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The Mystery of Success: How Family Background Shapes Social Mobility

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ABSTRACT

This study examines social mobility and its underlying drivers in Switzerland. We use a rich administrative dataset covering nearly 700,000 individuals across 23 birth cohorts. Rather than relying on traditional parent–child associations, we quantify the overall influence of familial factors, providing a wide-ranging indicator of social mobility. Using two-level linear mixed models, we find that family background accounts for 16.2% of the variation in income. Introducing an extensive set of economic and non-economic parental characteristics reveals that their combined explanatory power is limited. Even when all considered parental factors such as income, education, working status, birth country, religion, civil status, language, or family size are included simultaneously, they account for less than 12% of the sibling correlation. These results highlight the comparatively modest role of observable parental characteristics in shaping income differences in Switzerland.

JEL Classification: D31, I30, J62

1 | Introduction

Michael Jackson, the "King of Pop", was one of 10 siblings in the renowned Jackson family. Celebrated worldwide as one of the most influential and boundary-breaking artists of the twentieth century, he redefined popular music and performance. Alongside him, his sisters Rebbie, La Toya, and Janet, and his brothers Jackie, Tito, Jermaine, Marlon, and Randy each forged highly successful career in music and entertainment. Together they rose to fame as "The Jackson 5" before many of them achieved individual acclaim as solo artists, producers, or performers.

The intriguing question arises: How do siblings follow such parallel paths and attain success? Does this reflect unequal opportunities across families, or is it simply a result of their collective effort and talent? Sociologists and economists have long pondered these and similar inquiries. Solon (1999) concluded: "The mystery of what underlies the considerable resemblance between brothers in their long-run earnings remains a fascinating puzzle and should be a priority for continuing research." Today, 27 years later, this mystery is still largely unsolved.

While intergenerational social mobility is often measured through parent–child similarities,[1] an alternative approach involves examining sibling correlations. These correlations are considered an omnibus measure of the importance of family background (Solon 1999). Sibling-based estimates typically reveal a stronger effect of family belonging than single-variable parent–child mobility estimates because siblings share arguably more immutable circumstances than for example, parental income. These circumstances include shared schools, neighborhoods, or friends (Björklund and Jäntti 2012, 2020).

As Stuhler (2018) argues, public, and political debate often view meritocratic processes as key mechanisms for achieving equality of opportunity. Against this background, sibling correlations play an important role: they not only quantify the share of variation in individual outcomes attributable to family background, but also allow us to decompose how different observable parental characteristics contribute to the sibling correlation (Mazumder 2008). This decomposition helps to identify whether specific parental factors systematically reinforce sibling similarity, potentially reflecting underlying structural inequalities.

Switzerland offers an informative context for assessing the extent to which family background shapes individual success. The country combines a highly flexible labor market with a distinctive dual vocational education and training (VET) system, characterized by high permeability between vocational and academic pathways (Goller and Wolter 2025; SERI 2025). A graphical overview of the Swiss educational system, as published by the Swiss federal authorities, is presented in Appendix A, Figure A1. Moreover, Switzerland has remained largely unaffected by major wars, features comparatively low average taxation, is shaped by strong federalism, and has maintained a remarkably stable income distribution over the past decades (Frey et al. 2017; Schaltegger and Gorgas 2011). This institutional configuration provides an ideal setting for studying how individual outcomes are linked to family background.

In this study, we use a population-wide administrative dataset to estimate sibling correlations in income, a broad measure of social mobility. Our analysis is based on a rich administrative dataset covering the birth cohorts from 1966 to 1988, allowing us to account for individuals' childhood circumstances. Furthermore, the dataset includes comprehensive earnings information for employees and the self-employed since 1981, covering the full distribution of labor income in Switzerland.

To estimate sibling correlations and investigate the drivers of these correlations, we employ linear mixed models with both random and fixed effects, utilizing restricted maximum likelihood (REML) estimation. This approach allows us to model and decompose the factors contributing to the sibling correlation.

Our results reveal that family background accounts for 16.2% of the total income variance among siblings in Switzerland. By including both mixed- and same-sex siblings, our estimates reflect a society-wide perspective on social mobility, rather than a subgroup-specific effect. When all observed parental control variables are included simultaneously, their joint explanatory power remains limited, accounting for less than 12% of the ICC. This finding highlights the comparatively modest scope of observable family determinants in shaping income differences in Switzerland.

Empirical research on intergenerational and family-based mobility in Switzerland remains limited (Häner and Schaltegger 2021). By providing the first comprehensive estimates of sibling correlations in income for Switzerland and by decomposing the role of observable parental characteristics, this study fills an empirical gap in the literature. In particular, we evaluate a comprehensive set of parental characteristics—including income, nationality, civil status, family size, language region, community type, regional economic strength, education, working status, religion, and primary language—to assess their contribution to sibling similarity in income. Many of these factors are frequently discussed in both scientific and public debates as potential determinants of unequal opportunities.[2] Assessing their explanatory power therefore provides new evidence on the extent to which observable family background characteristics contribute to inequality of opportunity.

The remainder of this paper is structured as follows: Section 2 presents a literature review, followed by the description of the methods and data used (Section 3). Section 4 provides the presentation of our findings. Finally, Section 5 discusses the results, draws conclusions, and offers an outlook on future research opportunities.

2 | Literature Review

Studies on intergenerational social mobility evaluate the degree of intergenerational transmission of social status by examining various indicators such as income, wealth, occupational position, education, and political position (Björklund et al. 2012; Black and Devereux 2011; Corak and Piraino 2011; Corak 2013; Ermisch et al. 2006; Lee and Seshadri 2019; Solon 2018). Traditional economic research primarily investigates intergenerational associations between parents and children (Bügelmayer and Schnitzlein 2018). Estimates of the intergenerational elasticity of income (IGE) across a large number of countries typically range from about 0.15 in Scandinavian countries to about 0.5 for the United States (Bratberg et al. 2017; Chetty et al. 2017; Corak 2013; Corak et al. 2014; Vosters and Nybom 2017).

Simultaneously, a body of literature has emerged that measures the influence of family background on individual success using sibling correlations. Björklund and Jäntti (2020), Deutscher and Mazumder (2023), Torche (2015), and Jäntti and Jenkins (2015) provide comprehensive reviews of studies examining both sibling correlations and parent–child associations. Their findings indicate that the influence of family origin tends to be more substantial when estimated using sibling correlations rather than parent–child associations. Thus, sibling correlations provide a broader assessment of the importance of family belonging, capturing shared schools, social networks, and related influences.[3]

A comparison of countries shows the same patterns for sibling correlations as for parent–child relationships: The measured values are lower in Scandinavian countries than in the United States, indicating that family background is less important in the Nordic countries than in the US (Björklund and Jäntti 2012; Björklund et al. 2002, 2009, 2010; Hällsten and Thaning 2022; Pekkarinen et al. 2017; Raaum et al. 2006; Schnitzlein 2014). Björklund and Jäntti (2020) provide an overview showing that sibling correlations in long-term earnings range from 0.19 for sisters in Denmark to 0.49 for brothers in the United States.[4] Regarding years of schooling, in most Western countries family background accounts for 30% to 60% of total variation (Björklund and Salvanes 2011; Bredtmann and Smith 2018; Hällsten and Thaning 2022; Sieben et al. 2001). The meta-analysis of Anderson et al. (2024) across 18 countries again reveals significantly lower ICCs in Sweden, Norway, Finland, and Denmark compared to the US, where sibling correlations are approximately 25% higher. This country sub-ranking is consistent with the results provided by Jerrim and Macmillan (2015) and Hertz et al. (2008).

Grätz et al. (2021) report similar trends in their international comparison.

Our analysis provides an expanded view of the importance of family belonging, building on the scope of previous research. Specifically, we estimate sibling correlations in income while pre-controlling for gender and birth cohort, in line with standard practice in the literature. This approach ensures that the estimated intraclass correlation coefficient (ICC) captures only the share of income variation attributable to family-level factors, conditional on structural differences unrelated to the family, such as demographic composition or cohort effects (see Section 3.1 for details).

By distinguishing between within-and between-family variation, our approach allows for a comprehensive and unbiased assessment of how family background shapes individual economic outcomes. It further provides a consistent basis for identifying the observable parental characteristics that drive the sibling correlation, as analyzed in Section 4.2.

A few studies have already attempted to investigate the drivers of sibling correlation, mainly focusing on the explanatory power of parental income, educational attainment, or occupation status. For example, Mazumder (2008) shows that about 36% of brother correlations are explained by paternal income in the US. Björklund et al. (2010) and Hällsten and Thaning (2022) find lower contribution shares of parental income for Sweden. Their sibling correlations imply that around 20% of the variation in long-run income is attributable to factors that siblings share. After controlling for the father's income, Björklund et al. (2010) reveal a 10% decrease in the sibling correlation. Simultaneously considering parental income, education, and occupation results in a 22% decrease in the sibling correlation. Hällsten and Thaning (2022) explain 27% of the sibling correlation in children's income when controlling for parental income and 36% when controlling for all observable parental factors (education, occupation, wealth, and income) at once. Using a different methodological approach and allowing for heterogeneous intergenerational transmission across families, Bingley and Cappellari (2019) find a substantial influence of parental earnings on sibling correlations in Denmark. According to their results, intergenerational effects account for 72% of sibling correlations.[5]

To better understand the mechanisms underlying the family background effect, we extend our analysis beyond parental income. We focus on testing specific parental characteristics as potential determinants of individual economic outcomes. Existing research provides strong evidence that the parental characteristics included in our analysis are relevant determinants of individual outcomes. Prior studies highlight the importance of for example, civil status and family structure (e.g., Björklund and Chadwick 2003; Bloome 2017), parental birth country (e.g., Abramitzky et al. 2021; Boustan et al. 2025; Jensen and Manning 2025), urban–rural disparities (e.g., Chetty et al. 2014a; Cholli et al. 2024), parental education (e.g., Lee et al. 2024 or Forsberg et al. 2025), parental unemployment (e.g., Uguccioni 2022), religion (e.g., Chuah et al. 2016), language skills (e.g., Chiswick and Miller 1999 or Bleakley and Chin 2004), or family size (Black et al. 2005) may potentially undermine the principle of equality of opportunity. Therefore, we systematically evaluate the explanatory power of these factors in shaping the sibling correlation.

As mentioned earlier, existing evidence on intergenerational mobility in Switzerland remains limited (Häner and Schaltegger 2021). Chuard and Grassi (2020) show that income mobility in Switzerland is comparatively high (rank-rank slope of 0.14), exceeding levels in the United States and even in the Nordic countries. Complementing this evidence, Boustan et al. (2025) show that intergenerational rank–rank associations in Switzerland are remarkably similar for children of immigrants and Swiss-born parents. At the same time, educational mobility is significantly lower (Bauer and Riphahn 2006, 2007; Chuard and Grassi 2020; Schmutz 2024). According to Chuard and Grassi (2020), the divergence between income and educational mobility could highlight the effectiveness of Switzerland's dual educational system, which provides alternative pathways to economic success that do not solely rely on traditional academic education. Furthermore, Häner and Schaltegger (2024) examine multigenerational social mobility in Switzerland across 15 generations using surname-based data. Their findings show that family influence on social status gradually dissipates within three generations. As a related piece of evidence, focusing not on social status but on cognitive abilities, Bühler et al. (2026) show that cognitive gaps by parental SES emerge early and persist into adolescence, while grandparental SES does not exert an additional effect beyond parental SES. Taken together, these findings suggest that family socioeconomic influences attenuate substantially across generations, providing little evidence for strong, persistent dynastic effects.

To the best of our knowledge, however, sibling correlations have not yet been estimated for Switzerland. Our study addresses this gap by providing the first nationwide estimates based on administrative data and by systematically decomposing the sibling correlation into distinct parental drivers. This approach allows us to assess both the extent and the origins of family influence in a country with a unique institutional setting.

3 | Methods and Data

3.1 | Sibling Correlation

To estimate the sibling correlation, we use a linear mixed model based on the framework proposed by Solon et al. (1991) and Solon (1999). The sibling correlation serves as an omnibus variable measuring the importance of belonging to a particular family (Solon 1999). It includes factors that siblings share, such as parental income, parental education, the mother's age at the birth of the first child, common neighborhood, or the family structure.

Income y of the i^{th} sibling in the j^{th} family can be decomposed according to the following equation:

$$y_{ij} = \beta_{0j} + \varepsilon_{ij} \tag{1}$$

where β_{0j} corresponds to the family intercept term and ε_{ij} is the error term. The family intercept term β_{0j} is composed of a fixed component β_{00} and a random component α_{0j}. According to Equation (2), α_{0j} captures the permanent component of an individual's status that is shared among siblings in the same family:

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

By substituting β_{0j} from Equation (2) in Equation (1), we obtain Equation (3), which combines the fixed and random components as

$$y_{ij} = \beta_{00} + \alpha_{0j} + \varepsilon_{ij} \tag{3}$$

As in Equation (3), it is commonly assumed that the residuals, α_{0j} and ε_{ij}, are normally distributed and independent of each other.[6] Analyzing the variances in Equation (3), while considering the constancy of the grand mean β_{00}, yields Equation (4). It demonstrates the variance of y_{ij} as the sum of the variance of the random family-specific component α_{0j} and the variance of the individual error term ε_{ij}. The variance of α_{0j} is denoted by $\sigma^2_{\alpha_0}$, and the variance of ε_{ij} is denoted by σ^2_{ε}, according to

$$Var(y_{ij}) = Var(\alpha_{0j}) + Var(\varepsilon_{ij}) = \sigma^2_{\alpha_0} + \sigma^2_{\varepsilon} \tag{4}$$

Thus, the total variance in income corresponds to the sum of the variance *between* families $\left(\sigma^2_{\alpha_0}\right)$ and the variance *within* families $\left(\sigma^2_{\varepsilon}\right)$. As a result, the sibling correlation is derived as

$$\rho = \frac{\sigma^2_{\alpha_0}}{\sigma^2_{\alpha_0} + \sigma^2_{\varepsilon}} \tag{5}$$

The intraclass correlation coefficient (ICC) in Equation (5) shows the proportion of variation in siblings' income that can be attributed to family components as a share of the total variance in siblings' income (see Appendix B for a formal derivation of ρ). A lower sibling correlation indicates less impact of family background on individuals' 4-year average income.

To determine the sibling correlation in four-year average income, ρ, we employ a linear mixed-effects model that allows for the inclusion of control variables.[7] Specifically, we estimate the following two-level random intercept model:

$$y_{ij} = \beta X_{ij} + \alpha_{0j} + \varepsilon_{ij} \tag{6}$$

where the vector X_{ij} captures control variables, whereas α_{0j} again corresponds to the random family component, and ε_{ij} to the error term according to Equation (3).[8] In line with standard practice in the sibling correlation literature, we pre-control for gender and birth cohort by including both variables in the vector X_{ij}. This ensures that the intraclass correlation coefficient (ICC) captures only the share of income variation attributable to family-level factors conditional on structural differences unrelated to family circumstances, such as gender and cohort effects. Formally, this corresponds to the prototypical specification used in canonical studies, where pre-controls serve to purge systematic income variation stemming from demographic composition rather than family background.

By holding constant predictable differences across gender and cohorts, this approach isolates the between-family component in 4-year average income variation. The resulting ICC can therefore be interpreted as the extent to which family background explains 4-year average income inequality among individuals who are otherwise comparable in their demographic characteristics.

Second, we introduce specific parental control variables to the vector X_{ij} sequentially, to assess their effect on the reduction of the variance components. This allows us to determine the respective explanatory power of different family-related factors for the similarity of siblings. Our decomposition approach allows us to estimate the contribution of parental factors to the sibling correlation by examining changes in the between-family variance component. We analyze the entire income distribution of all siblings within a generation horizontally and extend this analysis to a vertical intergenerational dimension by incorporating parental characteristics into linear mixed models. All parental characteristics are defined at the family level and are therefore identical for all siblings within the same household. Consequently, the inclusion of these variables affects only the between-family variance component $\left(\sigma^2_{\alpha 0}\right)$, while the within-family variance $\left(\sigma^2_{\varepsilon}\right)$ remains unchanged. This property allows us to directly extract the explanatory contribution of parental characteristics by comparing changes in the between-family variance component across models.[9] The purpose of this decomposition is to explain differences between families, not differences within families. Consistent with the canonical sibling correlation framework (e.g., Mazumder 2008; Björklund et al. 2010), parental covariates are therefore treated as family-related explanatory variables, and their contribution is evaluated through the reduction in the estimated family variance component. Allowing parental income to vary across siblings would instead capture within-family heterogeneity in parental resource exposure and would therefore address a different research question while altering the interpretation of the decomposition undertaken here. Additionally, in our setting, parental income is measured when children are between the ages of 15 and 20, following Chetty et al. (2014b), which implies substantial overlap in parental income exposure across siblings who are typically born relatively close together.

By assuming that the within-family variance remains unchanged when including the vertical parental control variables, we can directly extract the contribution of parental drivers from the linear mixed model by comparing the between-family variance components. In contrast, Solon (1999) estimates intergenerational associations between parental income and offspring income in a separate linear regression model to decompose the ICC, as formally derived in Appendix C.[10] Using our comprehensive Swiss dataset, both decomposition approaches yield similar percentages of parental income's contribution to the ICC.[11] However, the decomposition approach relying exclusively on linear mixed models allows for the inclusion of binary parental variables and appropriately accounts for the hierarchical structure of the data (Level-1 and Level-2 variance).

In addition to sequentially adding control variables, we also estimate models that include multiple covariates simultaneously. This approach allows us to examine the combined effect of several parental characteristics on the variance components and the sibling correlation. By doing so, we gain a clearer understanding of how different factors jointly influence the similarity of siblings' four-year average incomes.

3.2 | Administrative Data

In this study, we utilize a large administrative dataset comprising almost 700,000 observations from 23 cohorts (1966–1988).

We combine social security earnings records (SSER) from the Central Compensation Office (CCO) with census data from the Population and Households Statistics (STATPOP) provided by the Federal Statistical Office (FSO). The linkage of individuals across different data sources is accomplished using the pseudonymized social security number. Demographic characteristics, family ties, civil status, and citizenship are derived from the Population and Households Statistics (STATPOP).[12] Individual information is matched to the longitudinal Social Security Earnings Records (SSER), which allow for an accurate depiction of the labor income distribution. This dataset includes comprehensive earnings information for both employees and the self-employed since 1981, collected for the purpose of calculating public old-age insurance. Because the earnings records are not subject to an upper limit, we can accurately represent the full distribution of labor income.

To enrich the analysis with additional parental background characteristics, we further integrate information from the Structural Survey (SE), an annual microcensus conducted by the FSO since 2010. Participation in the SE is mandatory, with sanctions for non-compliance, and the survey covers approximately 200,000 individuals per year, amounting to over 2.9 million unique records (with partial panel overlap). The SE provides detailed information on education,[13] religion, working status, and language, allowing us to extend the set of parental control variables beyond what is available in SSER and STATPOP.

A separate STATPOP robustness sample ($n = 1{,}133{,}917$ individuals), described in Appendix A, Table A2, differs from the main sample in Table 1. It includes all siblings for whom complete parental demographic information is available from the Population and Households Register (STATPOP), regardless of coverage in the Structural Survey (SE). Information on parental education, working status, religion, and primary language is not available in the STATPOP dataset.[14]

3.3 | Sample and Variable Selection

Following Chetty et al. (2014b), we measure children's income when they are about 30 years old and the parent's income approximately 15 years earlier. In our baseline analysis, we follow this approach by using a multi-year average of individual income to obtain a measure that is less affected by transitory fluctuations (see Chetty et al. 2014b; Solon 1992). We restrict our core sample to individuals aged between 30 and 33 years, born between 1966 and 1988. This selection ensures that cohorts were at least 15 years old by 1981 and 33 years old by 2021.[15] Inflation-adjusted four-year average income, expressed in 2021 prices (CHF), serves as our main outcome variable.[16] Further, we include the lowest incomes, including zero incomes, in the main analysis to accurately represent the full income distribution without imposing an arbitrary lower bound.[17] As an additional robustness check, however, we re-estimate the baseline model using lower-bound thresholds proposed by Mazumder (2008) and Björklund et al. (2010). The results are reported in Table A4.2.

In Section 4.3, we test the robustness of our baseline estimates using alternative age restrictions. Specifically, we measure income once at ages 40–43 (again as a four-year average) and once over the entire period when siblings are aged 30–40 (averaged over 11 years).

To construct parental income, we also follow Chetty et al. (2014b) and use the 6-year average of the combined incomes of both parents when the children were aged between 15 and 20 years. If income information is available for both parents, we first sum their annual earnings in each of the relevant years and then compute the average over this 6-year period.[18] We set the upper age limit for parents at the statutory pension age in Switzerland—65 for men and 64 for women—consistent with the rules of the Swiss Old Age and Survivors' Insurance (OASI) system. These statutory retirement ages serve as an important behavioral benchmark, as individuals tend to perceive the full retirement age as the "normal" retirement age and adjust retirement behavior accordingly (Lalive et al. 2023). As a robustness check, we also re-estimate our main models using a uniform upper age limit of 64 for both parents. Table A4.3 shows that the results remain virtually unchanged: the ICC is 0.161 instead of 0.162, and the reduction in the ICC after controlling for parental income amounts to 4.35% rather than 4.94%.

To assign siblings to a family, we use the information on the mother. If this information is not available, we identify family membership through the father. No distinction is made between adopted, biological siblings, or half-siblings.

3.4 | Descriptive Statistics

The descriptive statistics in Table 1 provide core information on the main variables, highlighting key demographic and socioeconomic characteristics of the individuals. In the final sample, a total of 698,911 siblings are identified. Of these, 362,340 are men (51.8%) and 336,571 are women (48.2%). In the mixed-sex sample, the average year of birth is 1978, while the mean four-year average income, in 2021 prices, is CHF 64,071. The mean is substantially higher for men (CHF 76,430) than for women (CHF 50,069).

When examining the parental characteristics, the mean 6-year average income of parents amounts to CHF 125,543. Parents have on average 2.8 children per family, and the mean educational attainment (maximum years of completed schooling between mother and father) equals 12.2 years. Regarding demographic background, approximately 20% of parents were born outside Switzerland, while 30% of families reside in non-German-speaking cantons. About one in four families live in rural municipalities, and nearly 40% are located in cantons with below-average GDP per capita. Roughly 23% of parents report a separated civil status. With respect to labor market and cultural factors, only 1% of parents are classified as unemployed, while 12% identify with a non-Christian religious affiliation. Moreover, 3% of families speak no national language at home (German, French, Italian, or Romansh).

In a robustness check in Section 4.3, we use years of education instead of earnings as an alternative status indicator. The average years of schooling amount to nearly 14 years.

To extend our main analysis, we use survey data from the Swiss Household Panel (SHP). In Table A3, we provide descriptive

TABLE 1 | Descriptive statistics of main variables.

	Full sibling sample	
Offspring characteristics		
Four-year average income (ages 30–33), mean (IQR)	64,071.31	(39,803.5–84,330.6)
Sex, *n* (%)	698,911	(100.0)
Male	362,340	(51.8)
Female	336,571	(48.2)
Year of birth, mean (IQR)	1978	(1972–1983)
Parental characteristics		
Six-year average income, mean (IQR)	125,543.00	(80,276.1–149,117.6)
Number of children per family, mean (IQR)	2.8	(2.0–3.0)
Educational attainment, mean (IQR)	12.2	(12.0–14.0)
Birth country, *n* (%)		
Switzerland	558,898	(80.0)
Not Switzerland	140,013	(20.0)
Civil status, *n* (%)		
Not separated	537,584	(76.9)
Separated	161,327	(23.1)
Language region, *n* (%)		
German	502,318	(71.9)
Other national language	196,593	(28.1)
Community type, *n* (%)		
Urban	451,964	(64.7)
Rural	246,947	(35.3)
Regional economic strength, *n* (%)		
High GDP-canton	433,000	(62.0)
Low GDP-canton	265,911	(38.0)
Working status, *n* (%)		
Non-unemployed	692,680	(99.1)
Unemployed	6231	(0.9)
Religion, *n* (%)		
Christian or no religion	611,813	(87.5)
Non-Christian	87,098	(12.5)
Primary language, *n* (%)		
A national language of Switzerland	680,963	(97.4)
Other language	17,948	(2.6)
	Sub-sample educational attainment	
Offspring characteristics		
Years of education, mean (IQR)	13.91	(12.0–16.0)
Sex, *n* (%)	158,007	(100.0)
Male	79,876	(50.6)
Female	78,131	(49.4)
Year of birth, mean (IQR)	1977	(1972–1982)

Note: Table 1 provides a description of the main sample. 4-year average income (CHF) is calculated over the period when individuals were aged 30–33, expressed in 2021 prices. Parental six-year average income (CHF) is calculated as the total income from both parents during the child's adolescence (ages 15–20). The education subsample includes $n = 158{,}007$ siblings (22.6% of the main sample of $n = 698{,}911$) for whom information on educational attainment is available, indicating that not all siblings from the main sample could be matched with Structural Survey (SE) education data. Descriptive statistics of the brothers-and-sisters sample are provided in Table A1. Table A2 reports an equivalent descriptive table for the STATPOP-only sample we use for sample size robustness checks. In the dataset described in Table A2, we include all siblings for whom complete parental demographic information is available from the Population and Household Register (STATPOP), but whose parents are not covered by the Structural Survey (SE). Consequently, this sample is substantially larger than the main sample described in Table 1 but contains less detailed parental information. Table A3 provides descriptive statistics for the Swiss Household Panel (SHP) data, which we use to explore additional explanatory factors that are not available in the administrative data.

statistics for the SHP sample used in Appendix D. The SHP data include 834 full siblings, born on average in 1986, with an average income of CHF 64,585. The average parental income amounts to CHF 135,803, and additional indicators capture broader family characteristics not available in the administrative dataset: parental BMI, frequency of contact with neighbors and relatives, parental health status, political position and interest, special working times, and reading behavior.

4 | Results

4.1 | Sibling Correlation in Income

Column 1 in Table 2 reports the sibling correlation in four-year average income and the corresponding variance-component estimates for a linear mixed model.[19] The full sibling sample model yields a value for the intraclass correlation coefficient (ICC)

TABLE 2 | Baseline model and the joint explanatory power of all family-specific aspects.

	Baseline model	Control model with all family-specific aspects
ICC	0.162	0.143
	(0.001)	(0.001)
	[0.160, 0.165]	[0.140, 0.146]
σ^2_{ε}	1111.24	1112.63
$\sigma^2_{\alpha 0}$	215.04	185.35
Comparison		
%ΔICC	—	−11.73
$\%\Delta\sigma^2_{\alpha 0}$	—	−13.81
Parental control variables	—	Six-year average income
		Birth country
		Civil status
		Family size
		Language region
		Community type
		Regional economic strength
		Education
		Working status
		Religion
		Primary language
Pre-controlling	Gender & cohort	Gender & cohort
Number of individuals	698,911	698,911
Number of families	299,566	299,566

Note: Four-year average income (CHF) is calculated over the period when individuals were aged 30–33, expressed in 2021 prices (CHF 1000). Standard errors (in parentheses) and 95% confidence intervals [in brackets] are obtained via parametric bootstrapping. Summary information on income levels and years of education for the full sibling sample, as well as for brothers and sisters separately, is reported in the descriptive statistics (Table 1 and Table A1). ICC denotes the intraclass correlation coefficient and indicates the proportion of total variation in four-year average income that can be attributed to differences between families. $\sigma^2{}_{\varepsilon}$ represents the estimated residual variance, which measures the within-family variation in four-year average income. $\sigma^2{}_{\alpha 0}$ represents the estimated variance component at the family level, capturing the between-family variation in four-year average income. %ΔICC reports the percentage change in the intraclass correlation coefficient relative to the baseline model in column 1, and $\%\Delta\sigma^2{}_{\alpha 0}$ reports the corresponding percentage change in the between-family variance component. In contrast to Table A4, all parental control variables are included jointly in the "Full Control" specification rather than being introduced sequentially. *Parental six-year average income* is a numeric variable indicating the total income from both parents during the child's adolescence (ages 15–20). *Birth country* indicates whether parents were born outside Switzerland; *the variable equals 1 if at least one parent was born abroad. Civil status* equals 1 if the parents were separated. *Family size* measures the number of children per family. *Language region equals* 1 for non-German language regions. *Community type* equals 1 for rural municipalities. *Cantonal GDP* equals 1 for low-GDP cantons. *Education* is the maximum number of completed schooling years between mother and father. *Working status* equals 1 if at least one parent was unemployed. *Religion* equals 1 if at least one parent reports a non-Christian and non-atheist affiliation. *Primary language* equals 1 if neither parent speaks one of the four Swiss national languages (German, French, Italian, Romansh). The models control for cohort and gender prior to estimating the variance components, following the standard approach in the sibling correlation literature. This ensures that the ICC captures family-level variation in four-year average income conditional on structural differences unrelated to the family, such as gender and cohort effects. The table also reports the number of individuals (siblings) and the number of families included in the estimation.

of 0.162 (SE = 0.001). This indicates that family background accounts for 16.2% of the total variance in income. A comparison of the within-family component $\left(\sigma^2_{\varepsilon}\right)$ and the between-family component $\left(\sigma^2_{\alpha 0}\right)$ reveals that within-family income variation is more than five times larger than the variation between families. This implies that differences among siblings within the same family contribute substantially more to overall income variation than differences across families. Taken together, an ICC of 0.162 indicates a comparatively low level of intergenerational persistence in Switzerland in terms of magnitude, consistent with a high degree of income mobility that is broadly comparable to that observed in Scandinavian countries.[20]

To accurately estimate sibling correlations, it is essential to analyze the full income distribution. Restricting the sample, such as examining only brothers, only sisters, or only mixed-gender sibling combinations, alters the underlying variance pool and limits the interpretation of the ICC to those specific subgroups. Such segmentation therefore shifts the focus from the general sibling correlation to subgroup-specific measures that are not directly comparable to estimates based on the full sample. For this reason, our primary analysis relies on the full sibling sample, ensuring generalizability and consistency across the income distribution and providing a comprehensive measure of the overall influence of family background.

Nevertheless, for completeness—and to explore potential heterogeneity in the role of family background—we also estimate ICCs separately for specific sibling subgroups. Table A4.1 in the Appendix reports results for brothers, sisters, and mixed-sex siblings. The influence of family background on the later success of brothers (ICC = 0.20, SE = 0.003) is very similar to that for sisters (ICC = 0.22, SE = 0.003), although both estimates are somewhat higher than the estimate for the full sample.

In addition, we assess the sensitivity of our baseline estimate to alternative lower-bound restrictions for very low (including zero) income observations using thresholds proposed in the literature. Applying the Mazumder (2008) cutoff (CHF 1707 in 2021 prices) excludes 2.8% of observations and yields an ICC of 0.156, while applying the Björklund et al. (2010) cutoff (CHF 1369 in 2021 prices) excludes 2.6% of observations and yields an ICC of 0.157. These estimates, reported in Table A4.2, are close to the baseline ICC of 0.162, indicating that our results are highly robust to the treatment of zero and very low income observations.

4.2 | Drivers of the Sibling Correlation

In the next step, we systematically decompose the overall sibling correlation to identify which observable parental characteristics contribute to the measured sibling correlation. Table A4 reports the results from a sequence of parental control models that progressively introduce potential family-level determinants.

Parental income explains approximately 5% of the intraclass correlation. Thus, the explanatory power of parental income is lower in Switzerland than in other countries in terms of magnitude (Björklund and Jäntti 2020; Deutscher and Mazumder 2023; Jäntti and Jenkins 2015; Mazumder 2008; Torche 2015). This aligns with the finding that the association between parent and child income in Switzerland is comparatively low in international comparisons in terms of levels (Chuard and Grassi 2020). Our analysis further enables us to determine the explanatory strength of additional family-specific factors potentially undermining the principle of equality of opportunity.

When extending the analysis to other parental control variables, the explanatory power remains modest. Characteristics such as parental education, birth country,[21] civil status, family size, community type, or regional economic strength each reduce the ICC by less than 2%–5%, and most variables show negligible changes in the between-family variance component. Even when incorporating educational attainment and cultural or religious background, the sibling correlation remains remarkably stable. Taken together, these results suggest that observable parental characteristics explain only a minor share of the sibling correlation in Switzerland.

To complement our main analysis, we further extend our investigation in Appendix D using representative survey data from the Swiss Household Panel (SHP). This allows us to examine the explanatory power of additional parental drivers that are not captured in the administrative data, such as health status, frequency of reading books, and special working times. These factors likewise explain only a small share of the sibling correlation.

Simultaneously considering these effects and comparing them with the baseline model allows us to assess the joint explanatory power of all family-specific factors. Column 2 in Table 2 presents the corresponding results. When all observed parental control variables are included simultaneously, the intraclass correlation coefficient (ICC) decreases from 0.162 to 0.143, corresponding to a reduction of 11.7%. This specification incorporates a comprehensive set of 11 parental control variables capturing a wide range of economic, demographic, and cultural family dimensions, including parental income, birth country, civil status, family size, language region, community type, regional economic strength, education, working status, religion, and primary language spoken at home. Despite this broad set of controls, the results show that these 11 factors—often discussed as potential sources of unequal opportunity—jointly account for less than one-eighth of the total sibling correlation. Our results suggest that these factors are not the dominant drivers of income variations, and they do not undermine the principle of equality of opportunity.

4.3 | Robustness Checks

We test the robustness of our estimates using alternative model specifications. Table 3 presents the respective results. In column (1), we analyze the effects on four-year average income for individuals aged 40–43 years. The results show that the ICC for this age group is 0.155 (SE = 0.002), indicating a slightly lower sibling correlation compared to the baseline model.

TABLE 3 | Age-specific robustness checks.

	Baseline model	(1) Model with individuals aged 40–43 years	(2) Model with individuals aged 30–40 years
ICC	0.162	0.155	0.181
	(0.001)	(0.002)	(0.002)
	[0.160, 0.165]	[0.150, 0.160]	[0.177, 0.184]
σ_{ε}^2	1111.24	4100.64	1605.26
$\sigma_{\alpha 0}^2$	215.04	751.39	353.70
Pre-controlling	Gender & cohort	Gender & cohort	Gender & cohort
Number of individuals	698,911	310,883	431,945
Number of families	299,566	138,379	189,024

Note: In the baseline model (column 1), four-year average income (CHF) is calculated over the period when individuals were aged 30–33, expressed in 2021 prices (CHF 1000). Standard errors (in parentheses) and 95% confidence intervals [in brackets] are obtained via parametric bootstrapping. Summary information on income levels and years of education for the full sibling sample, as well as for brothers and sisters separately, is reported in the descriptive statistics (Tables 1 and A1). The baseline model in column 1 again corresponds to the main estimates in Table 2. Models (1) and (2) present robustness checks based on alternative age windows used to measure average income. In model (1), column 2, we re-estimate the sibling correlation using the same specification and sample construction as in the baseline model but restrict the analysis to individuals for whom income information is available between ages 40 and 43. This provides a later-life measure of average income to assess the robustness of our results to the timing of income measurement. In this model, the main variable is four-year average income (CHF) calculated over the period when individuals were aged 40–43, expressed in 2021 prices. In model (2), column 3, we similarly restrict the sample to individuals observed between ages 30 and 40, thereby extending the observation window. In this model, the variable of interest is 11-year average income (CHF), calculated over the period when individuals were aged 30–40, expressed in 2021 prices. In both robustness models (1) and (2), we retain the same individuals from the main dataset where available and re-clean the data to ensure consistent age-based measurement. Both robustness models control for cohort and gender prior to estimating the variance components, following the standard approach in the literature. The table also reports the number of individuals and the number of families included in each estimation. The models are estimated using linear mixed-effects specifications.

In column (2), we consider the 11-year average income for individuals aged 30–40 years. The ICC for this age group is 0.181 (SE = 0.002), which is also comparable to the baseline model, suggesting that the familial influence remains consistent across these age ranges.

Overall, the robustness checks demonstrate that the familial influence on average income remains substantial across different age specifications, with the ICC values indicating consistent results. These findings support the stability of our baseline model.

4.4 | Sensitivity Analysis

Furthermore, we use educational attainment instead of income as an alternative status indicator in an additional sensitivity check. Table 4 presents the respective results. In column (1), we investigate the familial influence on educational attainment. Instead of 4-year average income, we analyze the effects on years of education. As the results reveal, the ICC is substantially higher for educational attainment than for four-year average income in terms of magnitude (0.333 vs. 0.162). This aligns with Bauer and Riphahn (2006, 2007) and Chuard and Grassi (2020), who show that intergenerational persistence in education is significantly higher than persistence in income in Switzerland. However, our estimates indicate that low educational mobility does not necessarily lead to low income mobility. This phenomenon is explained by Chuard and Grassi (2020), who attribute it to the effective Swiss vocational education and training (VET) system. This unique, distinctive, and popular dual educational system enables individuals to achieve high incomes without the need for a traditional university education.[22]

Analogous to Section 4.2, we further control for the effects of parental income and parental education as two drivers of the sibling correlation in educational attainment (see Table A7 for details). In total, 4.81% of the similarity in siblings' educational attainment is explained by parental income, but 20.12% is explained by parental education. As for average income, these findings suggest that the influence of parental income contributes only marginally to the sibling correlation. However, parental education explains a substantially larger share of the observed sibling similarity. This finding aligns with the notion that, in Switzerland, educational attainment exhibits stronger intergenerational persistence than income, reflecting the more stable and institutionalized nature of educational transmission across generations. These patterns are also closely mirrored in recent evidence by Schmutz (2024), who documents that circumstances beyond students' control account for approximately 21% of the variation in educational achievement at the end of compulsory schooling in Switzerland, with cantonal inequality ranging from 14% to 30%.

TABLE 4 | Sensitivity analysis.

	Baseline model	(1) Years of education
ICC	0.162	0.333
	(0.001)	(0.003)
	[0.160, 0.165]	[0.328, 0.338]
σ_{ε}^2	1111.24	4.73
$\sigma_{\alpha 0}^2$	215.04	2.36
Pre-controlling	Gender & cohort	Gender & cohort
Number of individuals	698,911	158,007
Number of families	299,566	74,011

Note: Four-year average income (ages 30–33) and educational attainment are expressed in their original units (CHF 1000 and years, respectively). Standard errors (in parentheses) and 95% confidence intervals [in brackets] are obtained via parametric bootstrapping. Summary information on income levels and years of education for the full sibling sample, as well as for brothers and sisters separately, is reported in the descriptive statistics (Tables 1 and Table A1). Model (1) in column 2 replicates the baseline specification using years of education as the outcome variable instead of four-year average income. The model is estimated on the same sibling sample as in the main analysis (Table 2, column 1) but restricted to those individuals for whom educational information is available. Consequently, the number of individuals and families is substantially smaller than in the baseline model (see Table 1, Descriptive Statistics of Main Variables, Sub-Sample Educational Attainment). As the baseline model does, model (1) also controls for cohort and gender prior to estimating the variance components, following the standard approach in the literature. The table also reports the number of individuals and the number of families included in the estimation. Both models are estimated using linear mixed-effects specifications.

5 | Discussion and Conclusion

In this study, we examine social mobility and its drivers based on a comprehensive measure using rich administrative data from Switzerland, comprising almost 700,000 observations from 23 cohorts. By applying a variance decomposition approach within a two-level linear mixed model, we provide a detailed assessment of the sibling correlation and its underlying drivers. This robust methodology enables us to capture a nuanced and holistic perspective on social mobility, offering insights that extend well beyond the traditional parent–child income correlations.

The baseline estimates show that family background explains 16.2% of the total variation in 4-year average income. This finding suggests that factors beyond the family, such as individual attributes and external influences not shared by siblings, contribute substantially to income differences among siblings. The low ICC of 16.2% suggests that Switzerland exhibits a higher degree of income mobility and social permeability, akin to Scandinavian countries and surpassing Germany or the United States (Schnitzlein 2014). This underscores the minor role of family background in explaining 4-year average income in Switzerland, indicating a high degree of social mobility.

Furthermore, we investigate drivers of the measured sibling correlation. In doing so, we specifically focus on a comprehensive set of 11 parental control variables known for their potential to undermine the principle of equality of opportunity. These variables capture a wide range of economic, demographic, and cultural family dimensions such as parental income, parental working status, family size, parental birth country, parental civil status, or parental religion. If these factors were found to significantly influence individual outcomes, it would suggest systemic barriers to social mobility.

Our analysis, however, shows that the combined explanatory power of the 11 simultaneously tested factors accounts for less than 12% of the sibling correlation. This finding suggests that these traditionally contentious drivers are not the dominant forces shaping social mobility in Switzerland. Instead, it highlights the comparatively modest role of observable family characteristics in explaining income variation.

This sheds new light on the "mystery" noted by Solon (1999), as the specific components driving the sibling similarity remain largely elusive. Rather than being disheartening, this ambiguity is a reassuring insight. In a permeable, liberal society that values equality of opportunity, deterministic and therefore discriminatory factors should exert minimal influence on individual success. Our findings suggest that this principle holds true in Switzerland.

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Ethics Statement

This study relies on anonymized administrative data collected by public institutions for official purposes. No direct interaction with individuals occurred, and no experimental interventions were conducted. The analysis complies with all relevant legal and institutional data protection regulations. Access to the data was granted under a formal data use agreement, and all analyses were conducted within a secure computing environment provided by the data provider. As the study involves only secondary anonymized data, no formal ethical approval or informed consent was required.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data supporting the findings are subject to data protection regulations, as they originate from administrative registers. While the original data cannot be shared, the full R code and, upon request, a simulated example dataset are available from the authors.

Endnotes

[1]See, for example, Chetty et al. (2014b), Jäntti and Jenkins (2015), and Corak (2013) for income mobility, and Hertz et al. (2008) and Black and Devereux (2011) for educational mobility.

[2]See e.g., Abramitzky et al. (2021), Björklund and Chadwick (2003), Black et al. (2005), Bleakley and Chin (2004), Bloome (2017), Chetty et al. (2014a), Chiswick and Miller (1999), Cholli et al. (2024), Chuah et al. (2016), Forsberg et al. (2025), Jensen and Manning (2024), Lee et al. (2024) or Uguccioni (2022).

[3]To compare sibling correlations and intergenerational parent–child estimates, the latter must be transformed, as a direct comparison can be misleading. Solon (1999) suggests a comprehensive methodological approach. $ICC = (IGC)^2 + \textit{other shared factors}$. See Appendix C for a formal derivation in the same notation used in Section 3.1, following Solon (1999).

[4]Most studies focus either on brothers or sisters only, due to the differences in labor market attachment between men and women (Schnitzlein 2014). Assuming that labor market equalization between men and women will continue to progress toward greater gender equality, these differences in labor market attachment will likely narrow. Therefore, in our view, restricting the analysis to brothers or sisters and omitting mixed-sex siblings would remove an informative dimension of how family background and environment shape sibling similarities.

[5]Bingley and Cappellari (2019) estimate sibling correlations and intergenerational transmission of life cycle earnings using data on the Danish population of father/first-son/s-son triads. Their findings highlight the importance of life-cycle bias, showing that sibling correlations follow a U-shaped pattern over the life-cycle, with correlations peaking around age 25, decreasing through middle age, and rising again as individuals approach 51. This U-shape reveals substantial life-cycle effects that were masked in previous studies that did not account for age variation, leading to potentially underestimated correlations at certain ages. To address life-cycle effects in our own analysis, we conduct robustness checks by adjusting age filters, testing cohorts aged 40–43 and 30–40 instead of the standard 30–33 years (see Table 3). These additional checks reinforce the robustness of our findings while allowing for life-cycle-related variability.

[6]This assumption allows for the conceptual separation of the permanent component into two parts: one that is perfectly correlated among siblings and another that is perfectly uncorrelated among siblings (Mazumder 2008).

[7]We estimate linear mixed models using restricted maximum likelihood (REML). *p-values* are reported in the summary tables using Satterthwaite's degrees-of-freedom method (Kuznetsova et al. 2017). While coefficient stability tests such as Oster (2019) cannot be applied to hierarchical variance-component models, we assess model robustness through parametric bootstrapping of the intraclass correlation coefficient (ICC) and by reporting 95% confidence intervals for each specification. This approach provides an assessment of estimate stability within the variance-decomposition framework (see Björklund and Jäntti 2012; Mazumder 2008; Schnitzlein 2014).

[8]The model does not contain a transitory error component, as we use 4-year average income directly in the estimation Equation (6). In line with Björklund et al. (2010), we do not use annual income and therefore do not include the transitory error component in the model.

[9]For non-numeric variables (e.g., birth country or religion), we use the earliest available observation from the Swiss Population Census (STATPOP) or the Structural Survey and assign this information uniformly to all siblings within the family. For parental income, we follow standard practice in the intergenerational mobility literature (e.g., Chetty et al. (2014b)) by computing the six-year average of combined parental income during each child's adolescence (ages 15–20) and then averaging these values across siblings to obtain a consistent family-level measure. Because siblings are typically close in age, the relevant parental income years overlap substantially, implying that they experience highly comparable monetary and cultural environments. Definitions of all parental control variables are provided in the table notes of Table 2.

[10]The intergenerational correlation (IGC) is related to the intergenerational elasticity (IGE) through the relationship:

$IGC = \beta * \left(\frac{\sigma_{parents}}{\sigma_{offsprings}}\right)$, where β represents the intergenerational elasticity, $\sigma_{parents}$ is the standard deviation of the parents' long-run income, and $\sigma_{offsprings}$ is the standard deviation of the offspring's long-run income. This relationship indicates that if income inequality differs between generations, the IGC will differ from the IGE by the ratio of the standard deviations of parental and offspring income.

[11]Solon (1999) identifies the effect of a single numerical parental factor on the between-family variance and interprets the squared regression coefficient as the proportion of the ICC that is not explained by the remaining circumstances siblings share according to $ICC = (IGC)^2 + \textit{other shared factors}$. Following this approach allows us to identify the explanatory power of continuous numeric parental influence factors for the ICC and thereby sets the stage for comparing the two different metrics of social mobility. A formal derivation is provided in Appendix C. In

contrast to our decomposition approach, Solon (1999) does not focus on changes in the variance components and the resulting relative changes in the ICC. Instead, he identifies a portion of the between-family variance by relating the squared value of the intergenerational parent–child correlations to the "other factors" that explain the ICC. Following Solon's approach, we find that parental income accounts for 5.99% of the ICC. This corroborates the results of our approach, where we estimated the explanatory power of parental income to be 4.94% of the total ICC.

[12]The STATPOP data are available from 2010 onwards and provide information on the size and structure of the resident population at the end of each year. To obtain relevant parental information for estimating the mixed-effects models, we use the earliest available information. We adopt this approach because we are interested in the parental influence during the children's early adolescence (ages 15–20).

[13]To transform the highest educational attainment into years of education, we use the official conversion scheme provided by the federal authorities. See Figure A1 in the Appendix for the scheme.

[14]Despite these missing parental variables, the descriptive statistics are highly similar to those of the main SE-based sibling sample presented in Table 1, confirming the representativeness of the restricted main sample. For our main analysis, we rely on the smaller but richer SE-linked sample, which includes comprehensive information on parental characteristics. This allows us to examine a broader set of potential family-level drivers of intergenerational influence. The corresponding estimates obtained with the broader STATPOP-only sample are reported in Tables A5.1 and A5.2 and show high consistency with our main SE-based results.

[15]Cohorts born before 1966 are excluded, as parental income cannot be measured when offspring are 15–20 years old due to social security earnings records being available only from 1981. The 1988 cohort is the latest included as individuals turn 30 in 2018 and 33 in 2021.

[16]We base the main outcome variable on incomes from employment and self-employment that are liable for social security contributions. This includes unemployment benefits, disability benefits, COVID-related compensation for loss of earnings, compensation for loss of earnings for military, civilian service, or civil defense, and maternity and paternity benefits. Additionally, it includes income for non-employed persons paying minimum yearly old-age and survivors' insurance contributions or certain incomes paid by municipal authorities. Their income is set to 0. Contributions exceeding the minimum yearly old-age and survivors' insurance contribution from non-employed persons not based on any form of employment are not taken into account, as they are wealth-based. For these individuals, we can assume that they do not live in an environment characterized by low financial resources. Persons without an OASI identification number are excluded. Incomes not pension-forming but earned in the year of retirement are included to account for partial parental incomes earned after retirement. Incomes from self-employed farmers, including capital gains, are also included. Negative cancellations and positive reversal adjustments are accounted for in the income calculations. Care credits and child-raising credits as well as splitting amounts are pension-forming but not taken into account, as they do not constitute direct income from employment.

[17]We do not perform a log transformation of the incomes, as the median and mean are nearly identical, and the dependent variable is not right-skewed. This is attributable to the fact that we measure incomes at a relatively young age, where high incomes occur infrequently.

[18]If only one parent's income is available, we do not compute an average. Within a family, we assign the same parental income to all siblings based on the assumption that children within a family are similarly influenced by their parents' financial resources.

[19]The model includes gender and birth cohort as pre-controls prior to estimating the variance components, following standard practice in the sibling correlation literature (e.g., Björklund et al. 2010; Mazumder 2008). This ensures that the ICC reflects family-level variation in four-year average income conditional on structural differences unrelated to family background, such as gender and cohort effects. Accordingly, the ICC measures the extent to which family background explains income differences among individuals who are otherwise comparable in these characteristics.

[20]To benchmark our ICC-based estimate against conventional intergenerational mobility measures, we additionally estimated the intergenerational elasticity (IGE) and the rank-rank slope (RRS) using the same administrative data. The resulting estimates, IGE = 0.122 and RRS = 0.150, are similarly low and in line with Chuard and Grassi (2020), reinforcing the conclusion that Switzerland exhibits comparatively high intergenerational mobility in terms of magnitude. The RRS and IGE estimates are documented graphically in Figure A2. This alignment across measurement approaches is consistent with the synthesis in Deutscher and Mazumder (2023), who emphasize that sibling correlations and parent–child estimators typically deliver convergent conclusions regarding the level of intergenerational mobility across countries.

[21]Recent Oaxaca–Blinder decomposition for Switzerland (Boustan et al. 2025) shows that the average income-rank gap between children of immigrants and natives is modest: sons of immigrant fathers rank on average 2.85 percentiles lower, whereas daughters of immigrant fathers rank 3.14 percentiles higher than their native-born counterparts. Only a small fraction of these small gaps can be attributed to differences in parental income distributions—approximately 14% for sons and 15% for daughters.

[22]There are strong theoretical reasons supporting the thesis that VET can enhance upward mobility. Financial constraints on parents often result in reduced investment in children's education, thereby lowering their future incomes as stated by for example, Becker and Tomes (1986) or Solon (1992). VET mitigates this constraint by being low-cost for the parents and even providing wages for offspring's during the time of the apprenticeships. Additionally, VET offers numerous opportunities for further education that can be pursued alongside employment, facilitating the accumulation of human capital investment.

[23]It will provide a parametric answer to questions like, if the parents' earnings are 1% above the average in their generation, what percent above the average should we predict the child's income to be?

[24]Otherwise, we have to adjust according to $IGC = IGE * \left(\frac{\sigma_{parentalgeneration}}{\sigma_{offspringgeneration}}\right)$.

[25]The variance of $\beta_1 X_j$ is indicated by $\beta_1^2 \sigma^2_{X_j}$, while the variance of z_{0j} is indicated by $\sigma^2_{z_0}$.

[26]As mentioned above, if σ_y^2 is not equal to $\sigma^2_{X_j}$, we have to adjust according to $IGC = IGE * \left(\frac{SD_{parentalgeneration}}{SD_{offspringgeneration}}\right)$, to get the intergenerational correlation.

References

Abramitzky, R., L. Boustan, E. Jácome, and S. Pérez. 2021. "Intergenerational Mobility of Immigrants in the United States Over Two Centuries." *American Economic Review* 111, no. 2: 580–608. https://doi.org/10.1257/aer.20191586.

Anderson, L. R., P. Präg, E. T. Akimova, and C. Monden. 2024. "The Total Effect of Social Origins on Educational Attainment: Meta-Analysis of Sibling Correlations From 18 Countries." *Demography* 61, no. 5: 1637–1666. https://doi.org/10.1215/00703370-11579806.

Bauer, P., and R. T. Riphahn. 2006. "Timing of School Tracking as a Determinant of Intergenerational Transmission of Education." *Economics Letters* 91, no. 1: 90–97. https://doi.org/10.1016/j.econlet.2005.11.003.

Bauer, P., and R. T. Riphahn. 2007. "Heterogeneity in the Intergenerational Transmission of Educational Attainment: Evidence From Switzerland on Natives and Second-Generation Immigrants." *Journal of Population Economics* 20, no. 1: 121–148. https://doi.org/10.1007/s00148-005-0056-5.

Becker, G. S., and N. Tomes. 1986. "Human Capital and the Rise and Fall of Families." *Journal of Labor Economics* 4, no. 3, Pt. 2: S1–S39. https://doi.org/10.1086/298118.

Bingley, P., and L. Cappellari. 2019. "Correlation of Brothers' Earnings and Intergenerational Transmission." *Review of Economics and Statistics* 101, no. 2: 370–383. https://doi.org/10.1162/rest_a_00753.

Björklund, A., and L. Chadwick. 2003. "Intergenerational Income Mobility in Permanent and Separated Families." *Economics Letters* 80, no. 2: 239–246. https://doi.org/10.1016/S0165-1765(03)00084-3.

Björklund, A., T. Eriksson, M. Jäntti, O. Raaum, and E. Österbacka. 2002. "Brother Correlations in Earnings in Denmark, Finland, Norway and Sweden Compared to the United States." *Journal of Population Economics* 15: 757–772. https://doi.org/10.1007/s001480100095.

Björklund, A., and M. Jäntti. 2012. "How Important Is Family Background for Labor-Economic Outcomes?" *Labour Economics* 19, no. 4: 465–474. https://doi.org/10.1016/j.labeco.2012.05.016.

Björklund, A., and M. Jäntti. 2020. "Intergenerational Mobility, Intergenerational Effects, Sibling Correlations, and Equality of Opportunity: A Comparison of Four Approaches." *Research in Social Stratification and Mobility* 70: 100455. https://doi.org/10.1016/j.rssm.2019.100455.

Björklund, A., M. Jäntti, and M. J. Lindquist. 2009. "Family Background and Income During the Rise of the Welfare State: Brother Correlations in Income for Swedish Men Born 1932–1968." *Journal of Public Economics* 93, no. 5–6: 671–680. https://doi.org/10.1016/j.jpubeco.2009.02.006.

Björklund, A., L. Lindahl, and M. J. Lindquist. 2010. "What More Than Parental Income, Education and Occupation? An Exploration of What Swedish Siblings Get From Their Parents." *B.E. Journal of Economic Analysis & Policy* 10, no. 1: 1–38. https://doi.org/10.2202/1935-1682.2449.

Björklund, A., J. Roine, and D. Waldenström. 2012. "Intergenerational Top Income Mobility in Sweden: Capitalist Dynasties in the Land of Equal Opportunity?" *Journal of Public Economics* 96, no. 5–6: 474–484. https://doi.org/10.1016/j.jpubeco.2012.02.003.

Björklund, A., and K. G. Salvanes. 2011. "Education and Family Background: Mechanisms and Policies." In *Handbook of the Economics of Education*, edited by E. A. Hanushek, S. Machin, and L. Woessmann, vol. 3, 201–247. Elsevier. https://doi.org/10.1016/B978-0-444-53429-3.00003-X.

Black, S. E., and P. J. Devereux. 2011. "Recent Developments in Intergenerational Mobility." In *Handbook of Labor Economics*, edited by D. Card and O. Ashenfelter, vol. 4B, 1487–1541. Elsevier. https://doi.org/10.1016/S0169-7218(11)02414-2.

Black, S. E., P. J. Devereux, and K. G. Salvanes. 2005. "The More the Merrier? The Effect of Family Size and Birth Order on Children's Education." *Quarterly Journal of Economics* 120, no. 2: 669–700. https://doi.org/10.1093/qje/120.2.669.

Bleakley, H., and A. Chin. 2004. "Language Skills and Earnings: Evidence From Childhood Immigrants." *Review of Economics and Statistics* 86, no. 2: 481–496. https://doi.org/10.1162/003465304323031067.

Bloome, D. 2017. "Childhood Family Structure and Intergenerational Income Mobility in the United States." *Demography* 54, no. 2: 541–569. https://doi.org/10.1007/s13524-017-0564-4.

Boustan, L., M. Fjællegaard Jensen, R. Abramitzky, et al. 2025. *Intergenerational Mobility of Immigrants in 15 Destination Countries (NBER Working Paper No. 33558)*. National Bureau of Economic Research. https://doi.org/10.3386/w33558.

Bratberg, E., J. Davis, B. Mazumder, M. Nybom, D. D. Schnitzlein, and K. Vaage. 2017. "A Comparison of Intergenerational Mobility Curves in Germany, Norway, Sweden, and the US." *Scandinavian Journal of Economics* 119, no. 1: 72–101. https://doi.org/10.1111/sjoe.12197.

Bredtmann, J., and N. Smith. 2018. "Inequalities in Educational Outcomes: How Important Is the Family?" *Oxford Bulletin of Economics and Statistics* 80, no. 6: 1117–1144. https://doi.org/10.1111/obes.12258.

Bügelmayer, E., and D. D. Schnitzlein. 2018. "Is It the Family or the Neighborhood? Evidence From Sibling and Neighbor Correlations in Youth Education and Health." *Journal of Economic Inequality* 16, no. 3: 369–388. https://doi.org/10.1007/s10888-017-9364-8.

Bühler, J., O. G. Jenni, C. A. Schaltegger, M. Häner-Müller, and F. M. Wehrle. 2026. "Mind the Gap: Multigenerational Family Effects on Cognitive Abilities." *Intelligence* 114: 101982. https://doi.org/10.1016/j.intell.2025.101982.

Chetty, R., D. Grusky, M. Hell, N. Hendren, R. Manduca, and J. Narang. 2017. "The Fading American Dream: Trends in Absolute Income Mobility Since 1940." *Science* 356, no. 6336: 398–406. https://doi.org/10.1126/science.aal4617.

Chetty, R., N. Hendren, P. Kline, E. Saez, and N. Turner. 2014a. "Is the United States Still a Land of Opportunity? Recent Trends in Intergenerational Mobility." *American Economic Review* 104, no. 5: 141–147. https://doi.org/10.1257/aer.104.5.141.

Chetty, R., N. Hendren, P. Kline, and E. Saez. 2014b. "Where Is the Land of Opportunity? The Geography of Intergenerational Mobility in the United States." *Quarterly Journal of Economics* 129, no. 4: 1553–1623. https://doi.org/10.1093/qje/qju022.

Chiswick, B. R., and P. W. Miller. 1999. "Language Skills and Earnings Among Legalized Aliens." *Journal of Population Economics* 12, no. 1: 63–89. https://doi.org/10.1007/s001480050091.

Cholli, N. A., S. N. Durlauf, R. Landersø, and S. Navarro. 2024. *Understanding the Heterogeneity of Intergenerational Mobility Across Neighborhoods (NBER Working Paper No. 33035)*. National Bureau of Economic Research. https://doi.org/10.3386/w33035.

Chuah, S.-H., S. Gächter, R. Hoffmann, and J. H. W. Tan. 2016. "Religion, Discrimination and Trust Across Three Cultures." *European Economic Review* 90: 280–301. https://doi.org/10.1016/j.euroecorev.2016.03.008.

Chuard, P., and V. Grassi. 2020. *Switzer-Land of Opportunity: Intergenerational Income Mobility in the Land of Vocational Education (Economics Working Paper Series No. 2020–11)*. University of St. Gallen, School of Economics and Political Science. https://ideas.repec.org/p/usg/econwp/202011.html.

Corak, M. 2013. "Income Inequality, Equality of Opportunity, and Intergenerational Mobility." *Journal of Economic Perspectives* 27, no. 3: 79–102. https://doi.org/10.1257/jep.27.3.79.

Corak, M. 2020. "The Canadian Geography of Intergenerational Income Mobility." *Economic Journal* 130, no. 631: 2134–2174. https://doi.org/10.1093/ej/uez019.

Corak, M., M. J. Lindquist, and B. Mazumder. 2014. "A Comparison of Upward and Downward Intergenerational Mobility in Canada, Sweden and the United States." *Labour Economics* 30: 185–200. https://doi.org/10.1016/j.labeco.2014.03.013.

Corak, M., and P. Piraino. 2011. "The Intergenerational Transmission of Employers." *Journal of Labor Economics* 29, no. 1: 37–68. https://doi.org/10.1086/656371.

Deutscher, N., and B. Mazumder. 2023. "Measuring Intergenerational Income Mobility: A Synthesis of Approaches." *Journal of Economic Literature* 61, no. 3: 988–1036. https://doi.org/10.1257/jel.20211413.

Ermisch, J., M. Francesconi, and T. Siedler. 2006. "Intergenerational Mobility and Marital Sorting." *Economic Journal* 116, no. 513: 659–679. https://doi.org/10.1111/j.1468-0297.2006.01105.x.

Federal Statistical Office FSO. 2015. Das Bildungswesen in Der Schweiz (vereinfacht) [Infografik].

Forsberg, E., A. Khan, and O. Rosenqvist. 2025. "Do Sibling Correlations in Skills, Schooling, and Earnings Vary by Socioeconomic Background?

Insights From Sweden." *Labour Economics* 96: 102741. https://doi.org/10.1016/j.labeco.2025.102741.

Frey, C., C. Gorgas, and C. A. Schaltegger. 2017. "The Long Run Effects of Taxes and Tax Competition on Top Income Shares: An Empirical Investigation." *Review of Income and Wealth* 63, no. 4: 792–820. https://doi.org/10.1111/roiw.12228.

Goller, D., and S. C. Wolter. 2025. "Reaching for Gold! The Impact of a Positive Reputation Shock on Career Choice." *European Economic Review* 175: 105017. https://doi.org/10.1016/j.euroecorev.2025.105017.

Grätz, M., K. J. Barclay, N. Wiborg, et al. 2021. "Sibling Similarity in Education Across and Within Societies." *Demography* 58, no. 3: 1011–1037. https://doi.org/10.1215/00703370-9164021.

Hällsten, M., and M. Thaning. 2022. "Wealth as One of the "Big Four" SES Dimensions in Intergenerational Transmissions." *Social Forces* 100, no. 4: 1533–1560. https://doi.org/10.1093/sf/soab080.

Häner, M., and C. A. Schaltegger. 2021. "Fällt Der Apfel Weit Vom Stamm? Ein Überblick Über den Forschungsstand Zur Intergenerationellen Sozialen Mobilität." *Perspektiven der Wirtschaftspolitik* 22, no. 2: 103–120. https://doi.org/10.1515/pwp-2020-0052.

Häner, M., and C. A. Schaltegger. 2024. "The Name Says It All: Multigenerational Social Mobility in Basel (Switzerland), 1550–2019." *Journal of Human Resources* 59, no. 3: 711–742. https://doi.org/10.3368/jhr.0621-11749R2.

Hertz, T., T. Jayasundera, P. Piraino, S. Selcuk, N. Smith, and A. Verashchagina. 2008. "The Inheritance of Educational Inequality: International Comparisons and Fifty-Year Trends." *B.E. Journal of Economic Analysis & Policy* 7, no. 2: 10. https://doi.org/10.2202/1935-1682.1775.

Jäntti, M., and S. P. Jenkins. 2015. "Income Mobility." In *Handbook of Income Distribution*, edited by A. B. Atkinson and F. Bourguignon, vol. 2, 807–935. Elsevier. https://doi.org/10.1016/B978-0-444-59428-0.00011-4.

Jensen, M. F., and A. Manning. 2025. "Background Matters, but Not Whether Parents Are Immigrants: Outcomes of Children Born in Denmark." *American Economic Journal: Applied Economics* 17, no. 3: 347–379. https://doi.org/10.1257/app.20230389.

Jerrim, J., and L. Macmillan. 2015. "Income Inequality, Intergenerational Mobility, and the Great Gatsby Curve: Is Education the Key?" *Social Forces* 94, no. 2: 505–533. https://doi.org/10.1093/sf/sov075.

Kuznetsova, A., P. B. Brockhoff, and R. H. B. Christensen. 2017. "lmerTest Package: Tests in Linear Mixed Effects Models." *Journal of Statistical Software* 82, no. 13: 1–26. https://doi.org/10.18637/jss.v082.i13.

Lalive, R., A. Magesan, and S. Staubli. 2023. "How Social Security Reform Affects Retirement and Pension Claiming." *American Economic Journal: Economic Policy* 15, no. 3: 115–150. https://doi.org/10.1257/pol.20200686.

Lee, S. Y. T., N. A. Roys, and A. Seshadri. 2024. "The Causal Effect of Parents' Education on Children's *Earnings* (*NBER Working Paper No.* 32223)." *National Bureau of Economic Research*: 1–43. https://doi.org/10.3386/w32223.

Lee, S. Y. T., and A. Seshadri. 2019. "On the Intergenerational Transmission of Economic Status." *Journal of Political Economy* 127, no. 2: 855–921. https://doi.org/10.1086/700765.

Mazumder, B. 2008. "Sibling Similarities and Economic Inequality in the US." *Journal of Population Economics* 21, no. 3: 685–701. https://doi.org/10.1007/s00148-006-0127-2.

Oster, E. 2019. "Unobservable Selection and Coefficient Stability: Theory and Evidence." *Journal of Business & Economic Statistics* 37, no. 2: 187–204. https://doi.org/10.1080/07350015.2016.1227711.

Pekkarinen, T., K. G. Salvanes, and M. Sarvimäki. 2017. "The Evolution of Social Mobility: Norway During the Twentieth Century." *Scandinavian Journal of Economics* 119, no. 1: 5–33. https://doi.org/10.1111/sjoe.12205.

Raaum, O., K. G. Salvanes, and E. Ø. Sørensen. 2006. "The Neighbourhood Is Not What It Used To Be." *Economic Journal* 116, no. 508: 200–222. https://doi.org/10.1111/j.1468-0297.2006.01053.x.

Schaltegger, C. A., and C. Gorgas. 2011. "The Evolution of Top Incomes in Switzerland Over the 20th Century." *Swiss Journal of Economics and Statistics* 147, no. 4: 479–519. https://doi.org/10.1007/BF03399357.

Schmutz, R. 2024. "Inequality of Educational Opportunity in Switzerland: Exploring Regional Differences and Institutional Factors." *International Journal of Educational Research* 128: 102495. https://doi.org/10.1016/j.ijer.2024.102495.

Schnitzlein, D. D. 2014. "How Important Is the Family? Evidence From Sibling Correlations in Permanent Earnings in the USA, Germany, and Denmark." *Journal of Population Economics* 27, no. 1: 69–89. https://doi.org/10.1007/s00148-013-0468-6.

SHP Group. 2022. "Living in Switzerland Waves 1–22 + Beta Version Wave 23 + Covid-19 Data [Dataset]." In *FORS–Swiss Centre of Expertise in the Social Sciences*. SWISSUbase. https://doi.org/10.48573/vaxa-3w42.

Sieben, I., J. Huinink, and P. M. De Graaf. 2001. "Family Background and Sibling Resemblance in Educational Attainment: Trends in the Former Frg, the Former GDR, and The Netherlands." *European Sociological Review* 17, no. 4: 401–430. https://doi.org/10.1093/esr/17.4.401.

Solon, G. 1992. "Intergenerational Income Mobility in the United States." *American Economic Review* 82, no. 3: 393–408. http://www.jstor.org/stable/2117312.

Solon, G. 1999. "Intergenerational Mobility in the Labor Market." In *Handbook of Labor Economics*, edited by O. Ashenfelter and D. Card, vol. 3A, 1761–1800. Elsevier. https://doi.org/10.1016/S1573-4463(99)03010-2.

Solon, G. 2018. "What Do We Know So Far About Multigenerational Mobility?" *Economic Journal* 128, no. 612: F340–F352. https://doi.org/10.1111/ecoj.12495.

Solon, G., M. Corcoran, R. Gordon, and D. Laren. 1991. "A Longitudinal Analysis of Sibling Correlations in Economic Status." *Journal of Human Resources* 26, no. 3: 509–534. https://doi.org/10.2307/146023.

State Secretariat for Education, Research and Innovation. 2025. Swiss Education System.

Stuhler, J. 2018. "A Review of Intergenerational Mobility and its Drivers." In *JRC Research Report No. JRC112247*. Publications Office of the European Union. https://doi.org/10.2760/610312.

Tillmann, R., M. Voorpostel, E. Antal, et al. 2022. "The Swiss Household Panel (SHP)." *Jahrbücher für Nationalökonomie Und Statistik* 242, no. 3: 403–420. https://doi.org/10.1515/jbnst-2021-0039.

Torche, F. 2015. "Analyses of Intergenerational Mobility: An Interdisciplinary Review." *Annals of the American Academy of Political and Social Science* 657, no. 1: 37–62. https://doi.org/10.1177/0002716214547476.

Uguccioni, J. 2022. "The Long-Run Effects of Parental Unemployment in Childhood (*CLEF Working Paper* No. 45)." In *Canadian Labour Economics Forum*. University of Waterloo.

Vosters, K., and M. Nybom. 2017. "Intergenerational Persistence in Latent Socioeconomic Status: Evidence From Sweden and the United States." *Journal of Labor Economics* 35, no. 3: 869–901. https://doi.org/10.1086/690827.

Appendix A

Additional Tables and Figures

TABLE A1 | Descriptive statistics of main variables, brothers and sisters sample.

	Brothers sample		Sisters sample	
Offspring characteristics				
Four-year average income (ages 30–33), mean (IQR)	76,429.83	(58,844.6–92,859.0)	50,068.82	(25,330.3–71,163.3)
Sex, *n* (%)				
Male	224,553	(100)	0	(0)
Female	0	(0)	196,937	(100)
Year of birth, mean (IQR)	1977	(1972–1983)	1978	(1972–1983)
Parental characteristics				
Six-year average income, mean (IQR)	122,963.81	(77,453.1–146,511.4)	124,650.36	(78,074.2–148,871.8)
Number of children per family, mean (IQR)	2.97	(2.0–3.0)	3.0	(2.0–3.0)
Educational attainment	12.14	(12.0–14.0)	12.19	(12.0–14.0)
Birth country				
Switzerland	181,962	(81.0)	158,348	(80.4)
Not Switzerland	42,591	(19.0)	38,589	(19.6)
Civil status, *n* (%)				
Not separated	174,437	(77.7)	151,949	(77.2)
Separated	50,116	(22.3)	44,988	(22.2)
Language region				
German	163,597	(72.9)	142,994	(72.6)
Other national language	60,956	(27.1)	53,943	(27.2)
Community type, *n* (%)				
Urban	140,558	(62.6)	124,501	(63.2)
Rural	83,995	(37.4)	72,436	(36.8)
Regional economic strength, *n* (%)				
High GDP-canton	136,464	(60.8)	119,980	(60.9)
Low GDP-canton	88,089	(39.2)	76,957	(39.1)
Working status				
Non-unemployed	222,714	(99.2)	195,175	(87.9)
Unemployed	1839	(0.8)	1762	(0.9)
Religion				
Christian or no religion	197,805	(88.1)	173,062	(87.9)
Non-Christian	26,748	(11.9)	23,875	(12.1)
Primary language				
A national language of Switzerland	219,052	(97.6)	191,546	(97.3)
Other language	5501	(2.4)	5391	(2.7)

Note: Table A1 provides a description of the *brother* and *sister* subsamples corresponding to the main sibling sample reported in Table 1. Descriptive patterns are largely similar across groups, with expected level differences in four-year average income (CHF) between brothers and sisters. Four-year average income levels are substantially higher among brothers than among sisters, reflecting the gender gap.

TABLE A2 | Descriptive statistics of main variables, Population and Household Statistics (STATPOP) sample.

	Full sibling sample	
Offspring characteristics		
Four-year average income (ages 30–33), mean (IQR)	63,068.27	(38,534.1–83,394.1)
Sex, *n* (%)	1,133,917	(100.0)
Male	589,663	(52.0)
Female	544,254	(48.0)
Year of birth, mean (IQR)	1977	(1972–983)
Parental characteristics		
Six-year average income, mean (IQR)	119,964.89	(74,534.6–144,659.8)
Number of children per family, mean (IQR)	2.84	(2.0–3.0)
Birth country		
Switzerland	909,758	(80.2)
Not Switzerland	224,159	(19.8)
Civil status, *n* (%)		
Not separated	812,516	(71.1)
Separated	321,401	(28.3)
Language region		
German	844,963	(74.5)
Other national language	288,954	(25.5)
Community type, *n* (%)		
Urban	731,199	(64.5)
Rural	402,718	(35.5)
Regional economic strength, *n* (%)		
High GDP-canton	712,775	(62.9)
Low GDP-canton	421,142	(37.1)

Note: Table A2 provides a description of the STATPOP robustness sample. Four-year average income (CHF) is calculated over the period when individuals were aged 30–33, expressed in 2021 prices. The sample includes all siblings for whom complete demographic information is available from the Population and Household Register (STATPOP), regardless of coverage in the Structural Survey (SE). Information on parental *education, working status, religion*, and *primary language* is not available in the STATPOP dataset. Despite these missing parental variables, the descriptive statistics are highly similar to those of the main SE-based sibling sample presented in Table 1, confirming the representativeness of the restricted main sample.

TABLE A3 | Descriptive statistics of main variables, Swiss Household Panel (SHP) sample.

	Full sibling sample	
Offspring characteristics		
Average income (ages 26–41), mean (IQR)	64,585.21	(46,066.9–81,787.2)
Sex, *n* (%)	834	(100.0)
Male	424	(50.8)
Female	410	(49.2)
Year of birth, mean (IQR)	1986	(1982–1990)
Parental characteristics		
Average income (measured between 1999–2021), mean (IQR)	135,803.33	(85,620.3–175,563.0)
Body mass index (BMI), mean (IQR)	25.07	(22.7–26.6)
Contact with neighbors per month, mean (IQR)	6.46	(2.9–9.17)
Contact with relatives per month, mean (IQR)	6.06	(3.1–8.0)
Health status, *n* (%)		
Good	221	(26.5)
Bad	613	(73.5)
Political position, *n* (%)		
Left	146	(17.5)
Centre	548	(65.7)
Right	140	(16.8)
Political interest, *n* (%)		
Interested	(533)	(63.9)
German	(301)	(36.1)
Special working times, *n* (%)		
No	83	(10.0)
Yes	751	(90.0)
Frequency of reading books, *n* (%)		
Regularly	577	(69.2)
Not regularly	257	(30.8)

Note: Table A3 provides a description of the Swiss Household Panel (SHP) robustness sample. For the SHP sample, income (CHF) is defined as the average of reported earnings observed between ages 26 and 41, expressed in 2021 prices. This broader age window ensures that no observations are lost due to missing income information in tight age intervals. The same is true for parental average income, which we measure as an average across all available years from 1999 to 2021. The SHP data are used to validate the external consistency of our main results. The mean offspring income closely matches the corresponding estimates from the administrative data, underscoring the high data quality of the SHP. Moreover, the survey-based parental indicators align well with national benchmarks. For example, the average body mass index (BMI) in our SHP sample is 25.07, which corresponds almost exactly to the official Swiss population mean of 25.10 reported by the Federal Food Safety and Veterinary Office (BLV). Health status is reported on a 1–5 scale and recoded as *bad* (1–3) and *good* (4–5). Political position is measured on a 1–10 scale and categorized as *left* (1–3), *centre* (4–6), and *right* (7–10). Political interest ranges from 1–10 and is recoded as *not interested* (1–5) and *interested* (6–10). *Special working times* indicates whether respondents regularly work during nights or weekends. *Frequency of reading books* is coded on a 1–5 scale, where 1 = every day, 2 = once a week, 3 = once a month, 4 = less than once a month, and 5 = never; responses 1–2 are classified as *regularly*, and 3–5 as *not regularly*. All offspring information is fully observed for the 834 individuals in the SHP sibling sample. Therefore, no missing values occur for offspring average income. To avoid losing observations due to missing parental information, we apply multiple imputation by chained equations (*MICE*) using random forest methods for both numerical and categorical variables. The share of missing information across the 834 individuals is modest: 2.2% for parental health status, 2.6% for parental income, around 4%–5% for parental BMI, political variables, and social contact frequencies, and 11% for the parental frequency of reading books. Summary statistics before and after imputation are nearly identical, confirming that the imputation procedure performed accurately and preserved the empirical distribution of all parental variables.

TABLE A4 | Drivers of sibling correlations.

	Baseline model	Parental control model 1	Parental control model 2	Parental control model 3	Parental control model 4	Parental control model 5	Parental control model 6	Parental control model 7	Parental control model 8	Parental control model 9	Parental control model 10	Parental control model 11
ICC	0.162	0.154	0.162	0.160	0.157	0.162	0.160	0.162	0.155	0.162	0.162	0.162
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
	[0.160–0.165]	[0.152, 0.157]	[0.160, 0.165]	[0.158, 0.163]	[0.154, 0.160]	[0.159, 0.165]	[0.157, 0.163]	[0.160, 0.165]	[0.153, 0.158]	[0.159, 0.165]	[0.159, 0.165]	[0.160, 0.165]
σ^2_ε	1111.24	1111.14	1111.23	1110.98	1112.51	1111.16	1111.60	1111.24	1112.04	1111.24	1111.23	1111.26
$\sigma^2_{\alpha 0}$	215.04	203.02	214.97	211.77	207.09	214.73	211.21	215.04	204.23	214.70	214.74	214.97
Comparison												
%Δ ICC	—	−4.94	−0.00	−1.24	−3.09	−0.00	−1.24	−0.00	−4.32	−0.00	−0.00	0.00
%Δ $\sigma^2_{\alpha 0}$	—	−5.59	−0.03	−1.52	−3.70	−0.14	−1.78	−0.00	−5.03	−0.16	−0.21	−0.03
Parental control variable	—	Six-year average income	Birth country	Civil status	Family size	Language region	Community type	Regional economic strength	Education	Working status	Religion	Primary language
Pre-controlling	Gender & cohort	Gender & cohort	Gender & cohort	Gender & cohort	Gender & cohort	Gender & cohort	Gender & cohort	Gender & cohort	Gender & cohort	Gender & cohort	Gender & cohort	Gender & cohort
Number of individuals	698,911	698,911	698,911	698,911	698,911	698,911	698,911	698,911	698,911	698,911	698,911	698,911
Number of families	299,566	299,566	299,566	299,566	299,566	299,566	299,566	299,566	299,566	299,566	299,566	299,566

Note: An 4-year average income (CHF) is calculated over the period when individuals were aged 30–33, expressed in 2021 prices (CHF 1000). Standard errors (in parentheses) and 95% confidence intervals [in brackets] are obtained via parametric bootstrapping. Summary information on income levels and years of education for the full sibling sample, as well as for brothers and sisters separately, is reported in the descriptive statistics (Tables 1 and A1). ICC indicates the proportion of total variation in 4-year average income that can be attributed to differences between families. σ^2_ε represents the estimated residual variance, while $\sigma^2_{\alpha 0}$ represents the estimated variance component at the family level. %Δ ICC reports the percentage change in the ICC relative to the baseline model in column 1 (transferred from Table 2, column 1) for each subsequent parental control model 1–11. %Δ $\sigma^2_{\alpha 0}$ reports the percentage change in the between-family variance component relative to the baseline model. Parental control variables are sequentially introduced across Models 1–11. *Parental six-year average income* is a numeric variable indicating the total income from both parents during the child's adolescence (ages 15–20). *Birth country* indicates whether parents were born outside Switzerland; *the variable equals 1 if at least one parent was born abroad*. *Civil status* equals 1 if the parents were separated. *Family size* measures the number of children per family. *Language Region equals* 1 for non-German language regions. *Community type* equals 1 for rural municipalities. *Cantonal GDP* equals 1 for low-GDP cantons. *Education* is the maximum number of completed schooling years between mother and father. *Working status* equals 1 if at least one parent was unemployed. *Religion* equals 1 if at least one parent reports a non-Christian and non-atheist affiliation. *National language* equals 1 if neither parent speaks one of the four Swiss national languages (German, French, Italian, Romansh). The model controls for cohort and gender prior to estimating the variance components, following the standard approach in the sibling correlation literature. This ensures that the ICC captures family-level variation in four-year average income conditional on structural differences unrelated to the family, such as gender and cohort effects. The table also reports the number of individuals and the number of families included in the estimation. The models are estimated using linear mixed-effects specifications.

TABLE A4.1 | Baseline models for brothers and sisters.

	Baseline model	(1) Baseline model brothers	(2) Baseline model sisters
ICC	0.162	0.201	0.215
	(0.001)	(0.003)	(0.003)
	[0.160, 0.165]	[0.195, 0.207]	[0.209, 0.220)
σ_{ε}^2	1111.24	1278.20	754.90
$\sigma_{\alpha 0}^2$	215.04	322.21	207.04
Pre-controlling	Gender & cohort	Cohort	Cohort
Number of individuals	698,911	224,553	196,937
Number of families	299,566	103,445	90,931

Note: Four-year average income (CHF) is calculated over the period when individuals were aged 30–33, expressed in 2021 prices (CHF 1000). Standard errors (in parentheses) and 95% confidence intervals [in brackets] are obtained via parametric bootstrapping. Summary information on income levels and years of education for brothers and sisters separately is reported in the descriptive statistics (Table A1). As shown in Table A1, average four-year income among brothers (CHF 76,430) exceeds that of sisters (CHF 50,069), reflecting the gender gap. Column 1 reports the baseline estimates from Table 2, column 1. Models (1) and (2) in columns 2 and 3 report the corresponding baseline models estimated separately for brothers and sisters, based on the subsamples described in Table A1. For the brothers-only and sisters-only samples, we include all families with exclusively same-gender siblings. This also covers cases where, for instance, two sisters from a mixed-gender family are analyzed within the sisters-only sample. Both subsamples comprise families with any number of same-gender siblings ($n \geq 2$). As mentioned above, the models are identical in specification to the main analysis in Table 2, except that only cohort controls are included as pre-controls, while gender is held constant within each subsample. The coefficient on the cohort control captures the long-term income trend across birth cohorts (1966–1988). Among women, the average income increases by approximately CHF 630 ($p < 0.001$) per birth cohort, while among men it slightly declines by around CHF 60 ($p < 0.001$) per cohort. This pattern reflects the gradual rise in female labor market participation and earnings convergence over time. For women, the observed income can be approximated by adding the model intercept (CHF 42,250) to half the 23-year cohort span (11.5 cohorts) multiplied by the cohort effect (≈ CHF 630), resulting in an average predicted income of roughly CHF 49,500—closely matching the empirical mean of CHF 50,069 reported in the descriptive statistics in Table A1. All models are estimated using linear mixed-effects specifications. The table also reports the number of individuals and the number of families included in each estimation.

TABLE A4.2 | Baseline models with lower income bounds.

	Baseline model	(1) Baseline model with an income threshold based on Mazumder (2008)	(2) Baseline model with an income threshold based on Björklund et al. (2010)
ICC	0.162	0.156	0.157
	(0.001)	(0.002)	(0.001)
	[0.160, 0.165]	[0.153, 0.159]	[0.153, 0.159]
σ_{ε}^2	1111.24	1059.60	1062.72
$\sigma_{\alpha 0}^2$	215.04	195.98	196.97
Pre-controlling	Gender & cohort	Gender & cohort	Gender & cohort
Number of individuals	698,911	679,379	680,732
Number of families	299,566	299,050	299,086

Note: Four-year average income (CHF) is calculated over the period when individuals were aged 30–33, expressed in 2021 prices (CHF 1000). Standard errors (in parentheses) and 95% confidence intervals [in brackets] are obtained via parametric bootstrapping. Columns (2) and (3) re-estimate the baseline model using lower income bounds proposed in the sibling correlation literature and excluding zero incomes. The Mazumder (2008) threshold corresponds to approximately CHF 1707 in 2021 prices and excludes 2.8% of observations; the Björklund et al. (2010) threshold corresponds to approximately CHF 1369 and excludes 2.6% of observations.

TABLE A4.3 | Baseline model and parental control model with the same parental retirement age.

	Baseline model	Parental control model	(1) Baseline model with 64 as the uniform parental retirement age	(2) Parental control model with 64 as the uniform parental retirement age
ICC	0.162	0.154	0.161	0.154
	(0.001)	(0.001)	(0.002)	(0.003)
	[0.160, 0.165]	[0.152, 0.157]	[0.158, 0.164]	[0.260, 0.271]
σ_{ε}^2	1111.24	1111.14	1117.82	1117.69
$\sigma_{\alpha 0}^2$	215.04	203.02	214.24	202.99
Comparison				
%Δ ICC	—	−4.94	—	−4.35
%Δ $\sigma_{\alpha 0}^2$	—	−5.59	—	−5.25
Parental control variable	—	Six-year average income	—	Six-year average income
Pre-controlling	Gender & Cohort	Gender & cohort	Gender & cohort	Gender & cohort
Number of individuals	698,911	698,911	631,952	631,952
Number of families	299,566	299,566	273,839	273,839

Note: An 4-year average income (CHF) is calculated over the period when individuals were aged 30–33, expressed in 2021 prices (CHF 1000). Standard errors (in parentheses) and 95% confidence intervals [in brackets] are obtained via parametric bootstrapping. Columns (3) and (4) re-estimate the baseline and parental income models using a uniform upper parental age limit of 64 for both mothers and fathers. This restriction serves as a robustness check relative to the main specification, which uses the statutory retirement ages in Switzerland (65 for men and 64 for women). The resulting ICC remains virtually unchanged (0.161 instead of 0.162), and the explanatory contribution of parental income is very similar to that in the main analysis (4.35% instead of 4.94%).

TABLE A5.1 | Drivers of sibling correlations using the STATPOP sample.

	Baseline model STATPOP sample	Parental control model A1	Parental control model A2	Parental control model A3	Parental control model A4	Parental control model A5	Parental control model A6	Parental control model A7
ICC	0.174	0.164	0.174	0.171	0.168	0.173	0.171	0.174
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
	[0.171, 0.176]	[0.162, 0.166]	[0.171, 0.176]	[0.169, 0.173]	[0.166, 0.170]	[0.171, 0.175]	[0.169, 0.173]	[0.171, 0.176]
σ^2_ε	1081.80	1082.06	1081.79	1081.57	1083.02	1081.73	1082.11	1081.80
$\sigma^2_{\alpha 0}$	227.18	212.02	227.14	223.07	218.44	226.89	223.31	227.18
Comparison								
%Δ ICC	—	−5.75	−0.00	−1.72	−3.45	−0.58	−1.72	−0.00
%Δ $\sigma^2_{\alpha 0}$	—	−6.67	−0.02	−1.81	−3.85	−0.13	−1.70	−0.00
Parental control variable available in the STATPOP sample	—	Six-year average income	Birth country	Civil status	Family size	Language region	Community type	Regional economic strength
Pre-controlling	Gender & cohort	Gender & cohort	Gender & cohort	Gender & cohort	Gender & cohort	Gender & cohort	Gender & cohort	Gender & cohort
Number of individuals	1,133,917	1,133,917	1,133,917	1,133,917	1,133,917	1,133,917	1,133,917	1,133,917
Number of families	484,112	484,112	484,112	484,112	484,112	484,112	484,112	484,112

Note: An 4-year average income (CHF) is calculated over the period when individuals were aged 30–33, expressed in 2021 prices (CHF 1000). Standard errors (in parentheses) and 95% confidence intervals [in brackets] are obtained via parametric bootstrapping. Summary information on income levels for the STATPOP sample is reported in the descriptive statistics (Table A2). All estimates in models A1–A7 are highly robust to sample size differences and closely mirror the results obtained in the main SE-based models (Table A4), confirming the stability of the findings across data sources. All categorical variables are coded identically to those in the main results (see Table A4). Parental control variables in the STATPOP sample are limited to those available in the Population and Household Register, namely: six-year average parental income, parental birth country, civil status, family size, language region, community type, and regional economic strength. In contrast to the main SE-based sample (Table A4), information on parental education, working status, religion, and primary language is not available in the STATPOP data. Consequently, the total number of observed individuals is substantially larger (> 1 million), but the number of tested family-level drivers is smaller. All models control for cohort and gender prior to estimating the variance components, following the standard approach in the literature. Models were estimated using linear mixed-effects specifications.

TABLE A5.2 | Joint explanatory power of all family-specific aspects using the STATPOP sample.

	Baseline model STATPOP sample	**Control model with all family-specific aspects available in the STATPOP sample**
ICC	0.174	0.155
	(0.001)	(0.001)
	[0.171, 0.176]	[0.153, 0.158]
σ^2_{ε}	1081.80	1083.00
$\sigma^2_{\alpha 0}$	227.18	199.4
Comparison		
%Δ ICC	—	−10.92
%Δ $\sigma^2_{\alpha 0}$	—	−12.23
Parental control Variables available in the STATPOP sample	—	Six-year average income Birth country Civil status Family size Language region Community type Regional economic strength
Pre-controlling	Gender & cohort	Gender & cohort
Number of individuals	1,133,917	1,133,917
Number of families	484,112	484,112

Note: 4-year average income (CHF) is calculated over the period when individuals were aged 30–33, expressed in 2021 prices (CHF 1000). Standard errors (in parentheses) and 95% confidence intervals [in brackets] are obtained via parametric bootstrapping. Summary information on income levels for the STATPOP sample is reported in the descriptive statistics (Table A2). %Δ ICC reports the percentage change in the intraclass correlation coefficient relative to the baseline model. %Δ $\sigma^2{}_{\alpha 0}$ reports the corresponding percentage change in the between-family variance component. Analogous to Table 2, column 2 in the main results, this specification jointly includes all family-specific aspects available in the STATPOP dataset rather than introducing them sequentially. The parental control variables comprise six-year average parental income, parental birth country, civil status, family size, language region, community type, and regional economic strength. In contrast to the SE-based models, the STATPOP data does not include information on parental education, working status, religion, or primary language. All categorical variables are coded identically to those in the main results (see Table A4), ensuring full comparability across datasets.

TABLE A6.1 | Drivers of sibling correlations using the SHP sample.

	Baseline model SHP sample	Parental control model A1	Parental control model A2	Parental control model A3	Parental control model A4	Parental control model A5	Parental control model A6	Parental control model A7	Parental control model A8	Parental control model A9
ICC	0.153	0.145	0.153	0.153	0.153	0.148	0.151	0.153	0.152	0.154
	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.039)	(0.040)	(0.040)	(0.040)	(0.040)
	[0.073, 0.226]	[0.066, 0.219]	[0.074, 0.222]	[0.074, 0.227]	[0.071, 0.225]	[0.070, 0.217]	[0.072, 0.225]	[0.073, 0.227]	[0.074, 0.226]	[0.074, 0.227]
σ^2_ε	664.15	663.39	664.73	664.42	663.00	664.96	663.30	664.02	664.30	663.96
$\sigma^2_{\alpha 0}$	119.58	112.20	119.81	119.96	119.57	115.73	117.97	120.23	119.31	120.70
Comparison										
%Δ ICC	—	−5.23	−0.00	−0.00	−0.00	−3.27	−1.31	−0.00	−0.65	−0.65
%Δ $\sigma^2_{\alpha 0}$	—	−6.17	−0.19	−0.32	−0.01	−3.22	−1.35	0.54	−0.26	−0.94
Parental control variable available in the SHP sample	—	Average income	Body mass index (BMI)	Contact with neighbors per month	Contact with relatives per month	Health status	Political position	Political interest	Special working times	Frequency of reading books
Pre-controlling	Gender & cohort	Gender & cohort	Gender & cohort	Gender & cohort	Gender & cohort	Gender & cohort	Gender & cohort	Gender & cohort	Gender & cohort	Gender & cohort
Number of individuals	834	834	834	834	834	834	834	834	834	834
Number of families	380	380	380	380	380	380	380	380	380	380

Note: Average income (ages 26–41) is expressed in 2021 prices (CHF 1000). Standard errors (in parentheses) and 95% confidence intervals [in brackets] are obtained via parametric bootstrapping. Summary information on income levels for the SHP sample is reported in the descriptive statistics (Table A3). %Δ ICC and %Δ $\sigma^2_{\alpha 0}$ report the percentage changes in the ICC and between-family variance relative to the baseline SHP model (column 1) for each subsequent specification (Model A1–A9). The ICCs obtained from the SHP data are closely aligned with those from the administrative samples. We use the SHP data to explore additional explanatory factors that are not available in the administrative data. Analogous to Table A4 in the main results, parental control variables are sequentially introduced across Models A1–A9 to assess their individual contribution to explaining between-family variation. The SHP-based parental indicators capture broader socio-behavioral dimensions beyond economic and demographic aspects (see Table A3 for details on the categories). The first four parental controls (Model A1–A4) are numeric. The remaining variables enter the regression as categorical indicators defined as follows (see Table A3) for: *Parental health status* = 1 if reported as "bad", 0 otherwise. *Political position* = 1 if "right", 0 otherwise. *Political interest* = 1 if "not interested", 0 otherwise. *Special working times* = 1 if parents regularly work at night or on weekends, 0 otherwise. *Frequency of reading books* = 1 if "not regularly", 0 otherwise.

TABLE A6.2 | Joint explanatory power of all family-specific aspects using the SHP sample.

	Baseline model SHP sample	Control model with all family-specific aspects available in the SHP sample
ICC	0.153	0.141
	(0.040)	(0.040)
	[0.073, 0.226]	[0.061, 0.209]
σ^2_ε	664.15	660.45
$\sigma^2_{\alpha 0}$	119.58	108.03
Comparison		
%Δ ICC	—	−7.84
%Δ $\sigma^2_{\alpha 0}$	—	−9.66
Parental control variables available in the SHP sample	—	Average income Body mass index (BMI) Contact with neighbors per month Contact with relatives per month Health status Political position Political interest Special working times Frequency of reading books
Pre-controlling	Gender & cohort	Gender & cohort
Number of individuals	834	834
Number of families	380	380

Note: Average income (ages 26–41) is expressed in 2021 prices (CHF 1000). Standard errors (in parentheses) and 95% confidence intervals [in brackets] are obtained via parametric. Summary information on income levels for the SHP sample is reported in the descriptive statistics (Table A3). %Δ ICC reports the percentage change in the intraclass correlation coefficient relative to the baseline model (column 1), and %Δ $\sigma^2{}_{\alpha 0}$ reports the corresponding percentage change in the between-family variance component. Analogous to Table 2, column 2 in the main results, this specification jointly includes all family-specific aspects available in the SHP dataset rather than introducing them sequentially. The parental control variables comprise average parental income, parental BMI, contact frequency with neighbors, contact frequency with relatives, health status, political position, political interest, special working times, and frequency of reading books (see Table A3 for details). The ICC and the explanatory contribution of parental characteristics are remarkably similar in magnitude to those obtained from the administrative data, demonstrating that the family-level variance structure is highly consistent across survey-and register-based samples. Notably, even when incorporating a broader range of family-specific characteristics, the explanatory power of these additional variables remains limited.

TABLE A7 | Drivers of sibling correlations in educational attainment.

	Baseline model education	Parental control model A1	Parental control model A2
ICC	0.333	0.317	0.266
	(0.003)	(0.003)	(0.003)
	[0.328, 0.338]	[0.312, 0.323]	[0.260, 0.271]
σ^2_ε	4.73	4.73	4.72
$\sigma^2_{\alpha 0}$	2.36	2.2	1.71
Comparison			
%Δ ICC	—	−4.81	−20.12
%Δ $\sigma^2_{\alpha 0}$	—	−6.78	−27.54
Parental control variable	—	6-year average income	Education
Pre-controlling	Gender & cohort	Gender & cohort	Gender & cohort
Number of individuals	158,007	158,007	158,007
Number of families	74,001	74,001	74,001

Note: Educational attainment is expressed in years of schooling. Summary information on educational attainment for the full sibling sample is reported in the descriptive statistics (Table 1). Standard errors (in parentheses) and 95% confidence intervals [in brackets] are obtained via parametric bootstrapping. %Δ ICC and %Δ $\sigma^2{}_{\alpha 0}$ report the percentage changes in the ICC and between-family variance relative to the baseline model for each subsequent specification (Model A1 and A2). Analogous to Table A4 in the main results, the models sequentially introduce parental control variables to assess their explanatory power for between-family variation in children's educational attainment. Column (1) presents the baseline model (see Table 4, column 2 in the robustness section). Column 2 adds parental six-year average income—defined as the combined income of both parents when the child was aged 15–20—while column (3) controls for parental education, measured as the higher number of completed schooling years between mother and father. The results show that parental income reduces the ICC only marginally (by about 5%), as in Table A4 where income is the dependent variable. In contrast, parental education substantially lowers the ICC—by nearly one-fifth—suggesting that in terms of education, parental schooling is a core component of the sibling correlation. All models control for cohort and gender prior to estimating the variance components.

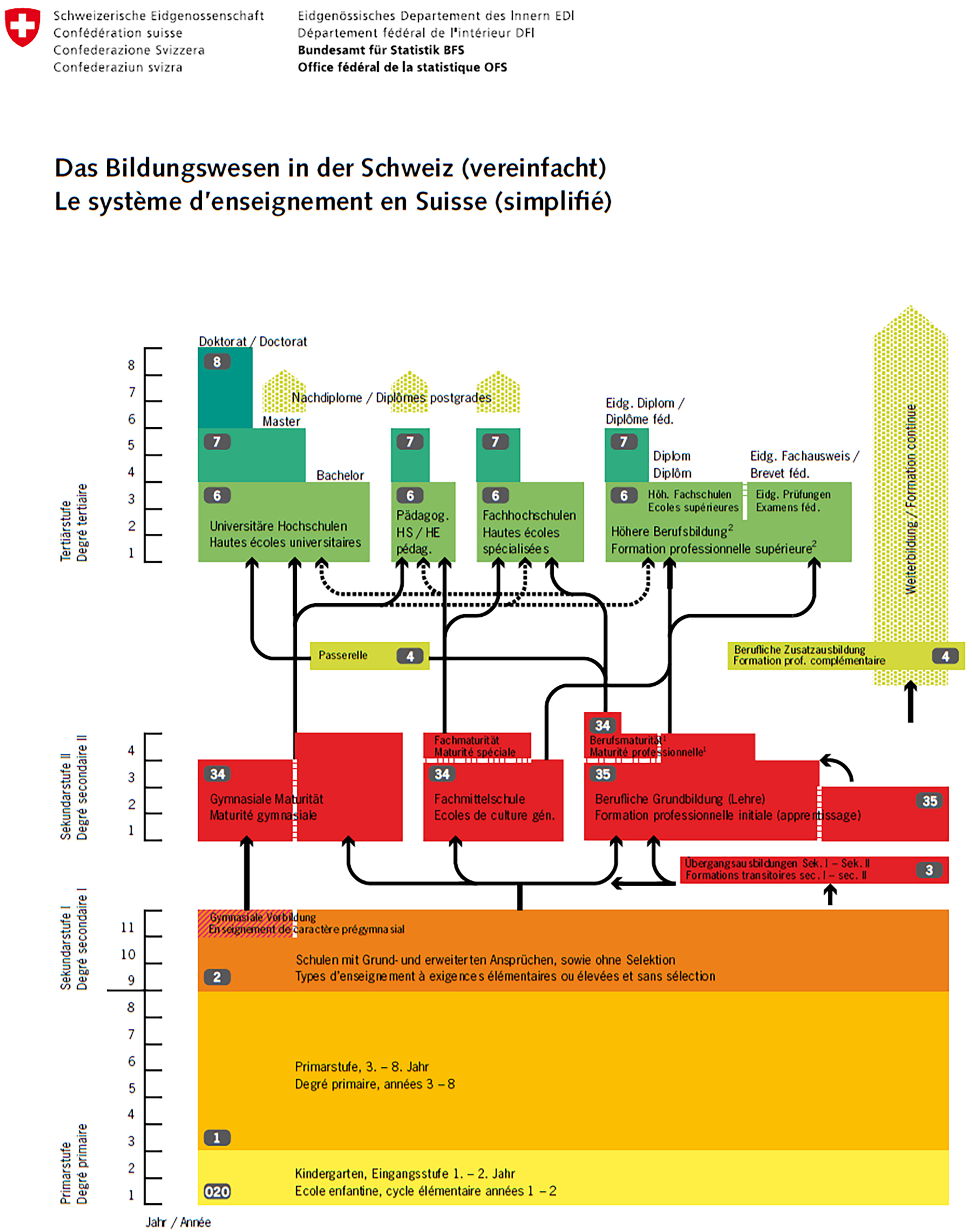

FIGURE A1 | Scheme of the Swiss educational system. *Note:* Figure A1 presents the official classification of the Swiss education system as published by the Federal Statistical Office (FSO 2015). The figure provides a simplified overview of the full educational structure, spanning compulsory schooling, upper-secondary general and vocational tracks, and tertiary academic and professional degrees. It depicts the duration and hierarchical ordering of each qualification level, including vocational pathways, higher vocational training, and university degrees. We rely on this official federal scheme to convert respondents' highest completed educational attainment into standardized years of education. In the subsample used to estimate the ICC in educational attainment, the maximum value of 20 years corresponds to habilitation. The figure therefore serves as the reference framework for all transformations from categorical educational qualifications into numeric years of schooling used throughout the analysis.

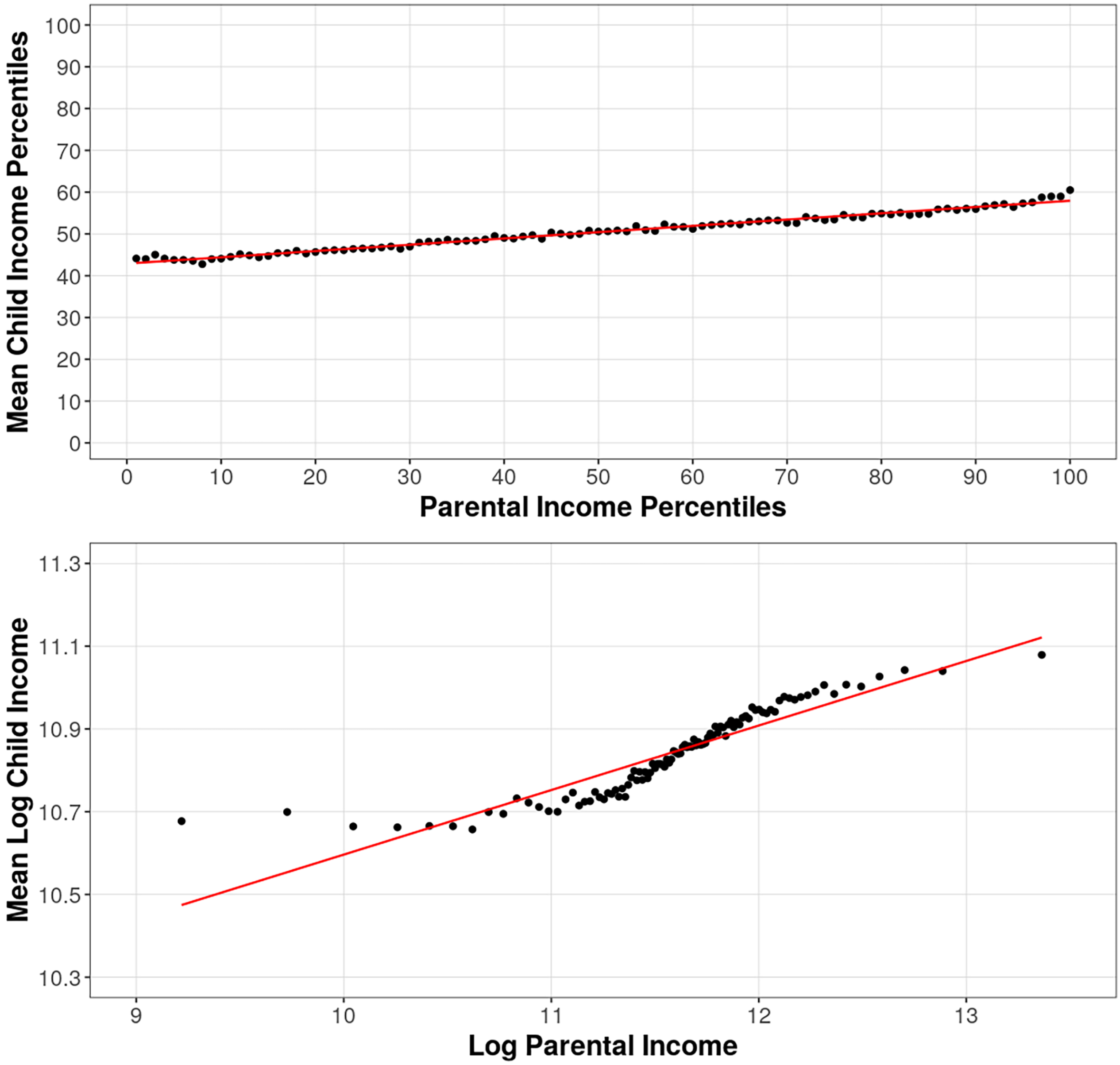

FIGURE A2 | Intergenerational income mobility in Switzerland: Rank-rank slope (RRS) and intergenerational elasticity (IGE). *Note:* The upper panel in the figure plots mean child income percentiles by parental income percentiles along with the fitted linear regression line. The estimated rank-rank slope is 0.150 (SE = 0.002), and the intercept is 42.90 (SE = 0.113). According to Corak (2020), this implies that a child whose parents are at the bottom of the income distribution (1st percentile) is expected to reach, on average, the 43rd percentile in the income distribution as an adult. The slope of 0.15 indicates that the entire parental income distribution maps into only 15 percentile ranks of the child income distribution (0.15×100), meaning that the difference between the highest and lowest parental ranks shifts expected child outcomes by merely 15 percentiles. The estimated slope closely aligns with the 0.14 rank-rank estimate reported by Chuard and Grassi (2020). The lower panel reports the corresponding intergenerational elasticity (IGE). Using log–log regressions that exclude zero incomes, following standard practice in the literature (see Chetty et al. 2014b), the estimated elasticity is 0.122 (SE = 0.001). All estimated slopes and intercepts in both panels are statistically significant at the 1% level. Furthermore, gender-specific estimates show that intergenerational persistence is somewhat higher for parent-daughter pairs (RRS = 0.181; IGE = 0.170) than for parent-son pairs (RRS = 0.169; IGE = 0.080).

Appendix B

Relationship Between the ICC and Pearson's Correlation Coefficient

Let us consider the correlation in 4-year average income between two individuals within the same family, denoted by y_{ij} and $y_{i\prime j}$, where i and i' represent the individuals, and j represents the family. Under a (individual-and family-specific) random effects model with i.i.d. residuals, the variance of any observation is:

$$Var\left(y_{ij}\right) = \sigma^2_{\alpha 0} + \sigma^2_{\varepsilon},$$

while the covariance of two observations from the same group j (for $i \neq i'$), using properties of covariance, is:

$$\begin{aligned} Cov\left(y_{ij}, y_{i\prime j}\right) &= Cov\left(\mu + \alpha_{0j} + \varepsilon_{ij}, \mu + \alpha_{0j} + \varepsilon_{i\prime j}\right) \\ &= Cov\left(\alpha_{0j} + \varepsilon_{ij}, \alpha_{0j} + \varepsilon_{i\prime j}\right) \\ &= Cov\left(\alpha_{0j}, \alpha_{0j}\right) + 2Cov\left(\alpha_{0j} + \varepsilon_{ii'}\right) + Cov\left(\varepsilon_{ij} + \varepsilon_{i\prime j}\right) \\ &= Cov\left(\alpha_{0j}, \alpha_{0j}\right) \\ &= Var\left(\alpha_{0j}\right) \\ &= \sigma^2_{\alpha 0}. \end{aligned}$$

Putting this together,

$$\begin{aligned} Cor\left(y_{ij}, y_{i\prime j}\right) &= \frac{Cov\left(y_{ij}, y_{i\prime j}\right)}{\sqrt{Var\left(y_{ij}\right) \, Var\left(y_{i\prime j}\right)}} \\ &= \frac{\sigma^2_{\alpha 0}}{\sigma^2_{\alpha 0} + \sigma^2_{\varepsilon}} \\ &= \rho. \end{aligned}$$

In this derivation of ρ, we assume that the random effects α and ε are normally distributed and independent of each other. We also consider a scenario where there are only two siblings' outcomes within each family.

Appendix C

Quantifying the Impact of Parental Income on the Intraclass Correlation Coefficient (ICC) Based on Solon et al. (1991)

We follow Solon et al. (1991) and Solon (1999) to derive an alternative decomposition approach to evaluate the importance of parental income in terms of the overall variation in 4-year average income. It is another approach if we want to know how much of the sibling correlation in 4-year average income is related to parental income and how much is related to factors uncorrelated with parental income. We use the same notation as above, where we derive our methodological approach.

Income y of the i^{th} sibling in the j^{th} family can be decomposed according to the following equation:

$$y_{ij} = \beta_{0j} + \varepsilon_{ij} \tag{C1}$$

where β_{0j} as in Section 3.1 corresponds to the family intercept term and ε_{ij} is the error term. The family intercept term β_{0j} is composed of a fixed component β_{00} and a random component α_{0j}, according to Equation (C2). α_{0j} captures the permanent component of an individual's status that is shared among siblings in the same family.

$$\beta_{0j} = \beta_{00} + \alpha_{0j} \tag{C2}$$

By assuming that α_{0j} can be further decomposed as in Equation (C2), we incorporate the influence of parental income X_j:

$$\alpha_{0j} = \beta_1 X_j + z_{0j} \tag{C3}$$

By substituting α_{0j} from Equation (C3) into Equation (C2) and then into Equation (C1), we obtain Equation (C4), which combines the fixed and random components. As in Equation (C4), it is commonly assumed that the residuals, z_{0j} and ε_{ij} are normally distributed and independent of each other.

$$y_{ij} = \beta_{00} + \beta_1 X_j + z_{0j} + \varepsilon_{ij} \tag{C4}$$

This model describes the intergenerational association between child's earnings y_{ij} and parental income X_j. This is similar to formal IGE estimates, but now we are denoting parental income by X_j instead of y_{t-1}, with the subscript j used to index families instead of generations. Further, we follow the empirical literature in using logarithmic earnings measures for $y_{ij}$and X_j. The regression coefficient β_1 therefore represents the elasticity of child's four-year average income with respect to parents' six-year average income.[23] In addition, if the variances in the logarithmic earnings variables are about the same in the child's and parents' generations, then β_1 also will approximately equal the intergenerational correlation (IGC) between y_{ij} and X_j.[24]

Analyzing the variances in Equation (C3), yields Equation (C5). It demonstrates the variance of α_{0j}, that can be substituted with the sum of the variances $\beta_1 X_j + z_{0j}$, as:[25]

$$Var\left(\alpha_{0j}\right) = Var\left(\beta_1 X_j\right) + Var\left(z_{0j}\right) = \beta_1^2 \sigma^2_{X_j} + \sigma^2_{z_0} \tag{C5}$$

Thus, the total variance in income *between* families corresponds to the part that is explained by parental income $\left(\beta_1^2 \sigma^2_{X_j}\right)$ plus the sum of the remaining variance *between* families $\left(\sigma^2_{z_0}\right)$. As a result, the alternative sibling correlation, given the decomposition of α_{0j} into $\beta_1^2 \sigma^2_{X_j}$ and $\sigma^2_{z_0}$ and dividing Equation (C5) through the total variation in long run income in the offspring generation σ^2_y, yields:

$$\rho_{alternative} = \frac{\beta_1^2 \sigma^2_{X_j} + \sigma^2_{z_0}}{\sigma^2_y} = \frac{\beta_1^2 \sigma^2_{X_j}}{\sigma^2_y} + \frac{\sigma^2_{z_0}}{\sigma^2_y} \tag{C6}$$

If inequality in 4-year average income is about the same in both generations, so that σ^2_y is equal to $\sigma^2_{X_j}$, then $\rho_{alternative}$ simplifies to:[26]

$$\rho_{alternative} = \beta_1^2 + \frac{\sigma^2_{z_0}}{\sigma^2_y} = \beta_1^2 + \text{other factors than parental income} \tag{C7}$$

The alternative intraclass correlation coefficient (ICC) in Equation (C7) again shows the proportion of variation in siblings' income that can be attributed to family components as a share of the total variance in siblings' income. Additionally, it allows us to decompose the total sibling correlation into components attributed to intergenerational transmission of economic status and other shared environmental or familial factors. This derivation assumes that the total variation in 4-year average income in the offspring generation, σ^2_y, can also be expressed as a part of the variation within siblings, ε_{ij}, plus a remaining part of the variation between families. This latter part can be further expressed as the proportion of parental income contributing to the between-group variance $\beta_1 X_j$, plus a remaining part of the variation between groups that is not attributable to parental income z_{0j}.

Appendix D

Extension With Survey Data.

The administrative data restrict the inclusion of certain parental covariates, such as detailed neighborhood characteristics, parental health, or socio-behavioral traits. To extend our main results, we therefore draw on additional evidence from the representative Swiss Household Panel (SHP). The SHP is a large-scale, longitudinal panel study using random sampling to survey private households and individuals annually since 1999 (SHP 2022; Tillmann et al. 2022).

The mean offspring income closely matches the corresponding estimates from the administrative data, underscoring the high data quality of the

SHP. Moreover, the survey-based parental indicators align well with national benchmarks (see Table A3).

The SHP dataset allows us to extend our main findings by including a wider range of parental control variables that are unavailable in the administrative records. Specifically, the SHP data provide parent-level indicators of average income, body mass index (BMI), frequency of contact with relatives and neighbors, health status, political position, political interest, special working times (night or weekend work), and frequency of reading books. This enables a more comprehensive assessment of non-economic and behavioral family characteristics (see Tables A6.1 and A6.2).

The results reveal that the estimated sibling correlation based on the SHP survey data closely mirrors the corresponding estimate from the administrative records, with an ICC of 0.153 (SE = 0.040). In the single-driver models, parental income remains the strongest explanatory factor, reducing the ICC by approximately 5%, while other factors such as parental health, parental political attitudes, and social or cultural parental engagement exhibit only marginal effects. When all family-specific variables are included simultaneously, the sibling correlation decreases only slightly—from 0.153 in the baseline model to 0.141 in the full model—corresponding to an overall ICC reduction of about 8%. Thus, the additional parental characteristics available in the SHP likewise account for only a small share of the sibling correlation.