26	35,929	41,520	51	62,639	55,631	76	81,896	75,247
2	126	10,554	27	37,367	42,129	52	63,407	56,228	77	82,854	76,394
3	858	14,228	28	38,757	42,730	53	64,156	56,838	78	83,861	77,608
4	2,106	16,830	29	40,107	43,318	54	64,906	57,457	79	84,919	78,869
5	3,372	19,000	30	41,427	43,890	55	65,656	58,079	80	86,004	80,204
6	3,133	20,908	31	42,704	44,458	56	66,383	58,709	81	87,144	81,592
7	4,477	22,644	32	43,946	45,023	57	67,096	59,354	82	88,315	83,071
8	5,772	24,297	33	45,153	45,581	58	67,813	60,013	83	89,566	84,671
9	7,263	25,862	34	46,353	46,141	59	68,522	60,679	84	90,862	86,388
10	8,813	27,322	35	47,497	46,693	60	69,232	61,367	85	92,205	88,193
11	10,454	28,715	36	48,609	47,246	61	69,930	62,078	86	93,649	90,163
12	12,209	30,018	37	49,685	47,798	62	70,630	62,800	87	95,173	92,363
13	14,008	31,228	38	50,754	48,348	63	71,343	63,546	88	96,815	94,760
14	15,829	32,342	39	51,790	48,897	64	72,061	64,305	89	98,585	97,449
15	17,637	33,369	40	52,811	49,450	65	72,789	65,084	90	100,492	100,524
16	19,456	34,304	41	53,811	50,003	66	73,530	65,880	91	102,606	104,020
17	21,271	35,185	42	54,806	50,550	67	74,279	66,689	92	104,933	108,078
18	23,031	36,011	43	55,764	51,104	68	75,048	67,507	93	107,569	112,908
19	24,764	36,791	44	56,705	51,652	69	75,831	68,360	94	110,609	118,867
20	26,471	37,530	45	57,618	52,210	70	76,642	69,264	95	114,237	126,510
21	28,128	38,250	46	58,510	52,760	71	77,462	70,181	96	118,826	136,106
22	29,746	38,935	47	59,373	53,323	72	78,290	71,121	97	124,954	148,861
23	31,355	39,611	48	60,224	53,891	73	79,154	72,096	98	133,953	168,553
24	32,909	40,265	49	61,055	54,462	74	80,040	73,106	99	149,561	203,690
25	34,426	40,901	50	61,857	55,049	75	80,955	74,160	100	223,951	379,043

Notes: This table shows the mean real income in 2017 Swiss Francs for fathers and children.

Table A5: National Estimates

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Sample							
Child's outcome	Parent's inc def	Core sample	1979-1981 Cohorts	Male children	Female Children	Foreign Father	Swiss Father	Fixed age at child birth	Married
IGE:									
Log individual income excluding zeros	Log father income	0.166	0.160	0.111	0.235	0.122	0.168	0.171	0.167
		(0.0017)	(0.0038)	(0.0017)	(0.0028)	(0.0086)	(0.0017)	(0.0028)	(0.0019)
recoding 0 to 1	Log father income	0.188	0.176	0.083	0.299	0.086	0.198	0.213	0.202
		(0.0028)	(0.0059)	(0.0021)	(0.0050)	(0.0092)	(0.0029)	(0.0049)	(0.0031)
recoding 0 to 1000	Log father income	0.192	0.177	0.103	0.284	0.117	0.196	0.199	0.198
		(0.0019)	(0.0042)	(0.0018)	(0.0032)	(0.0086)	(0.0020)	(0.0032)	(0.0021)
RRS:									
Individual income rank	Family income rank	0.141	0.142	0.122	0.162	0.114	0.142	0.143	0.147
		(0.0010)	(0.0025)	(0.0013)	(0.0014)	(0.0057)	(0.0011)	(0.0017)	(0.0011)
Individual income rank	Father income rank	0.153	0.154	0.152	0.152	0.132	0.154	0.154	0.152
		(0.0010)	(0.0025)	(0.0013)	(0.0014)	(0.0059)	(0.0011)	(0.0017)	(0.0011)
Individual income rank	Mother income rank	0.026	0.025	0.004	0.053	0.020	0.027	0.030	0.036
		(0.0009)	(0.0028)	(0.0012)	(0.0012)	(0.0048)	(0.0009)	(0.0015)	(0.0010)
Observations		923,107	155,003	471,989	451,118	35,059	888,048	333,097	775,377

Notes: Each cell reports the coefficient from an OLS regression of a child's outcome on a measure of its family income. Column (1) uses the core sample, which includes all children (i) born in birth cohorts 1969 to 1989 (ii) for whom we have been able to link both parents (iii) whose mean income at age 30 to 33 is positive and (iv) whose mean parent's income when child is between 15-20 is non-negative. Column (2) reports the estimates for birth cohorts 1979 to 1981. Columns (3) and (4) restrict the sample to male and female. Columns(5) and (6) limit the sample to children whose father is either foreign or Swiss. Column (8) estimates income mobility among children whose mother was between 13 and 19 years old at child birth. Column (8) limits the core sample to children whose father fall into a 5-year window of median father age at time of child birth. Column (9) restricts the sample to children whose parents are still married in 2012 and live in the same household in 2012. Child income is the mean of the individual income between age 30 to 33, while parent family income is the mean income when the child is between age 15 and 20. Individual earnings include wage earnings, self-employment earnings, unemployment insurance and disability benefits. Income percentile ranks are constructed by ranking all children relative to other children in the same birth cohort, and ranking parents relative to other parents in the core sample. Ranks are not redefined within sub-samples except in column (2). The number of observations correspond to the specification in row 4.

Table A6: National Quintile Transition Matrix (sample with both parents)

	Family quintile				
Child quintile	1	2	3	4	5
1	23.75	21.72	19.59	17.88	17.06
2	21.57	20.31	19.53	19.11	19.48
3	20.98	22.07	20.52	18.90	17.54
4	17.57	21.00	21.38	20.83	19.22
5	11.74	15.22	19.00	23.02	31.02

Notes: This table shows in which quintile children end up in the income distribution for every quintile of the parent's income distribution. Each cell describes in which quintile (row) children end up conditional on the parent quintile (column). Parent quintile is based on father and mother income. For example, 16.3% of children from parents in the top quintile of the income distribution will end up in the bottom quintile of the income distribution. 11.74% of children from parents of the bottom quintile of the income distribution end up in the top quintile («American Dream measure»). Income ranks are measured relative to child cohort. The table includes children born in Switzerland from 1967 to 1984 and comprises 849,849 observations (child-father pairs).

Table A7: IGE by Age and Parent Tertile

	Child Income Age 30-33					Child Income Age 38-41				
	(1) All	(2) Std	(3) Fam T1	(4) Fam T2	(5) Fam T3	(6) All	(7) Std	(8) Fam T1	(9) Fam T2	(10) Fam T3
IGE	0.166^{***}		0.100^{***}	0.414^{***}	0.119^{***}	0.215^{***}		0.089^{***}	0.423^{***}	0.222^{***}
	(0.0017)		(0.0037)	(0.0153)	(0.0047)	(0.0027)		(0.0059)	(0.0241)	(0.0078)
IGE (std)		0.103^{***}					0.116^{***}			
		(0.0011)					(0.0015)			
Observations	894, 399	894, 399	295, 535	298, 666	300, 198	476, 098	476, 098	157, 459	159, 087	159, 552
R-Squared	0.01	0.01	0.00	0.00	0.00	0.01	0.01	0.00	0.00	0.01

Notes: This table shows the IGE for different ages at which child income is measured and for different parts of the parental income distribution. T1 refers to the lowest parent income tertile, T3 refers to the highest parental income tertile. Columns (2) and (7) show the standardized IGE coefficient. This means, the log-incomes are divided by the standard deviation in order to abstract from changes in inequality over time.

Table A8: Income Mobility by Labor Market Region

	RRS		Q1Q5		Q1Q1		Q5Q5		IGE		AM P=25	.
LaborMarket												
Aarau	0.145	(0.006)	0.132	(0.005)	0.225	(0.006)	0.305	(0.007)	0.231	(0.022)	48.047	(0.234)
Aaretal	0.148	(0.010)	0.094	(0.006)	0.258	(0.008)	0.259	(0.013)	0.315	(0.030)	45.108	(0.325)
Aigle	0.122	(0.017)	0.100	(0.011)	0.269	(0.016)	0.263	(0.019)	0.291	(0.054)	44.538	(0.599)
Appenzell A.Rh.	0.180	(0.011)	0.106	(0.007)	0.289	(0.010)	0.320	(0.014)	0.251	(0.031)	45.269	(0.388)
Appenzell I.Rh.	0.186	(0.022)	0.107	(0.010)	0.318	(0.014)	0.303	(0.034)	0.192	(0.050)	44.952	(0.647)
Baden	0.130	(0.012)	0.189	(0.014)	0.232	(0.015)	0.330	(0.009)	0.221	(0.039)	50.816	(0.499)
Basel-Stadt	0.148	(0.010)	0.121	(0.008)	0.301	(0.011)	0.273	(0.008)	0.316	(0.031)	44.527	(0.404)
Bellinzona	0.118	(0.015)	0.102	(0.008)	0.242	(0.011)	0.258	(0.019)	0.267	(0.043)	46.802	(0.453)
Bern	0.138	(0.006)	0.119	(0.005)	0.250	(0.007)	0.274	(0.005)	0.270	(0.018)	46.272	(0.241)
Biel/Bienne	0.139	(0.011)	0.120	(0.008)	0.248	(0.011)	0.258	(0.011)	0.283	(0.036)	45.345	(0.392)
Brig	0.135	(0.018)	0.171	(0.012)	0.231	(0.013)	0.304	(0.023)	0.203	(0.055)	50.194	(0.521)
Brugg-Zurzach	0.146	(0.011)	0.167	(0.011)	0.217	(0.012)	0.329	(0.011)	0.247	(0.040)	49.385	(0.429)
Burgdorf	0.166	(0.009)	0.079	(0.005)	0.242	(0.007)	0.278	(0.013)	0.210	(0.029)	45.018	(0.291)
Chur	0.136	(0.011)	0.134	(0.009)	0.257	(0.011)	0.273	(0.012)	0.204	(0.039)	46.570	(0.402)
Davos	0.107	(0.029)	0.117	(0.021)	0.188	(0.025)	0.310	(0.031)	0.195	(0.104)	47.648	(1.068)
Einsiedeln	0.166	(0.019)	0.108	(0.010)	0.276	(0.014)	0.298	(0.027)	0.207	(0.054)	46.087	(0.590)
Engiadina Bassa	0.156	(0.026)	0.083	(0.012)	0.288	(0.020)	0.261	(0.036)	0.174	(0.069)	43.466	(0.776)
Entlebuch	0.128	(0.021)	0.099	(0.007)	0.245	(0.010)	0.292	(0.042)	0.140	(0.049)	45.915	(0.489)
Erlach-Seeland	0.112	(0.012)	0.108	(0.008)	0.205	(0.010)	0.256	(0.015)	0.254	(0.040)	47.155	(0.386)
Freiamt	0.124	(0.012)	0.158	(0.009)	0.192	(0.010)	0.332	(0.014)	0.194	(0.043)	50.466	(0.420)
Fricktal	0.110	(0.012)	0.140	(0.009)	0.224	(0.011)	0.307	(0.013)	0.251	(0.041)	49.140	(0.422)
Genève	0.099	(0.006)	0.232	(0.007)	0.245	(0.007)	0.328	(0.005)	0.137	(0.017)	50.610	(0.304)
Glarner Hinterland	0.175	(0.028)	0.111	(0.015)	0.262	(0.022)	0.357	(0.043)	0.108	(0.078)	46.314	(0.833)
Glarner Unterland	0.131	(0.018)	0.134	(0.013)	0.248	(0.016)	0.269	(0.020)	0.128	(0.049)	47.794	(0.614)
Glattal-Furttal	0.134	(0.009)	0.181	(0.011)	0.214	(0.011)	0.349	(0.007)	0.235	(0.029)	50.877	(0.422)
Glâne-Veveyse	0.155	(0.016)	0.117	(0.008)	0.225	(0.010)	0.276	(0.026)	0.198	(0.042)	46.647	(0.453)
Goms	0.126	(0.038)	0.117	(0.017)	0.255	(0.022)	0.259	(0.058)	0.314	(0.109)	46.098	(0.958)
Grenchen	0.131	(0.017)	0.124	(0.013)	0.205	(0.016)	0.318	(0.020)	0.190	(0.047)	48.329	(0.587)
Gros-de-Vaud	0.123	(0.013)	0.118	(0.010)	0.222	(0.012)	0.266	(0.014)	0.227	(0.050)	45.639	(0.495)
Innerschwyz	0.184	(0.010)	0.102	(0.005)	0.271	(0.008)	0.328	(0.014)	0.229	(0.029)	46.481	(0.329)
Jura	0.158	(0.010)	0.108	(0.005)	0.252	(0.008)	0.284	(0.015)	0.206	(0.030)	44.737	(0.305)
Jura bernois	0.147	(0.015)	0.101	(0.009)	0.275	(0.013)	0.261	(0.020)	0.385	(0.044)	44.410	(0.477)
Kandertal	0.164	(0.020)	0.064	(0.006)	0.286	(0.012)	0.205	(0.032)	0.231	(0.055)	40.815	(0.489)
Knonaueramt	0.126	(0.014)	0.165	(0.015)	0.229	(0.016)	0.334	(0.011)	0.246	(0.046)	50.392	(0.647)
La Broye	0.135	(0.012)	0.125	(0.007)	0.247	(0.009)	0.275	(0.015)	0.156	(0.038)	46.012	(0.375)
La Chaux-de-Fonds	0.169	(0.012)	0.114	(0.008)	0.278	(0.011)	0.248	(0.016)	0.229	(0.037)	44.218	(0.402)
La Gruyère	0.149	(0.014)	0.112	(0.008)	0.237	(0.011)	0.286	(0.020)	0.261	(0.043)	46.302	(0.445)
La Sarine	0.155	(0.010)	0.119	(0.007)	0.227	(0.009)	0.301	(0.011)	0.264	(0.030)	46.994	(0.365)
La Vallée	0.100	(0.031)	0.150	(0.023)	0.259	(0.028)	0.228	(0.035)	0.172	(0.096)	46.711	(1.060)
Laufental	0.135	(0.013)	0.124	(0.010)	0.240	(0.012)	0.323	(0.015)	0.266	(0.043)	48.359	(0.472)
Lausanne	0.134	(0.008)	0.159	(0.008)	0.257	(0.009)	0.295	(0.006)	0.251	(0.024)	47.054	(0.347)
Leuk	0.159	(0.028)	0.144	(0.016)	0.212	(0.018)	0.256	(0.046)	0.213	(0.079)	48.784	(0.712)
Limmattal	0.121	(0.014)	0.189	(0.016)	0.229	(0.018)	0.356	(0.011)	0.194	(0.045)	51.731	(0.631)
Linthgebiet	0.147	(0.012)	0.152	(0.008)	0.248	(0.010)	0.348	(0.013)	0.231	(0.034)	48.952	(0.423)
Locarno	0.129	(0.011)	0.104	(0.006)	0.247	(0.009)	0.270	(0.014)	0.197	(0.032)	44.570	(0.378)
Lugano	0.131	(0.009)	0.111	(0.006)	0.248	(0.008)	0.286	(0.010)	0.192	(0.025)	45.204	(0.327)
Luzern	0.140	(0.007)	0.136	(0.005)	0.223	(0.006)	0.311	(0.007)	0.219	(0.020)	48.538	(0.244)
March	0.151	(0.012)	0.168	(0.010)	0.230	(0.011)	0.359	(0.012)	0.247	(0.035)	50.078	(0.476)
Martigny	0.146	(0.012)	0.109	(0.007)	0.244	(0.009)	0.321	(0.017)	0.264	(0.036)	44.448	(0.372)
Mendrisio	0.130	(0.014)	0.126	(0.009)	0.237	(0.011)	0.287	(0.017)	0.162	(0.039)	47.794	(0.449)
Mesolcina	0.154	(0.033)	0.074	(0.015)	0.257	(0.025)	0.293	(0.051)	0.319	(0.126)	45.098	(0.932)
Mittelbünden	0.128	(0.026)	0.137	(0.016)	0.226	(0.020)	0.302	(0.034)	0.239	(0.070)	47.733	(0.822)
Monthey	0.153	(0.015)	0.110	(0.009)	0.247	(0.013)	0.248	(0.018)	0.265	(0.047)	44.896	(0.490)
Morges	0.107	(0.012)	0.166	(0.012)	0.212	(0.013)	0.292	(0.010)	0.218	(0.038)	47.730	(0.541)
Murten/Morat	0.126	(0.012)	0.140	(0.008)	0.203	(0.010)	0.286	(0.016)	0.163	(0.038)	47.096	(0.410)
Mutschellen	0.156	(0.012)	0.169	(0.013)	0.215	(0.014)	0.355	(0.011)	0.301	(0.041)	50.015	(0.525)
Neuchâtel	0.154	(0.010)	0.132	(0.008)	0.238	(0.010)	0.298	(0.010)	0.237	(0.033)	45.655	(0.391)
Nidwalden	0.165	(0.012)	0.104	(0.007)	0.244	(0.010)	0.326	(0.016)	0.234	(0.035)	47.613	(0.406)
Nyon	0.102	(0.014)	0.204	(0.015)	0.209	(0.016)	0.320	(0.010)	0.116	(0.035)	49.351	(0.682)
Oberaargau	0.157	(0.009)	0.087	(0.005)	0.234	(0.007)	0.275	(0.013)	0.262	(0.030)	45.932	(0.280)
Oberengadin	0.206	(0.019)	0.106	(0.012)	0.259	(0.017)	0.348	(0.022)	0.291	(0.062)	45.292	(0.679)
Oberes Baselbiet	0.123	(0.010)	0.115	(0.007)	0.227	(0.010)	0.277	(0.010)	0.234	(0.033)	47.347	(0.370)
Oberes Emmental	0.195	(0.015)	0.069	(0.005)	0.244	(0.008)	0.321	(0.030)	0.202	(0.039)	43.659	(0.358)
Oberland-Ost	0.168	(0.013)	0.078	(0.006)	0.275	(0.010)	0.253	(0.018)	0.269	(0.039)	43.604	(0.368)
Oberthurgau	0.149	(0.012)	0.133	(0.008)	0.268	(0.010)	0.322	(0.016)	0.239	(0.041)	46.025	(0.403)
Olten	0.136	(0.011)	0.159	(0.009)	0.209	(0.010)	0.335	(0.012)	0.205	(0.034)	49.365	(0.384)
Pays d’Enhaut	0.128	(0.041)	0.088	(0.019)	0.301	(0.031)	0.145	(0.048)	0.232	(0.130)	41.738	(1.205)
Pfannenstiel	0.122	(0.011)	0.194	(0.013)	0.240	(0.014)	0.348	(0.007)	0.179	(0.028)	50.145	(0.547)
Prättigau	0.209	(0.021)	0.088	(0.010)	0.309	(0.016)	0.293	(0.029)	0.233	(0.071)	42.315	(0.639)
Rheintal	0.130	(0.013)	0.125	(0.008)	0.284	(0.011)	0.285	(0.016)	0.158	(0.041)	46.125	(0.404)
Saanen-Obersimmental	0.179	(0.019)	0.072	(0.007)	0.254	(0.012)	0.283	(0.032)	0.295	(0.055)	42.965	(0.520)
Sarganserland	0.137	(0.015)	0.112	(0.008)	0.275	(0.011)	0.281	(0.021)	0.187	(0.050)	44.087	(0.436)
Sarneraatal	0.173	(0.014)	0.090	(0.006)	0.257	(0.010)	0.258	(0.021)	0.208	(0.041)	47.214	(0.412)
Schaffhausen	0.133	(0.012)	0.131	(0.010)	0.226	(0.012)	0.307	(0.012)	0.284	(0.040)	47.443	(0.452)
Schanfigg	0.205	(0.043)	0.122	(0.026)	0.205	(0.032)	0.368	(0.056)	0.281	(0.126)	45.979	(1.382)
Schwarzwasser	0.158	(0.018)	0.074	(0.007)	0.255	(0.012)	0.241	(0.030)	0.233	(0.051)	44.431	(0.501)
Sense	0.156	(0.013)	0.106	(0.007)	0.227	(0.009)	0.302	(0.020)	0.160	(0.038)	47.006	(0.366)
Sierre	0.139	(0.014)	0.143	(0.011)	0.218	(0.012)	0.322	(0.017)	0.260	(0.041)	47.499	(0.483)
Sion	0.150	(0.011)	0.123	(0.007)	0.215	(0.009)	0.318	(0.013)	0.192	(0.030)	47.295	(0.352)
Solothurn	0.143	(0.010)	0.131	(0.008)	0.214	(0.010)	0.312	(0.011)	0.269	(0.032)	47.992	(0.372)
St.Gallen	0.166	(0.007)	0.139	(0.006)	0.253	(0.007)	0.337	(0.008)	0.269	(0.023)	47.364	(0.272)
Sursee-Seetal	0.126	(0.009)	0.134	(0.006)	0.204	(0.007)	0.313	(0.013)	0.185	(0.029)	49.284	(0.301)
Surselva	0.149	(0.016)	0.098	(0.008)	0.257	(0.011)	0.261	(0.021)	0.209	(0.047)	45.319	(0.472)
Thal	0.201	(0.024)	0.115	(0.013)	0.260	(0.018)	0.365	(0.039)	0.384	(0.082)	47.032	(0.703)
Thun	0.154	(0.008)	0.083	(0.004)	0.265	(0.007)	0.225	(0.009)	0.279	(0.024)	44.216	(0.244)
Thurtal	0.103	(0.010)	0.158	(0.007)	0.216	(0.008)	0.287	(0.011)	0.245	(0.034)	48.875	(0.340)
Toggenburg	0.224	(0.013)	0.098	(0.006)	0.292	(0.009)	0.318	(0.020)	0.279	(0.034)	44.920	(0.386)
Tre Valli	0.133	(0.021)	0.106	(0.009)	0.219	(0.012)	0.272	(0.036)	0.091	(0.049)	46.600	(0.526)
Unteres Baselbiet	0.129	(0.008)	0.146	(0.009)	0.223	(0.011)	0.315	(0.007)	0.331	(0.025)	48.419	(0.370)
Untersee	0.121	(0.013)	0.144	(0.009)	0.243	(0.011)	0.289	(0.015)	0.153	(0.042)	47.388	(0.455)
Uri	0.233	(0.014)	0.092	(0.006)	0.294	(0.009)	0.316	(0.024)	0.198	(0.039)	45.106	(0.367)
Val-de-Travers	0.151	(0.028)	0.105	(0.014)	0.275	(0.021)	0.265	(0.042)	0.247	(0.077)	43.771	(0.829)
Vevey	0.131	(0.012)	0.143	(0.011)	0.247	(0.013)	0.290	(0.011)	0.238	(0.035)	46.373	(0.510)
Viamala	0.188	(0.023)	0.084	(0.011)	0.273	(0.018)	0.263	(0.032)	0.373	(0.075)	43.223	(0.704)
Visp	0.116	(0.016)	0.136	(0.009)	0.221	(0.011)	0.331	(0.023)	0.119	(0.049)	48.208	(0.445)
Weinland	0.158	(0.017)	0.144	(0.014)	0.263	(0.018)	0.315	(0.017)	0.308	(0.058)	46.891	(0.675)
Werdenberg	0.130	(0.016)	0.131	(0.008)	0.336	(0.012)	0.259	(0.021)	0.053	(0.036)	41.950	(0.493)
Wil	0.143	(0.009)	0.158	(0.006)	0.244	(0.007)	0.313	(0.011)	0.189	(0.027)	48.510	(0.311)
Willisau	0.159	(0.011)	0.107	(0.005)	0.237	(0.006)	0.313	(0.019)	0.152	(0.030)	47.716	(0.286)
Winterthur	0.122	(0.008)	0.164	(0.008)	0.236	(0.010)	0.315	(0.007)	0.289	(0.028)	49.091	(0.347)
Yverdon	0.130	(0.014)	0.107	(0.009)	0.278	(0.014)	0.216	(0.015)	0.346	(0.047)	44.440	(0.496)
Zimmerberg	0.143	(0.010)	0.160	(0.012)	0.241	(0.013)	0.344	(0.007)	0.286	(0.032)	49.860	(0.493)
Zug	0.141	(0.009)	0.168	(0.009)	0.212	(0.010)	0.362	(0.009)	0.271	(0.026)	51.037	(0.394)
Zürcher Oberland	0.132	(0.008)	0.150	(0.008)	0.246	(0.009)	0.314	(0.007)	0.285	(0.026)	48.771	(0.335)
Zürcher Unterland	0.134	(0.011)	0.164	(0.011)	0.225	(0.013)	0.333	(0.009)	0.245	(0.035)	50.027	(0.467)
Zürich	0.099	(0.008)	0.191	(0.009)	0.265	(0.010)	0.298	(0.006)	0.224	(0.024)	49.550	(0.362)

Notes: This table shows the income mobility estimates by labor market regions (n=106). RRS indicates the rank-rank slope, *Q1Q5* is the American Dream measure, Q1Q1 is the cycle of poverty measure, *Q5Q5* is the cycle of privileges measure, IGE is the intergenerational elasticity, AUM P=25 shows the expected rank of children below the median of the income distribution. The estimates are based on 923,107 observations. Corresponding standard errors are shown in parentheses.

Table A9: Income Mobility by Canton

	RRS		Q1Q5		Q1Q1		Q5Q5		IGE		AM P=25	.
Cantons												
AG	0.142	(0.004)	0.150	(0.004)	0.219	(0.004)	0.324	(0.004)	0.242	(0.014)	49.171	(0.157)
AI	0.181	(0.021)	0.110	(0.009)	0.306	(0.013)	0.307	(0.032)	0.188	(0.047)	45.253	(0.604)
AR	0.182	(0.011)	0.104	(0.007)	0.294	(0.010)	0.319	(0.014)	0.254	(0.032)	45.145	(0.399)
BE	0.157	(0.003)	0.090	(0.002)	0.251	(0.002)	0.265	(0.003)	0.275	(0.008)	44.958	(0.092)
BL	0.132	(0.006)	0.130	(0.005)	0.226	(0.007)	0.305	(0.005)	0.299	(0.019)	47.855	(0.249)
BS	0.148	(0.010)	0.121	(0.008)	0.301	(0.011)	0.273	(0.008)	0.316	(0.031)	44.527	(0.404)
FR	0.148	(0.005)	0.118	(0.003)	0.226	(0.004)	0.294	(0.007)	0.224	(0.016)	46.797	(0.178)
GE	0.099	(0.006)	0.232	(0.007)	0.245	(0.007)	0.328	(0.005)	0.137	(0.017)	50.610	(0.304)
GL	0.145	(0.015)	0.126	(0.010)	0.253	(0.013)	0.288	(0.018)	0.129	(0.041)	47.287	(0.495)
GR	0.164	(0.006)	0.106	(0.004)	0.262	(0.005)	0.289	(0.008)	0.238	(0.020)	45.304	(0.209)
JU	0.158	(0.010)	0.108	(0.005)	0.252	(0.008)	0.284	(0.015)	0.206	(0.030)	44.737	(0.305)
LU	0.146	(0.004)	0.121	(0.003)	0.226	(0.003)	0.311	(0.006)	0.206	(0.013)	48.239	(0.144)
NE	0.160	(0.008)	0.125	(0.006)	0.260	(0.008)	0.285	(0.009)	0.234	(0.024)	45.031	(0.286)
NW	0.168	(0.013)	0.099	(0.007)	0.240	(0.010)	0.334	(0.017)	0.233	(0.037)	47.722	(0.421)
OW	0.168	(0.013)	0.094	(0.006)	0.259	(0.010)	0.259	(0.019)	0.213	(0.038)	47.119	(0.398)
SG	0.169	(0.004)	0.130	(0.003)	0.274	(0.004)	0.323	(0.005)	0.211	(0.012)	46.353	(0.145)
SH	0.133	(0.012)	0.131	(0.010)	0.226	(0.012)	0.307	(0.012)	0.284	(0.040)	47.443	(0.452)
SO	0.141	(0.006)	0.135	(0.005)	0.221	(0.006)	0.323	(0.007)	0.261	(0.020)	48.570	(0.223)
SZ	0.178	(0.007)	0.121	(0.005)	0.261	(0.006)	0.341	(0.009)	0.244	(0.021)	47.470	(0.252)
TG	0.121	(0.006)	0.150	(0.004)	0.237	(0.005)	0.295	(0.007)	0.218	(0.020)	47.846	(0.205)
TI	0.126	(0.006)	0.110	(0.003)	0.241	(0.004)	0.279	(0.007)	0.186	(0.015)	45.927	(0.183)
UR	0.233	(0.014)	0.092	(0.006)	0.294	(0.009)	0.316	(0.024)	0.198	(0.039)	45.106	(0.367)
VD	0.133	(0.004)	0.140	(0.004)	0.247	(0.004)	0.288	(0.004)	0.244	(0.013)	46.285	(0.170)
VS	0.141	(0.005)	0.129	(0.003)	0.229	(0.004)	0.308	(0.007)	0.227	(0.016)	47.007	(0.168)
ZG	0.141	(0.009)	0.168	(0.009)	0.212	(0.010)	0.362	(0.009)	0.271	(0.026)	51.037	(0.394)
ZH	0.128	(0.003)	0.170	(0.003)	0.240	(0.004)	0.329	(0.003)	0.253	(0.010)	49.629	(0.142)

Notes: This table shows the income mobility estimates by cantons (n=26). RRS indicates the rank-rank slope, *Q1Q5* is the American Dream measure, Q1Q1 is the cycle of poverty measure, *Q5Q5* is the cycle of privileges measure, IGE is the intergenerational elasticity, AUM P=25 shows the expected rank of children below the median of the income distribution. The estimates are based on 923,107 observations. Corresponding standard errors are shown in parentheses.

Table A10: Educational Mobility by Canton

	Share Bottom 20 in HS		Child-Parent Years Edu		Child-Parent HS	
Cantons						
AG	0.084	(0.005)	0.247	(0.006)	0.353	(0.009)
AI	0.077	(0.015)	0.201	(0.037)	0.414	(0.072)
AR	0.089	(0.012)	0.251	(0.023)	0.336	(0.039)
BE	0.076	(0.003)	0.263	(0.006)	0.392	(0.008)
BL	0.121	(0.010)	0.259	(0.013)	0.377	(0.017)
BS	0.171	(0.019)	0.309	(0.020)	0.435	(0.027)
FR	0.112	(0.006)	0.268	(0.011)	0.380	(0.020)
GE	0.273	(0.012)	0.265	(0.009)	0.247	(0.013)
GL	0.083	(0.016)	0.234	(0.033)	0.245	(0.051)
GR	0.096	(0.007)	0.277	(0.014)	0.410	(0.022)
JU	0.099	(0.008)	0.229	(0.015)	0.318	(0.025)
LU	0.076	(0.003)	0.234	(0.006)	0.369	(0.010)
NE	0.129	(0.009)	0.282	(0.011)	0.313	(0.016)
NW	0.081	(0.012)	0.187	(0.027)	0.281	(0.049)
OW	0.071	(0.011)	0.265	(0.029)	0.259	(0.063)
SG	0.098	(0.005)	0.221	(0.009)	0.346	(0.014)
SH	0.094	(0.017)	0.278	(0.025)	0.399	(0.033)
SO	0.100	(0.008)	0.245	(0.013)	0.411	(0.019)
SZ	0.072	(0.007)	0.263	(0.015)	0.403	(0.027)
TG	0.079	(0.005)	0.209	(0.010)	0.291	(0.015)
TI	0.149	(0.005)	0.268	(0.009)	0.316	(0.013)
UR	0.062	(0.009)	0.297	(0.023)	0.527	(0.044)
VD	0.148	(0.005)	0.294	(0.006)	0.311	(0.008)
VS	0.121	(0.006)	0.243	(0.011)	0.343	(0.018)
ZG	0.093	(0.011)	0.270	(0.013)	0.377	(0.020)
ZH	0.128	(0.006)	0.277	(0.006)	0.347	(0.009)

Notes: This table shows the educational mobility estimates by cantons (n=26). Share Bottom 20 in HS shows the share of children from the bottom quintile in the national parental income distribution that visit a high school (gymnasium), *Child-Parent Years Edu* shows the correlation in years of education between children and parents, Child-Parent HS shows how much more likely children are to visit a high school if at least one of their parents went to high school as well. Corresponding standard errors are shown in parentheses.

Table A11: Educational Mobility by Labor Market Region

	Share Bottom 20 in HS		Child-Parent Years Edu		Child-Parent HS	
LaborMarket						
Aarau	0.070	(0.006)	0.240	(0.010)	0.357	(0.014)
Aaretal	0.073	(0.009)	0.242	(0.023)	0.443	(0.029)
Aigle	0.110	(0.018)	0.289	(0.026)	0.397	(0.033)
Appenzell A.Rh.	0.085	(0.012)	0.251	(0.022)	0.336	(0.038)
Appenzell I.Rh.	0.083	(0.016)	0.198	(0.040)	0.438	(0.077)
Baden	0.148	(0.021)	0.258	(0.017)	0.303	(0.024)
Basel-Stadt	0.171	(0.019)	0.309	(0.020)	0.435	(0.027)
Bellinzona	0.125	(0.013)	0.318	(0.024)	0.244	(0.031)
Bern	0.123	(0.010)	0.280	(0.011)	0.381	(0.014)
Biel/Bienne	0.125	(0.016)	0.247	(0.026)	0.363	(0.031)
Brig	0.121	(0.020)	0.202	(0.033)	0.330	(0.050)
Brugg-Zurzach	0.085	(0.013)	0.241	(0.017)	0.404	(0.026)
Burgdorf	0.085	(0.009)	0.262	(0.021)	0.332	(0.030)
Chur	0.107	(0.015)	0.254	(0.024)	0.439	(0.037)
Davos	0.090	(0.035)	0.200	(0.064)	0.362	(0.093)
Einsiedeln	0.065	(0.016)	0.174	(0.036)	0.130	(0.071)
Engiadina Bassa	0.088	(0.023)	0.276	(0.060)	0.324	(0.090)
Entlebuch	0.058	(0.008)	0.168	(0.023)	0.431	(0.050)
Erlach-Seeland	0.085	(0.013)	0.244	(0.027)	0.420	(0.039)
Freiamt	0.068	(0.010)	0.198	(0.018)	0.295	(0.029)
Fricktal	0.079	(0.012)	0.245	(0.018)	0.358	(0.031)
Genève	0.273	(0.012)	0.265	(0.009)	0.247	(0.013)
Glarner Hinterland	0.091	(0.026)	0.240	(0.058)	0.205	(0.086)
Glarner Unterland	0.078	(0.019)	0.232	(0.040)	0.265	(0.063)
Glattal-Furttal	0.108	(0.016)	0.245	(0.018)	0.380	(0.027)
Glâne-Veveyse	0.115	(0.014)	0.212	(0.030)	0.320	(0.061)
Goms	0.094	(0.029)	0.212	(0.075)	0.442	(0.106)
Grenchen	0.073	(0.020)	0.286	(0.042)	0.435	(0.060)
Gros-de-Vaud	0.097	(0.013)	0.232	(0.019)	0.261	(0.027)
Innerschwyz	0.063	(0.008)	0.260	(0.020)	0.472	(0.036)
Jura	0.099	(0.008)	0.229	(0.015)	0.318	(0.025)
Jura bernois	0.077	(0.013)	0.250	(0.024)	0.367	(0.036)
Kandertal	0.031	(0.009)	0.121	(0.042)	0.222	(0.065)
Knonaueramt	0.090	(0.021)	0.275	(0.030)	0.328	(0.036)
La Broye	0.103	(0.011)	0.235	(0.019)	0.289	(0.029)
La Chaux-de-Fonds	0.105	(0.011)	0.251	(0.018)	0.382	(0.025)
La Gruyère	0.070	(0.012)	0.206	(0.030)	0.332	(0.052)
La Sarine	0.143	(0.015)	0.298	(0.018)	0.371	(0.033)
La Vallée	0.037	(0.016)	0.255	(0.041)	0.343	(0.053)
Laufental	0.102	(0.017)	0.216	(0.027)	0.297	(0.040)
Lausanne	0.184	(0.013)	0.315	(0.011)	0.295	(0.015)
Leuk	0.113	(0.026)	0.158	(0.052)	0.462	(0.119)
Limmattal	0.151	(0.028)	0.206	(0.027)	0.315	(0.038)
Linthgebiet	0.103	(0.014)	0.186	(0.024)	0.343	(0.041)
Locarno	0.165	(0.012)	0.236	(0.017)	0.375	(0.027)
Lugano	0.158	(0.010)	0.281	(0.014)	0.305	(0.020)
Luzern	0.091	(0.007)	0.253	(0.010)	0.363	(0.014)
March	0.096	(0.015)	0.283	(0.024)	0.349	(0.043)
Martigny	0.088	(0.012)	0.278	(0.025)	0.316	(0.041)
Mendrisio	0.160	(0.014)	0.234	(0.021)	0.293	(0.033)
Mesolcina	0.112	(0.031)	0.319	(0.072)	0.481	(0.135)
Mittelbünden	0.083	(0.024)	0.334	(0.067)	0.380	(0.090)
Monthey	0.093	(0.016)	0.286	(0.030)	0.331	(0.048)
Morges	0.192	(0.019)	0.312	(0.018)	0.303	(0.024)
Murten/Morat	0.126	(0.014)	0.260	(0.026)	0.388	(0.038)
Mutschellen	0.114	(0.018)	0.282	(0.022)	0.344	(0.029)
Neuchâtel	0.159	(0.013)	0.290	(0.014)	0.287	(0.020)
Nidwalden	0.080	(0.012)	0.194	(0.026)	0.302	(0.047)
Nyon	0.246	(0.025)	0.272	(0.022)	0.260	(0.029)
Oberaargau	0.073	(0.008)	0.233	(0.021)	0.444	(0.030)
Oberengadin	0.171	(0.029)	0.350	(0.045)	0.364	(0.070)
Oberes Baselbiet	0.102	(0.013)	0.251	(0.021)	0.386	(0.028)
Oberes Emmental	0.038	(0.007)	0.186	(0.030)	0.244	(0.046)
Oberland-Ost	0.044	(0.009)	0.203	(0.027)	0.409	(0.036)
Oberthurgau	0.061	(0.009)	0.219	(0.021)	0.295	(0.032)
Olten	0.084	(0.013)	0.209	(0.023)	0.424	(0.037)
Pays d'Enhaut	0.084	(0.029)	0.208	(0.061)	0.221	(0.066)
Pfannenstiel	0.206	(0.026)	0.286	(0.020)	0.315	(0.027)
Prättigau	0.046	(0.014)	0.281	(0.042)	0.462	(0.065)
Rheintal	0.107	(0.014)	0.205	(0.024)	0.462	(0.046)
Saanen-Obersimmental	0.061	(0.012)	0.180	(0.035)	0.275	(0.054)
Sarganserland	0.101	(0.014)	0.169	(0.033)	0.232	(0.048)
Sarneraatal	0.071	(0.011)	0.263	(0.030)	0.196	(0.069)
Schaffhausen	0.094	(0.017)	0.278	(0.025)	0.399	(0.033)
Schanfigg	0.025	(0.025)	0.140	(0.129)	0.509	(0.160)
Schwarzwasser	0.045	(0.011)	0.134	(0.036)	0.398	(0.054)
Sense	0.096	(0.012)	0.260	(0.026)	0.443	(0.055)
Sierre	0.134	(0.019)	0.226	(0.032)	0.296	(0.052)
Sion	0.162	(0.015)	0.269	(0.023)	0.361	(0.036)
Solothurn	0.123	(0.016)	0.280	(0.021)	0.425	(0.030)
St.Gallen	0.117	(0.010)	0.255	(0.015)	0.369	(0.023)
Sursee-Seetal	0.082	(0.007)	0.214	(0.013)	0.366	(0.020)
Surselva	0.099	(0.015)	0.238	(0.038)	0.400	(0.058)
Thal	0.032	(0.014)	0.210	(0.045)	0.560	(0.070)
Thun	0.070	(0.007)	0.225	(0.016)	0.300	(0.023)
Thurtal	0.091	(0.009)	0.194	(0.017)	0.290	(0.023)
Toggenburg	0.069	(0.010)	0.175	(0.025)	0.209	(0.043)
Tre Valli	0.107	(0.014)	0.274	(0.028)	0.352	(0.040)
Unteres Baselbiet	0.166	(0.019)	0.257	(0.018)	0.352	(0.023)
Untersee	0.102	(0.013)	0.254	(0.022)	0.330	(0.033)
Uri	0.062	(0.009)	0.297	(0.023)	0.527	(0.044)
Val-de-Travers	0.090	(0.020)	0.221	(0.035)	0.370	(0.057)
Vevey	0.164	(0.018)	0.305	(0.019)	0.304	(0.024)
Viamala	0.079	(0.021)	0.349	(0.060)	0.329	(0.071)
Visp	0.129	(0.017)	0.148	(0.028)	0.367	(0.056)
Weinland	0.076	(0.021)	0.274	(0.039)	0.293	(0.050)
Werdenberg	0.107	(0.015)	0.249	(0.034)	0.333	(0.051)
Wil	0.065	(0.008)	0.179	(0.018)	0.279	(0.026)
Willisau	0.069	(0.006)	0.195	(0.012)	0.361	(0.024)
Winterthur	0.094	(0.013)	0.285	(0.018)	0.299	(0.023)
Yverdon	0.131	(0.016)	0.239	(0.019)	0.331	(0.028)
Zimmerberg	0.155	(0.022)	0.271	(0.022)	0.340	(0.029)
Zug	0.093	(0.011)	0.270	(0.013)	0.377	(0.020)
Zürcher Oberland	0.089	(0.012)	0.260	(0.017)	0.292	(0.021)
Zürcher Unterland	0.090	(0.017)	0.240	(0.023)	0.277	(0.032)
Zürich	0.204	(0.017)	0.292	(0.014)	0.393	(0.018)

Notes: This table shows the educational mobility estimates by labor market regions (n=106). Share Bottom 20 in HS shows the share of children from the bottom quintile in the national parental income distribution that visit a high school (gymnasium), *Child-Parent Years Edu* shows the correlation between years of education of children and parents, Child-Parent HS shows how much more likely children are to visit a high school if at least one of their parents went to high school as well. Corresponding standard errors are shown in parentheses.

Table A12: Correlation with Alternative Location Specifications

	Mother Location Child 16	Child Place of Birth	Child Location in 2010
Income Mobility			
RRS	0.985	0.942	0.828
Q1Q5	0.998	0.986	0.913
Q1Q1	0.979	0.912	0.778
Q5Q5	0.981	0.838	0.836
AUM25	0.997	0.968	0.925
IGE	0.954	0.816	0.688
Educational Mobility			
YearsEdu	0.963	0.831	0.881
Share Bottom20 in HS	0.993	0.989	0.912
Parents HS when Child was	0.967	0.875	0.868

Notes: This table shows how the mobility estimates on a cantonal level are correlated when children are assigned to regions according to different rules. Mother Location 16 restricts the sample to children for which we know for sure that the mother lived in this place when the child was 16 (this is true for 75% of children). Child Place of Birth is the place where the child was born. Child Location in 2010 used the location where the child lives when adult. Correlations are weighted by cantonal population in 2010.

Table A13: Robustness Regional Housing Price Index

	(1)	(2)	(3)	(4)
			Regional	
	CPI	HPI 1	HPI 2	HPI 3
Panel A:				
Rank-Rank Slope	0.141	0.117	0.120	0.127
	(0.0010)	(0.0010)	(0.0010)	(0.0010)
Constant	43.323	44.579	44.390	44.068
	(0.0601)	(0.0603)	(0.0602)	(0.0602)
Observations	923,107	923,107	923,107	923,107
Panel B:				
American Dream (Q1Q5)	0.124	0.125	0.123	0.121
	(0.0008)	(0.0008)	(0.0008)	(0.0008)
Observations	184,628	184,628	184,628	184,628
Panel C:				
Poverty Circle (Q1Q1)	0.247	0.231	0.233	0.234
	(0.0010)	(0.0010)	(0.0010)	(0.0010)
Observations	184,628	184,628	184,628	184,628

Notes: This table shows the sensitivity of our measures to regional price indices. Column (1) uses the «Residential Property Privately Owned Apartments Price Index», Column (2) Residential Property Regional Housing Price Index. Column (3) Rented properties, rental housing units price index. Source: Swiss National Bank.

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