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Abstract

This study investigates social mobility and its drivers based on a comprehensive measure using a new administrative dataset from Switzerland, comprising over 1,100,000 observations from 23 cohorts. We examine the overall impact of familial factors instead of traditional parent-child associations to provide a wide-ranging indicator of social mobility. Using two-level linear mixed models, we find that family background accounts for 15% of the variation in income. Our approach further sheds light on the underlying factors contributing to the measured family influence, with parental income, parental marital status, nationality and community type showing limited impact. Notably, about 90% of the family effect remain unexplained, indicating a high degree of equality of opportunity.

Keywords: social mobility, sibling correlation, drivers, decomposition
JEL Classification: I30, J62, J12

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1 Introduction

The 35^{th} president of the United States, John F. Kennedy, had three brothers among his eight siblings. Joseph Junior, the eldest brother, tragically perished in a plane crash in 1944. However, the remaining brothers all embarked on successful political careers. Robert Kennedy achieved distinction as the Attorney General and U.S. Senator from New York, while Edward M. Kennedy left an indelible mark with his 47-year tenure as a U.S. Senator. The intriguing question arises: How do siblings follow such parallel paths and attain success? Does it 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, 25 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. They are considered as an omnibus variable describing the importance of family background (Solon, 1999). Siblings-based estimates usually show a stronger family effect than single-variable parent-child mobility estimates because siblings share arguably more immutable circumstances than e.g. parental income, such as schools, neighborhoods or friends (Björklund and Jäntti, 2020, 2012).

Whereas most studies on social mobility focus on assessing societal permeability, understanding the drivers of family influence is equally important and politically relevant. Decomposing sibling correlations helps to uncover the factors contributing to upward and

[1]See e.g., Chetty et al. (2014), Jäntti and Jenkins (2015), or Corak (2013) for income mobility and Hertz et al. (2008), or Black and Devereux (2010) for educational mobility.

downward mobility within a society.

Our goal is to investigate social mobility and its drivers. We make a twofold contribution to the existing literature.

First, we are the first to assess the overall family background effect, a comprehensive indicator of social mobility. In doing so, we distinguish between family and non-family effect, without further controlling for any factors. By capturing the full impact of familial factors, rather than focusing solely on direct income transmission between parents and their children, our approach provides a complete assessment of how much family background shapes long-term income. Our analysis uncovers that family background accounts for 15% of the total income variance among siblings. Moreover, we find higher family background effects for same-sex siblings (about 22%).

Second, we delve deeper into the drivers of the measured family background effect, using a new systematic decomposition approach. Parental long-run income explains approximately 6% of the overall family background effect. Notably, the influence of parental income in Switzerland is comparatively lower than in other countries (Björklund and Jäntti, 2020; Deutscher and Mazumder, 2023; Jäntti and Jenkins, 2015; Mazumder, 2008; Torche, 2015). Furthermore, we analyze the impact of other factors that are frequently addressed in both scientific and societal discussions, such as parental nationality, parental civil status and parental community type. They all show limited explanatory power. All potential factors together jointly explain less than 10% of the overall variance in long-run income. Thus, the family effect remains a mystery indicating high degree of equality of opportunity.

Our analysis is based on a large, new administrative dataset covering the birth cohorts from 1966 to 1988, enabling us to account for individuals' childhood circumstances. Furthermore, this dataset includes comprehensive earnings information for employees and self-employed since 1981, covering the full distribution of labor income in Switzerland. To investigate the drivers of family background effects, 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 family background effects.

The remainder of this paper is structured as follows: Section 2 consists of 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 grants 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 (Black and Devereux, 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). Comparable results of the estimated intergenerational elasticity of income (IGE) for a large number of countries range from about 0.15 for 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) conduct comprehensive reviews of studies examining both sibling correlations and parent-child associations. Their findings indicate that the family background effect in terms of income and education tend to be considerably higher when estimating it via sibling correlations, instead of parent-child associations. Thus, sibling correlations provide a broader assessment of the overall family background effect, including shared schools, social networks, etc.[2]

A comparison of countries shows the same tendencies 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 compared to the US (Björklund and Jäntti, 2012; Björklund et al., 2010, 2009, 2002; 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.[3] Regarding years of schooling, in most Western countries, the family background is responsible 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) over 18 countries again reveals significantly lower ICC's in Sweden, Norway, Finland, and Denmark compared to the US, where sibling correlations are approximately 25% higher.[4]

Unlike existing analyses, our study captures the family background effect more comprehensively. Specifically, we consider all potential influencing factors on an individual's income and decompose them only into family effects and other effects on individual success, without controlling for any variables such as age, gender, etc. (see Section 3.1 for details). This approach allows for a holistic assessment of the family background effect. This is

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

[3] Most studies focus either on brothers or sisters only due to the differences in labor market attachment between brothers and sisters (Schnitzlein, 2014). Assuming, the equalization in the labor market between men and women will continue to develop in the direction of gender equality, differences in labor market attachment will probably narrow. Therefore, in our opinion, looking exclusively at brothers or sisters and omitting mixed-sex siblings would deprive the whole research of an informative dimension of how family background and environment shape sibling similarities.

[4] This country sub-ranking is in line with the results provided by Jerrim and Macmillan (2015) and Hertz et al. (2008). Grätz et al. (2021) reveal similar trends in their international comparison.

crucial for understanding the role that family background plays in determining one's social status. Additionally, it provides the ideal foundation for identifying the drivers of this overall family background effect.

A few studies have already attempted to investigate the drivers of sibling correlation, mainly focusing on the explanatory content of parental income, educational attainment, or occupation status. E.g., 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 correlation both implies around 20% of the variation in long-run income is attributed to factors 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.

While there are findings on the impact of family structure (e.g., Björklund and Chadwick, 2003), nationality (e.g., Abramitzky et al., 2021), and urban-rural differences (e.g., Chetty et al., 2014) on social mobility, a systematic decomposition of the family effect in those factors is still missing in the literature. With our paper, we contribute to the closing of this gap.

Research on intergenerational social mobility in Switzerland is limited (Häner and Schaltegger, 2021b). Chuard and Grassi (2020) show that income mobility in Switzerland is higher (0.14) than in the US and even higher than in Nordic countries with significant regional differences, expressing parent-child correlation in percentile rankings. At the same time, educational mobility is significantly lower (Bauer and Riphahn, 2006, 2007; Chuard and Grassi, 2020). 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 (2021a), examining multigenerational social mobility in Switzerland over 15 generations based on surnames, show that the family influence on social status dissipates over three generations. To the best of our knowledge, sibling correlations have not been derived for Switzerland so far.

With our study, however, we are not only the first in Switzerland to look at similarity between siblings. Rather, we want to contribute to the literature by fully assessing the family background effect (Section 4.1) and systematically investigating its drivers (Section 4.2).

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 siblings share, such as parental income, parental education, the mother's age at 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:

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

where β_{0j} corresponds to the family intercept term and ϵ_{ij} is the error term. The family intercept term β_{0j} is composed by a fixed component β_{00} and a random component α_{0j}, according to Eq.(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 Eq.(2) in Eq.(1), we obtain Eq.(3), which combines the fixed and random components. As in Eq.(3), it is commonly assumed that the residuals, α_{0j} and ϵ_{ij}, are normally distributed and independent of each other.[5]

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

Analyzing the variances in Eq.(3), while considering the constancy of the grand mean β_{00}, yields Eq.(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}[6].

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

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

[5]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).

[6]The variance of α_{0j} is indicated by $\sigma^2_{\alpha_0}$ and the variance of ϵ_{ij} is indicated by σ^2_{ϵ}.

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

The intraclass correlation coefficient (ICC) in Eq.(5) shows the proportion of variation in the 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 in shaping individuals' long-run incomes.

In order to determine the sibling correlation in long-run income, ρ, we employ a linear mixed-effects model[7] that allows for the inclusion of control variables. Specifically, we estimate the following 2-Level random intercept model:

$$y_{ij} = \beta \mathbf{X}_{ij} + \alpha_{0j} + \epsilon_{ij}, \tag{6}$$

where the vector $\mathbf{X}_{ij}$ captures all fixed effects, whereas α_{0j} again corresponds to the random family component and ϵ_{ij} to the error term according to Eq.(3).[8] First, we estimate an "empty model" without including any control variables in the X-vector. We do not pre-control for individual-specific variables such as gender and cohort. Pre-controlling explains part of the family background but primarily accounts for differences within families, not between them. By not pre-controlling, we aim to measure the total variation in income attributed to family-specific aspects, considering the inherent presence of individual-specific factors. This approach provides a comprehensive understanding of how family background influences the income distribution, reflecting the actual combined impact of both family-

[7]We use linear mixed models using restricted maximum likelihood (REML) estimates by applying the lmer function in the lme4 Package to identify the parameters (Bates et al., 2015). P-values are provided in summary tables via Satterthwaite's degrees of freedom method (Kuznetsova et al., 2017).

[8]The model does not contain a transitory error component as we use long-run income directly in the model (Eq.6). In line with Björklund et al. (2010), we will not use annual income and, therefore, not include the transitory error component in the models.

specific and individual-specific factors.[9]

This allows us to capture the baseline sibling correlation and the inherent within-family and between-family variation.

Second, we introduce specific parental fixed effects to the vector $\mathbf{X}_{ij}$ 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 to the similarity of siblings. Our decomposition approach allows us to estimate the contribution of parental factors to the overall family background effect 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. By assuming that the within-family variance remains unchanged by the inclusion of the vertical fixed parental effect, 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[10] between parental income and offspring income in a separate linear regression model to decompose the ICC. Using our comprehensive Swiss dataset, both decomposition approaches result in similar percentages of parental income's contribution to the ICC.[11] However, the decomposition approach exclusively using linear

[9]Specifically, pre-controlling for gender and cohort fixed effect reduces the within-family variance by 14% but only reduces the between-family variance by 1.3%. If we pre-control for gender and cohort fixed effect we might overestimate the extent of the overall family background effect, given the definition of the ICC as $\rho = \frac{\sigma^2_{\alpha_0}}{\sigma^2_{\alpha_0}+\sigma^2_{\epsilon}}$.

[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 parent's 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 the incomes of the parents and the offspring.

[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 to identify the explanatory power of continuous numeric parental influence factors on the

mixed models allows for the inclusion of binary parental variables and accounts for the hierarchical structure of the data (Level-1 and Level-2 variance).

In addition to the subsequent inclusion of control variables, we analyze models that include multiple covariates simultaneously. This approach allows us to examine the combined effect of multiple parental characteristics on the variance components and sibling correlation. By doing so, we can better understand how different factors interact to influence the similarity of siblings' long-term income outcomes.

3.2 Administrative Data

In this study, we utilize a large administrative dataset comprising over 1,100,000 observations from 23 cohorts (1966-1988). The data combine social security earnings records (SSER) from the Central Compensation Office (CCO) with census data (STATPOP)[12] 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)[13]. Individual information is matched to the longitudinal "social security earnings records" (SSER), which allows 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

ICC and thereby sets the stage to compare the two different metrics of social mobility. In contrast to our decomposition approach, Solon (1999) does not focus on the changes in the variance components and the resulting relative changes in the ICC. Instead, he identifies a portion of the variance between families through 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 4.33% of the ICC. This corroborates the results of our approach, where we estimated the explanatory power of parental income to be 5.96% of the total ICC.

[12]The "Population and Households Statistics" (STATPOP) is part of the federal census system. It provides information on the size and structure of the resident population at the end of the year.

[13]The STATPOP data are available from 2010 onwards. To obtain relevant parental information to estimate the mixed-effect 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 (aged 15-20 years).

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 estimate the sibling correlation in educational attainment, we use data from the Structural Survey (SE). The SE dataset has been available since 2010 and annually surveys approximately 200,000 individuals, with mandatory participation enforced by sanctions for non-compliance. With data spanning 12 years, the sample size exceeds 2,900,000 unique observations, though some individuals are surveyed multiple times. The survey collects a wide range of information, including education, religion, and language. To transform the highest educational attainment into years of education, we utilized the official data provided by the federal authorities.[14]

3.3 Sample and Variable Selection

Common literature such as Chetty et al. (2014) measures the children's income when they are about 30 years old and the parent's income approximately 15 years prior. 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] In Section 4.3, we test the robustness of our baseline estimates using alternative age restrictions. We measure income once at ages 40-43 and once when the siblings are between 30-40 years old. Inflation-adjusted[16] long-run income, in 2021 prices (CHF), is the main outcome variable.[17] We use the the 4-years average income to smooth out transitory

[14] see Figure A1 in the Appendix for the scheme.

[15] Cohorts born before 1966 are excluded, as parental income cannot be measured when offsprings 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] To adjust prices, we employ the R package priceR developed by Condylios (2022). Inflation adjustment calculations in the package are based on the theoretical framework presented in Principles of Macroeconomics by Gregory Mankiw et al (2014), as referenced by (Condylios, 2022)

[17] 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

income shocks.[18] Further, we also incorporate the lowest incomes, including zero incomes, into the analysis. By avoiding a lower income threshold, we accurately represent the entire income distribution.

To construct long-run parental income, we use the 6-years average of the combined incomes of both the mother and father when the children are aged between 15 and 20 years.[19] We set an upper age limit for parents to the regular pension age of 65 for men and 64 for women in Switzerland. To assign siblings to a family, we use the information of the mother. If this information is not available, we identify family belonging through the father. No distinction is made on whether the children are 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 1,137,967 siblings are identified. Of these, 591,747 are men (52.0%) and 546,220 are women (48.0%). Among the sibling relationships, 368,684 consist of only

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, earned in the year of retirement but after the retirement date 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 these are not considered as direct incomes from employment.

[18] 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.

[19] If only one parent's income is available, we do not take 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.

males, and 320,004 consist of only females[20]. In the mixed sexes sample, the mean long-run income, in 2021 prices, is CHF 63,043, while the average year of birth is 1977. The mean long-run income is substantially higher for men (CHF 75,634) than for women (CHF 49,403).

When examining the parental characteristics, the mean long-run income of parents amounts to 118,787 CHF. The vast majority of parents are Swiss, accounting for 95.4% of the sample, while 4.6% are non-Swiss[21]. Regarding civil status, 28.2% of parents are separated, whereas 71.8% are not separated. According to the classification by the Federal Statistical Office (FSO), 35.5% of the parents resides in municipalities designated as rural, while 64.5% are part of the urban population.[22]

In a robustness check in Section 4.3, we use years of education instead of earnings as an alternative status indicator. To get information about individuals educational attainment, we use data available in the Structural Survey (SE) provided by the Federal Statistical Office (FSO). Ultimately, we were able to assign years of education to nearly 250,000 individuals from same siblings in the main sample, considered for calculating the ICC for long-run income. The average years of schooling amounts to nearly 14 years.[23]

[20]see Table A1 for the descriptive statistics of the brothers and sisters sample.

[21]The proportion of non-Swiss parents is not representative for the overall Swiss society. We have access to the STATPOP data only since 2010. Therefore, this is the earliest year we can use to assign the nationality of parents when the children were between 15 and 20 years old. When classifying parents who are Swiss but not born in Switzerland as non-Swiss, the proportion of non-Swiss parents increases to 8.2%. However, the effects of parental nationality in the model estimates in the next section remain almost identical, regardless of which definition of Swiss versus non-Swiss is used.

[22]The assignment of parental civil status and parental community type, in contrast to parental nationality, accurately reflects the overall Swiss society.

[23]In the sub-sample we use to estimate the ICC in educational attainment, the maximum of 20 years of education correspond to a habilitation. See Figure A1 for the scheme we use to transform educational attainment to years to education.

Table 1: Descriptive statistics of main variables.

	Full Sibling Sample	
Offspring Characteristics		
Long-run Income, mean (IQR)	63,042.97	(38,507.45–83,369.65)
Sex, n(%)	1,137,967	(100.0)
Male	591,747	(52.0)
Female	546,220	(48.0)
Year of Birth, mean (IQR)	1977	(1972-1983)
Parental Characteristics		
Parental Long-run Income, mean (IQR)	119,746.47	(74,282.90–144,506.10)
Parental Civil Status, n(%)		
Separated	324,239	(28.5)
Not Separated	813,728	(71.5)
Parental Nationality, n(%)		
Swiss	1,086,785	(95.5)
Non-Swiss	51,182	(4.5)
Parental Community Type, n(%)		
Urban	734,152	(64.5)
Rural	403,815	(35.5)
	Sub-Sample Educational Attainment	
Offspring Characteristics		
Years of Education, mean (IQR)	13.79	(12.0–16.0)
Sex, n(%)	245,473	(100.0)
Male	124,568	(50.7)
Female	120,905	(49.3)
Year of Birth, mean (IQR)	1977	(1972-1982)

Notes: Table 1 provides a description of the main sample. Long-run Income (CHF) is expressed in 2021 prices. The proportion of non-Swiss parents increases from 4.5% to 8.2% when we include parents who are Swiss citizens but not born in Switzerland in the non-Swiss category. Descriptive statistics of the brothers and sisters sample are provided in Table A1.

4 Results

4.1 Extent of the Family Effect

Table 2 shows the sibling correlation and variance component estimates using linear mixed models for long-run income. The full sibling sample model yields a value for the intraclass correlation coefficient of 0.151. This indicates that, on average, the family background explains 15% of the total variance in income. As the comparison between the within-family component (σ^2_ϵ) and the between-family component ($\sigma^2_{\alpha_0}$) reveals, the variance within families is more than 5 times bigger than the variance between families. This suggests that variations between siblings within the same family contribute significantly more to the overall variation in income than differences between different families. In Table A2 in the Appendix, we limit the analysis to brothers or sisters only, respectively. The influence of family background on the later success of brothers (0.22) is almost the same as that for sibling relationships consisting exclusively of women (0.23), but higher than in the overall sample.

Table 2: Sibling correlations in long-run income (CHF)

	baseline model
Long-run Income	63.21***
	(0.04)
σ^2_{ϵ}	1,258.57
$\sigma^2_{\alpha_0}$	224.24
ICC	0.151
Obs.	1,137,967
Nb families	485,899

Notes: Significance Codes: '***' 0.01 '**' 0.05 '*' 0.1. The standard errors (SE) are shown in parentheses. Long-run income is expressed in 2021 prices (in 1,000 CHF). The overall intercept or "grand-mean" is an estimate for the expected long-run income of an individual from a randomly chosen family, randomly selected from the whole sample. σ^2_{ϵ} represents the estimated residual variance, which measures the within-family variation in long-run income. $\sigma^2_{\alpha_0}$ represents the estimated variance component at the family level, capturing the between-family variation in long-run income. ICC stands for intraclass correlation coefficient and indicates the proportion of total variation in long-run income that can be attributed to differences between families. The table provides information on the number of observations (Obs.) and the number of families (Nb. families) included in the analysis for each sibling group. The model was estimated using the linear mixed-effects modeling approach (`lmer` function) from the `lme4` package in R (see Bates et al. (2015)).

4.2 Drivers of the Family Effect

Finally, we systematically examine the components of the measured family background effect. Starting from the baseline model, we sequentially introduce specific parental fixed effects to evaluate their impact on the reduction of the variance components. This approach enables us to determine the explanatory power of various family-related factors on the similarity of siblings. Specifically, we evaluate how much of the family background can be explained by parental characteristics.

As depicted in Table 3, parental income explaining approximately 6% of the intraclass correlation. Thus, the explanatory power of parental income is significantly lower in Switzerland than in other countries (see Section 2). This aligns with the finding that the association between parent-child income in Switzerland is notably lower when compared internationally (Chuard and Grassi, 2020). Our analysis further enables us to determine the explanatory strength of additional family-specific factors. Table 3 demonstrates that variables such as parental nationality, parental civil status or the parental community type show limited explanatory power.

Table 3: Drivers of sibling correlations

	baseline	par. income	par. nationality	par. civil status	par. community type
Intercept	63.21***	59.42***	63.31***	64.64***	64.52***
	(0.04)	(0.05)	(0.04)	(0.05)	(0.05)
FE Estimate	-	0.03***	-2.12***	-4.99***	-3.76***
	-	(0.00)	(0.19)	(0.09)	(0.08)
σ^2_{ϵ}	1,258.57	1,258.89	1,258.63	1,258.29	1,258.93
$\sigma^2_{\alpha_0}$	224.24	208.46	223.97	219.49	220.57
ICC	0.151	0.142	0.151	0.149	0.149
Obs.	1,137,967	1,137,967	1,137,967	1,137,967	1,137,967
Nb families	485,899	485,899	485,899	485,899	485,899
Comparison					
$\%\Delta$ *ICC*	-	-5.96	0.00	-1.33	-1.33
$\%\Delta\ \sigma^2_{\alpha_0}$	-	-7.04	-0.12	-2.12	-1.64

Notes: Significance Codes: '***' 0.01 '**' 0.05 '*' 0.1. Long-run income is expressed in 2021 prices (in 1,000 CHF). The standard errors (SE) are shown in parentheses. The intercept represents overall grand-mean. It is an estimate for the expected long-run income of an individual from a randomly chosen family, randomly selected from the whole sample. $\%\Delta$ *ICC* represents the percentage change in the ICC compared to the baseline model for each subsequent model. $\%\Delta\ \sigma^2_{\alpha_0}$ represents the percentage change in the between-family variance component compared to the baseline model for each subsequent model. The fixed effects in the regression output are defined as follows: Parental nationality indicates non-Swiss status; parental civil status indicates separation; and parental community type indicates rural residence.

Simultaneously considering these effects and comparing them with the baseline model, allows us to assess the joint explanatory power of the family-specific effects. Table 4 presents the corresponding results. The statistical analysis reveals that only 8.61% of the total family background effect can be attributed to parental income, parental nationality, parental civil status and parental community type. The remaining 91% remain unexplained by these factors.

Table 4: Joint explanatory power of family-specific aspects

	baseline	family-specific aspects
Intercept	63.21***	63.31***
	(0.04)	(0.07)
FE Parental Income		0.03***
		(0.00)
FE Parental Nationality		-2.28***
		(0.19)
FE Parental Civil Status		-4.64***
		(0.09)
FE Parental Community Type		-3.25***
		(0.08)
σ^2_{ϵ}	1,258.57	1,258.98
$\sigma^2_{\alpha_0}$	224.24	201.94
ICC	0.151	0.138
Obs.	1,137,967	1,137,967
Nb. families	485,899	485,899
Comparison		
%Δ ICC	-	-8.61
%Δ $\sigma^2_{\alpha_0}$	-	-9.95

Notes: Significance Codes: '***' 0.01 '**' 0.05 '*' 0.1. Long-run income is expressed in 2021 prices (in 1,000 CHF). %Δ ICC represents the percentage change in the ICC compared to the baseline model for the joint family-specific model. %Δ $\sigma^2_{\alpha_0}$ represents the percentage change in the between-family variance component compared to the baseline model for the joint family-specific model. The fixed effects in the regression output are defined as follows: Parental nationality indicates non-Swiss status; parental civil status indicates separation; and parental community type indicates rural residence.

4.3 Robustness Checks

We test the robustness of our estimates using alternative model specifications. Table 5 presents the respective results. In column (1), we analyze the effects on long-run income for individuals aged 40-43 years. The results show that the ICC for this age group is 0.134, indicating a slightly lower familial influence compared to the baseline model.

In column (2), we consider the long-run income for individuals aged 30-40 years. The ICC for this age group is 0.153, which is 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 long-run income remains significant across different age specifications, with the ICC values indicating consistent results. The estimates show high consistency when applying various age filters. These findings support the stability of our baseline model.

Table 5: Robustness Checks

	baseline	(1) age 40-43 yrs	(2) age 30-40 yrs
Intercept	63.21***	78.58***	67.33***
	(0.04)	(0.11)	(0.06)
σ^2_ϵ	1,258.57	4,797.39	2,004.23
$\sigma^2_{\alpha_0}$	224.24	739.55	360.94
ICC	0.151	0.134	0.153
Obs.	1,137,967	564,119	761,852
Nb. families	485,899	248,821	330,662

Notes: Significance Codes: '***' 0.01 '**' 0.05 '*' 0.1
The standard errors (SE) are shown in parentheses.
Baseline model for individuals aged 40-43 years (1) and individuals aged 30-40 years (2), incomes in 1,000 CHF.

Furthermore, we use educational attainment instead of income as an alternative status indicator in an additional sensitivity check. Table 6 presents the respective results. In column (1), we investigate the familial influence on educational attainment. Instead of long-run income, we analyze the effects on years of education. As the results reveal, the ICC is substantially higher for educational attainment than for long-run income (0.334 vs. 0.151). 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.[24]

Analogous to Section 4.2 we further control for the effect of parental income as one driver of the ICC. In total, 6.19% of the similarity in siblings' educational attainment is explained by parental income.[25] As for long-run income, also when educational attainment is used as a status indicator, the findings suggest that the influence of parental income contributes only marginally to the overall family background effect, with other shared sibling factors predominantly explaining their similarity in educational outcomes.

[24]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 e.g. Becker and Tomes (1986) or Solon (1992). VET mitigates this constraint by being low-cost for the parents and even providing a salary 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.

[25]See Appendix A3 for the summary table of the linear mixed model.

Table 6: Sensitivity Analysis

	baseline long-run income	(1) baseline yrs of education
Intercept	63.21***	13.80***
	(0.04)	(0.01)
σ^2_{ϵ}	1,258.57	4.86
$\sigma^2_{\alpha_0}$	224.24	2.44
ICC	0.151	0.334
Obs.	1,137,967	245,473
Nb. families	485,899	114,937

Notes: Significance Codes: '***' 0.01 '**' 0.05 '*' 0.1
The standard errors (SE) are shown in parentheses.
(1): The overall intercept or "grand-mean" is an estimate for the expected years of education of an individual from a randomly chosen family, randomly selected from the whole sample. To estimate the baseline model for years of education we use the same siblings as we did to derive the ICC for long-run income.

5 Discussion and Conclusion

In this study, we examine social mobility and its drivers based on a comprehensive measure using a new administrative dataset from Switzerland, comprising over 1,100,000 observations from 23 cohorts. By applying a variance decomposition approach within a two-level linear mixed model, we provide a detailed assessment of the overall family background effect 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-belonging explains 15% of the total variation in long-run 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 15% 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 long-run incomes in Switzerland, indicating a high degree of social mobility.

Furthermore, we investigate the drivers of the measured overall family background effect. Our analysis shows that parental income explains a comparatively low share of overall family background effect in Switzerland (Björklund et al., 2010; Hällsten and Thaning, 2022; Mazumder, 2008). Moreover, we highlight the limited explanatory power of simultaneously tested family-specific effects of parental income, parental nationality, parental civil status and parental community type. The overall family background effect seems not no be driven by the tested specific parental characteristics.

This finding suggests that the factors frequently debated in academic and societal circles have limited explanatory power for the family background effect in Switzerland. It sheds new light on the 'mystery' noted by Solon (1999), as the specific components driving the family effect remain elusive. Yet, this ambiguity aligns with what we might expect from a permeable, liberal society — where individual success is not primarily dictated by parental income, nationality, marital status, or the region of upbringing. In this sense, it is reassuring that the drivers of family background effects remain a mystery, aligning closely with the principle of equality of opportunity.

Considering these insights within Switzerland's context, one might wonder: Would the Kennedy brothers have achieved the same greatness if they had grown up among the Swiss Alps?

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Appendix

A Additional Figures and Tables

Table A1: Descriptive statistics of main variables, brothers and sisters sample.

	Brothers Sample		*Sisters Sample*	
Offspring Characteristics				
Long-run Income, mean (IQR)	75,306.11	(57,808.75–91,759.45)	49,058.18	(24,006.92–70,245.1)
Sex, n(%)	368,684	(100.0)	320,004	(100.0)
Male	368,684	(100.0)	0	(0)
Female	0	(0)	320,004	(100.0)
Year of Birth, mean (IQR)	1977	(1972-1982)	1977	(1972-1983)
Parental Characteristics				
Parental Long-run Income, mean (IQR)	117,048.96	(71,174–141,838.52)	118,786.91	(71,813.22–144,139.65)
Parental Civil Status, n(%)				
Separated	102,854	(27.9)	90,284	(28.2)
Not Separated	265,830	(72.1)	229,720	(71.8)
Parental Nationality, n(%)				
Swiss	352,927	(95.7)	305,327	(95.2)
Non-Swiss	15,757	(4.3)	14,677	(4.8)

Notes: Table A1 provide a description of the brothers and sisters sample. Long-run Income (CHF) is expressed in 2021 prices.

Table A2: Brother and sister correlations in long-run income (CHF)

	baseline model brothers	**baseline model sisters**
Long-run Income	75.38***	49.18***
	(0.07)	(0.06)
σ^2_{ϵ}	1,234.91	758.8
$\sigma^2_{\alpha_0}$	349.05	225.57
ICC	0.220	0.229
Obs.	368,684	320,004
Nb families	169,441	147,449

Notes: Significance Codes: '***' 0.01 '**' 0.05 '*' 0.1. The standard errors (SE) are shown in parentheses. Long-run income is expressed in 2021 prices (in 1,000 CHF). The overall intercept is an estimate for the expected long-run income of an individual from a randomly chosen family, randomly selected from the whole sample. σ^2_{ϵ} represents the estimated residual variance, which measures the within-family variation in long-run income. $\sigma^2_{\alpha_0}$ represents the estimated variance component at the family level, capturing the between-family variation in long-run income. ICC stands for intraclass correlation coefficient and indicates the proportion of total variation in long-run income that can be attributed to differences between families. The table provides information on the number of observations (Obs.) and the number of families (Nb. families) included in the analysis for each sibling group. The model was estimated using the linear mixed-effects modeling approach (`lmer` function) from the `lme4` package in R. See Bates et al. (2015).

Table A3: Drivers of Sibling Correlations in Educational Attainment

	baseline	parental income
Intercept	13.80***	13.42***
	(0.01)	(0.01)
FE Estimate	-	0.003***
	-	(0.00)
σ^2_ϵ	4.86	4.86
$\sigma^2_{\alpha_0}$	2.44	2.22
ICC	0.334	0.313
Obs.	245,473	245,573
Nb families	114,937	114,937
Comparison		
%Δ *ICC*	-	-6.19
%Δ $\sigma^2_{\alpha_0}$	-	-8.95

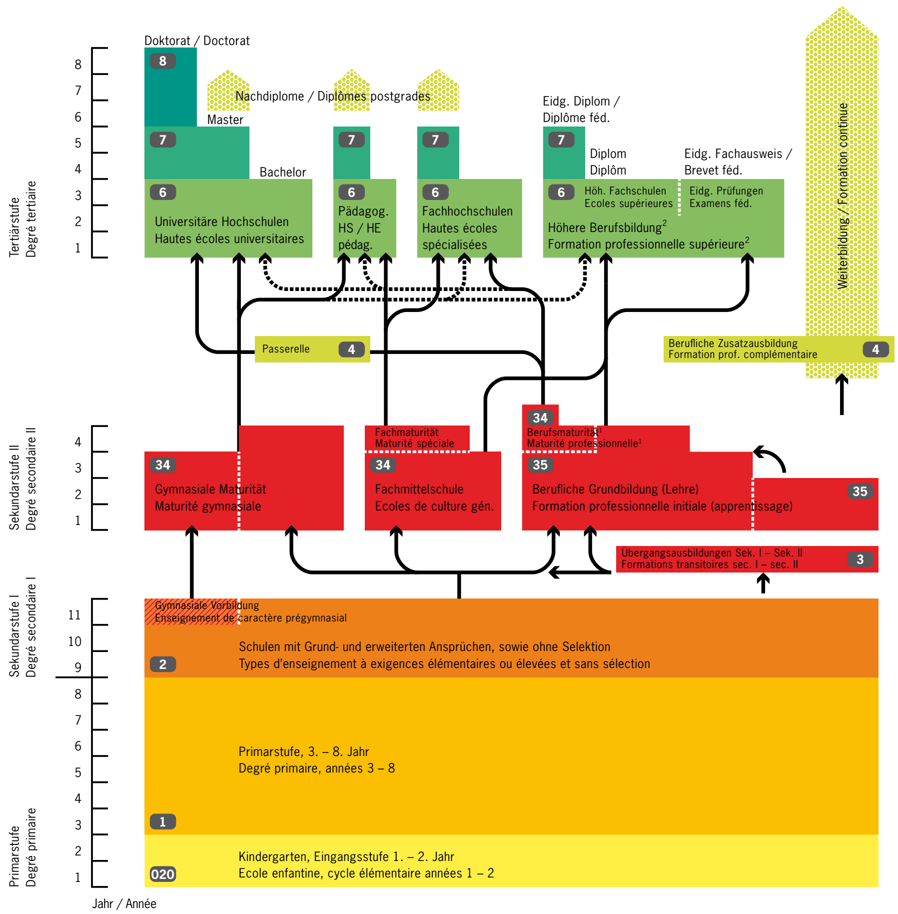
Notes: Significance Codes: '***' 0.01 '**' 0.05 '*' 0.1. Educational attainment is exressed in years of school. The standard errors (SE) are shown in parentheses. The intercept represents overall grand-mean. It is an estimate for the expected years of education of an individual from a randomly chosen family, randomly selected from the whole sample. %Δ *ICC* represents the percentage change in the ICC compared to the baseline model for each subsequent model. %Δ $\sigma^2_{\alpha_0}$ represents the percentage change in the between-family variance component compared to the baseline model for each subsequent model.
If the parental income (measured in 1000 CHF) increases by 1,000CHF the dependent variable (years of education) increases by 0.003 years. An increase of 0.3 years in education corresponds to 1.1 days.
If the parental income (measured in 1000 CHF) increases by 100,000CHF, the dependent variable (years of education) increases by 0.3 years. An increase of 0.3 years in education corresponds to 3.6 months.

Figure A1: Scheme of the Swiss Educational System

Schweizerische Eidgenossenschaft
Confédération suisse
Confederazione Svizzera
Confederaziun svizra

Eidgenössisches Departement des Innern EDI
Département fédéral de l'intérieur DFI
Bundesamt für Statistik BFS
Office fédéral de la statistique OFS

Das Bildungswesen in der Schweiz (vereinfacht)
Le système d'enseignement en Suisse (simplifié)



123 ISCED-Klassifikationsschema 2011 der UNESCO, siehe Glossar
Schéma de classification CITE 2011 défini par l'UNESCO, voir glossaire

→ Direkter Zugang
Accès direct

⇢ Zusatzqualifikation oder Berufspraxis erforderlich
Qualification supplémentaire ou pratique professionnelle requises

1 Parallel zur drei- oder vierjährigen beruflichen Grundbildung oder ein Jahr im Anschluss an die Lehre
Parallèlement aux trois ou quatre ans de la formation professionnelle initiale ou une année après l'apprentissage

2 Zu den eidgenössischen Prüfungen gehören die eidg. Berufsprüfungen (BF) und die eidg. höheren Fachprüfungen (HFP).
Font partie des examens fédéraux les examens prof. fédéraux les examens prof. fédéraux et les examens prof. féd supérieurs.

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B Relationship between the ICC and Pearson's Correlation Coefficient

Let's consider the correlation in long-run income between two individuals within the same family, denoted by y_{ij} and $y_{i'j}$, 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:

$$\text{Var}(y_{ij}) = \sigma^2_{\alpha_0} + \sigma^2_{\epsilon}$$

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

$$\begin{aligned}
\text{Cov}(y_{ij}, y_{i'j}) &= \text{Cov}(\mu + \alpha_{0j} + \epsilon_{ij}, \mu + \alpha_{0j} + \epsilon_{i'j}) \\
&= \text{Cov}(\alpha_{0j} + \epsilon_{ij}, \alpha_{0j} + \epsilon_{i'j}) \\
&= \text{Cov}(\alpha_{0j}, \alpha_{0j}) + 2\text{Cov}(\alpha_{0j}, \epsilon_{ii'}) + \text{Cov}(\epsilon_{ij}, \epsilon_{i'j}) \\
&= \text{Cov}(\alpha_{0j}, \alpha_{0j}) \\
&= \text{Var}(\alpha_{0j}) \\
&= \sigma^2_{\alpha_0}.
\end{aligned}$$

Put together,

$$
\begin{aligned}
\mathrm{Cor}(y_{ij}, y_{i'j}) &= \frac{\mathrm{Cov}(y_{ij}, y_{i'j})}{\sqrt{\mathrm{Var}(y_{ij})\mathrm{Var}(y_{i'j})}} \\
&= \frac{\sigma_{\alpha_0}^2}{\sigma_{\alpha_0}^2 + \sigma_\epsilon^2} \\
&= \rho.
\end{aligned}
$$

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' scores within each family.

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 and the evaluate the importance of parental income in terms of the overall variation in long-run income. It is another approach if we want to know how much of the sibling correlation in long-run 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:

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

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 by a fixed component β_{00} and a random component α_{0j}, according to Eq.(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 assuming that α_{0j} can be further decomposed as in Eq.(2), we incorporate the influence of parental income X_j:

$$\alpha_{0j} = \beta_1 X_j + z_{0j} \tag{3}$$

By substituting α_{0j} from Eq.(3) into Eq.(2) and then into Eq.(1), we obtain Eq.(4), which combines the fixed and random components. As in Eq.(4), it is commonly assumed that the residuals, z_{0j} and ϵ_{ij}, are normally distributed and independent of each other.

$$y_{ij} = \beta_{00} + \beta_1 X_j + z_{0j} + \epsilon_{ij} \tag{4}$$

This model describes the intergenerational association between child's earnings y_{ij} and parental income X_j. This is similar to normal IGE estimations, 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 long-run income with respect to parents' long-run income.[26] 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.[27]

Analyzing the variances in Eq.(3), yields Eq.(5). It demonstrates the variance of α_{0j}, that can be substituted with the sum of the variances $\beta_1 X_j + z_{0j}$, as :[28]

$$\text{Var}(\alpha_{0j}) = \text{Var}(\beta_1 X_j) + \text{Var}(z_{0j}) = \beta_1^2 \sigma_{X_j}^2 + \sigma_{z_0}^2 \tag{5}$$

Thus, the total variance in income *between* families corresponds to the part that is explained by parental income ($\beta_1^2 \sigma_{X_j}^2$) plus the sum of the remaining variance *between* families ($\sigma_{z_0}^2$). As a result, the alternative sibling correlation, given the decomposition of $\sigma_{\alpha_0}^2$ into $\beta_1^2 \sigma_{X_j}^2$ and $\sigma_{z_0}^2$ and dividing Eq.(5) through the total variation in long run income in the offspring generation σ_y^2, yields:

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

[27] Otherwise, we have to adjust according to IGC = IGE $\times \left(\frac{SD_{parentalgeneration}}{SD_{offspringgeneration}} \right)$

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

$$\rho_{alternative} = \frac{\beta_1^2\sigma_{X_j}^2 + \sigma_{z_j}^2}{\sigma_y^2} = \frac{\beta_1^2\sigma_{X_j}^2}{\sigma_y^2} + \frac{\sigma_{z_j}^2}{\sigma_y^2} \tag{6}$$

If inequality in long-run income is about the same in both generations, so that σ_y^2 is equal to $\sigma_{X_j}^2$, then $\rho_{alternative}$ simplifies to[29]:

$$\rho_{alternative} = \beta_1^2 + \frac{\sigma_{z_j}^2}{\sigma_y^2} = \beta_1^2 + \text{“}\textit{other factors than parental income}\text{“} \tag{7}$$

The alternative intraclass correlation coefficient (ICC) in Eq.(7) again shows the proportion of variation in the 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 long-run income in the offspring generation, σ_y^2, 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}.

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