ISSN 2704-7407

UNIVERSITÀ CATTOLICA DEL SACRO CUORE

Dipartimento di Economia e Finanza

Working Paper Series

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Working Paper n. 101

April 2021

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del Sacro Cuore

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Parental Assortative Mating and the Intergenerational Transmission of Human Capital[*]

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Abstract

We study the contribution of parental similarity in schooling levels to the intergenerational transmission of educational attainment. We develop an empirical model for educational correlations within the family in which parental sorting can translate into intergenerational transmission, or transmission can originate from each parent independently. Estimating the model using educational attainment from Danish population-based administrative data for over 400,000 families, we find that about 75 percent of the intergenerational correlation in education is driven by the joint contribution of the parents. We also document a sizeable secular decline of parental assortative mating in education, with a corresponding fall in joint intergenerational transmission from both parents; a fall compensated by an increase in parent-specific intergenerational transmission, leaving total intergenerational persistence unchanged. The mechanisms of intergenerational transmission have changed, with an increased importance of one-to-one parent-child relationships.

Keywords: Assortative mating, intergenerational transmission, human capital, inequality

JEL Codes: I24, J62

[*]We thank the Editors, one anonymous referee and participants at the 2020 EALE SOLE AASLE World Conference in Berlin for comments on an earlier draft of this paper. We gratefully acknowledge funding from the Danish Council for Independent Research (grant DFF-6109-00226) and the Università Cattolica D3.2 Strategic Research Grant "Evidence-based anti-poverty policies".

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1. Introduction

Understanding the mechanisms of intergenerational transmission of socioeconomic status is key for the design of policies aimed at promoting equal opportunities. Parental human capital has long been considered the engine of the intergenerational transmission of advantage (Becker, 1973). Parental assortative mating in education can also affect intergenerational transmission by generating segmentation in the distribution of parental human capital, with some households characterized by high (or low) levels of human capital for both parents (Doepke et al., 2019). In this way, parental sorting can act as an amplifier of intergenerational persistence.

In this paper, we study how much of the intergenerational transmission of human capital is due to factors shared and transmitted jointly by both parents, relative to factors transmitted by each parent independently of their co-parent. We develop an empirical model of educational correlations within the family where parental human capital has a common factor among the parental generation (parental assortative mating), which may not be fully transferred to their children. In addition, each parent may transmit human capital to the children independently from the co-parent. Therefore, intergenerational persistence can arise both from the joint contribution of the parents and from the independent contributions of each parent. We estimate the model using educational attainment from Danish population-based administrative data for over 400,000 families. Identifying the contribution of parental assortative mating to the intergenerational transmission of human capital is achieved by exploiting *family quartets* composed of two parents and two children.

We find that about 75 percent of the intergenerational correlation in education is driven by the joint contribution of the two parents, while the independent transmission from each parent is only one sixth of the size of the joint parental contribution, with father-specific transmission being larger for sons, and mother-specific transmission being larger for daughters.

Exploring trends over time, we document that parental assortative mating in Denmark has been declining for the cohorts born since 1920, while intergenerational persistence has been more stable.[1] We estimate the evolution in the components of assortative mating and intergenerational transmission over birth cohorts, finding that the decline in assortative mating corresponds with a fall in joint intergenerational transmission from both parents. This fall in joint transmission is compensated by an increase in parent-specific intergenerational transmission, leaving total intergenerational persistence unaffected. The nature of intergenerational transmission is changing, with a growing importance of one-to-one parent-child relationships.

This paper relates to a growing literature in economics on the relationship between assortative mating and intergenerational transmission. One strand of the literature focuses on educational sorting in the *offspring generation*, taking the view that non-random sorting among offspring might affect measures of intergenerational mobility, slowing down regression to the mean in socioeconomic status between parents and children (e.g., Chadwick and Solon, 2002; Ermisch et al., 2006; Güell et al., 2015; Holmlund, 2020).

Another strand of the literature, which is closer to our study, examines the effect of sorting in the *parental generation* on the socioeconomic status of the offspring generation. Although this literature has mostly focused on inequality (e.g., Fernandez et al., 2005; Bratsberg et al., 2018), the influence of parental sorting on intergenerational mobility may be even more important than on inequality (e.g., Kremer, 1997) but the empirical evidence is still limited. Recently, Collado et al., (2019) exploiting extended families to infer the characteristics of multi-generational transmission find a predominant role of assortative mating for explaining intergenerational persistence.

[1] Trends in educational assortative mating vary across countries. The declining trend in educational assortative mating in Denmark is consistent with the evidence in Eika et al., (2019), which reports a decline in assortative mating in Denmark for cohorts born between 1920 and 1987 for all educational levels, except for a small increase for those without a high school degree, which does not affect the overall trend due to their small weight in the distribution. The declining trend in Denmark is also consistent with the development in Norway (Eika et al., 2019; Bratsberg et al., 2018) and Sweden (Holmlund, 2020). For the U.S., Eika et al., (2019) report an average increasing trend in assortative mating from 1940 until the 1980s, after which it changed little, while Güell et al., (2005) report an increasing trend in educational assortative mating in Catalonia, Spain.

By developing an empirical model of educational correlations within the family we contribute to the literature in three ways. First, we decompose parental assortative mating into intergenerational and intragenerational components, where only the former contributes to parent-child educational correlation. Second, we quantify how much of the intergenerational persistence is due to parental assortative mating relative to factors that are passed on to children from each parent independently from the co-parent. Third, we trace out how the components of educational correlations within the family have evolved over time.

The time evolution of the relative importance of joint versus parent-specific contributions is also related to the literature documenting the evolution of assortative mating, which concludes that changes in assortative mating over time have a limited impact on overall income inequality (e.g. Eika et al., 2019; Fremeaux and Lefranc, 2015). We contribute to this literature by showing that the impact of the declining importance of assortative mating for intergenerational transmission is compensated by countervailing trends in parent-specific transmission of education to children, leaving total intergenerational persistence unchanged.

The remainder of the paper is structured as follows. In the next section we describe the data source and provide a summary of raw statistics on the extent of intra-family correlations in education. In Section 3 we outline the econometric model of educational correlations of family members, while in Section 4 we present the estimation results. In Section 5 we provide a concluding discussion.

2. Data description and raw patterns of educational correlations within the family

We use data from administrative registers of the Danish population. The civil registration system was established in 1968 and everyone resident in Denmark then and since has been issued with a unique personal identification number, which has subsequently been used in all national registers enabling accurate linkage. We base our analysis on *family quartets* composed of two parents and their first two children observed in the civil register.[2] Although, in principle, data on siblings are not needed to estimate parental assortative mating or intergenerational correlations separately from one another, we show in the next section that observing two children per family is key for identifying the contribution of parental assortative mating to the intergenerational transmission of human capital.

We match the civil register with data on the educational attainment of family members. We observe qualifications in the education register, and use the norms produced by the Ministry of Education to calculate the time that would be taken to obtain each qualification by the shortest route. Educational attainment is imputed from the qualification with the highest normed duration on October 31 in the year of turning 29.[3]

We draw data on the full population of Danish families with at least two children for parents born from 1920 (the first birth year for which we have educational information) to 1979, a total of 639,516 families. We exclude families for which either parent was younger than 18 at the birth of a child, resulting in a sample of 624,883 families. Next, we select families where we observe a child is born in 1956 or later, which is the first year the parent-child linkage is complete; and where the second child is born in 1988 or earlier, which is the last birth year for which we observe educational attainment at age 29, because our data were sourced in early 2018. Selecting on children's year of birth returns a sample of 530,390 families. Next, we drop families with sibling age spacing smaller than one year, or larger than ten years, corresponding to the first and last percentile of the distribution of age spacing, resulting in a sample of 524,577 families. We also drop families whose first child was born after 1978 to allow for a maximum sibling spacing of ten years also among younger families, resulting in a sample of 477,953 families. Among these families, those with parents born in the 1950s tend to be considerably younger at first birth by design, with average age at first birth declining from about 23 for mothers born in 1951, or earlier, to 18 for mothers born in 1960. To avoid selectivity

[2] In robustness checks we consider alternative sampling schemes, either extending the sample by including half siblings or by using the second and third children rather than the first and second. All the conclusions reached in the paper are robust to these alternative sampling schemes.

[3] Educational qualifications obtained before 1971 are self-reports from the 1970 population census. From 1971, educational institutions report qualifications obtained to the Ministry of Education. See Jensen and Rasmussen (2011).

into early parenthood among later cohorts, we therefore further exclude families with either parent born after 1951, yielding a sample of 432,715 families. Finally, we drop families with missing information on educational attainment for any member, resulting in an estimating sample of 417,746 families and 1,670,984 individuals.

We group individuals into three-year cohorts based on birth year. Table 1 describes the cohort structure of the data, indicating each three-year cohort by its central year. The average year of birth is around 1939 for fathers and 1942 for mothers, while it is around 1966 for first children and 1969 for second children. The table also shows the evolution of the distribution of years of education over birth cohorts. In the 66 years that separate the first and the last cohort, average attainment has grown by about 4.5 years, while the standard deviation has decreased by about 1 year. These patterns are in line with expectations given the educational expansions that have characterized the 20^{th} century. To remove common trends in education that may induce spurious patterns of correlation, we residualize years of education on year-of-birth dummies throughout the analysis. Moreover, we conduct the empirical analysis by modelling intra-family educational correlations which are insensitive to variations in marginal dispersion.

Table 2 provides a summary of raw intra-family correlations in years of education for different family types defined by the gender mix of the two children. Correlations are estimated by birth cohorts after excluding cells with fewer than 100 pairs.[4] The educational correlation among parents is 0.5, which is not only substantial but also stable across family types. This correlation is our basic raw measure of parental assortative mating. The intergenerational correlation in education is substantially lower at about 0.27, exhibiting almost no variation across family types for mothers, while there is some evidence that it is larger in all-son families for fathers. Comparing these intergenerational correlations with those for parental assortative mating suggests that not all factors that make parents similar to each other are transmitted to their children, because otherwise intergenerational and spousal

[4] Estimating correlations by cohorts will enable us to consider secular changes. We also compute bootstrapped standard errors of these correlation coefficients that will be used later in the paper to adjust inference.

correlations would be of similar sizes. Table 2 also shows that the sibling correlation in education is sensitive to the type of family, being larger in families with same-gender children than it is in those with mixed-gender children. This heterogeneity of the sibling correlation in education by the gender mix of the children is consistent with evidence of a greater exposure to shared community effects for siblings of the same gender (e.g., Martin and Fabes, 2001; Fabes et al., 2003).

Taking advantage of the cohort structure of the estimated raw correlations, we plot them against cohort of birth, after pooling across family types. Figure 1 shows that parental assortative mating in human capital has been steadily declining by a third for the cohorts of parents born between the early-1920s and early-1950s, which corresponds approximately with matches formed from the mid- 1940s to the late 1970s.[5] This pattern is consistent with the declining trends of educational assortative mating reported by Eika et al., (2019) for Denmark for cohorts born 1920-1987, as well as for Norway (Bratsberg et al., 2018) and Sweden (Holmlund, 2020), which is generally associated with educational expansions that affected those cohorts. We also observe in Figure 1 a mild declining trend of the intergenerational correlation in education, which changes from about 0.3 to 0.26 over thirty years.

That the declining assortative mating of the parents is reflected in intergenerational transmission only to a very limited extent is consistent with two possible explanations that are not mutually exclusive. One explanation may be that the *joint contribution* of parents to the human capital of their children has been declining, but this decline has been compensated by the *individual contributions* of each parent and their ability to independently transmit human capital to their children. For example, parenting style might have been shifting to a one-to-one parent-child relationship. An alternative explanation for the decline of assortative mating may be less sorting based on traits that are irrelevant for intergenerational transmission. This alternative explanation indicates a more efficient matching process in the marriage market, in which traits that are not contributing to the human capital of

[5] If we extend the period of observation of parental assortative mating to the cohorts born until 1970, corresponding to matches formed until the mid to late 1990s, we find that the decline in assortative mating continues with spousal correlation in education halving with respect to the initial value in Figure 1. However, these younger cohorts do not contribute to our estimating sample because their children are too young to observe completed education.

children are less and less valued. Assessing the relevance of the two alternative scenarios is not possible based only on the contrast between raw parental assortative mating and intergenerational transmission. The model presented in the next Section allows us to understand their relative importance.

3. An econometric model of educational correlations among family members

In this section we present a model for the educational attainment of family members which we use to measure the contribution of parental assortative mating to the intergenerational transmission of human capital. Families are composed of four members: father (*F*), mother (*M*), first child (C_1) and second child (C_2). Let y_{ij} denote years of education for person i in family j residualized on year-of-birth dummies to remove common trends, and let $H(i)$ denote the role of i in the family, that is $H(i) \in \{M, F, C_1, C_2\}$. For the parental generation, years of education of parent i are given by

$$y_{ij} = a_{ij} + \gamma_{Aj} + \gamma_{H(i)j} + \mu_j, \quad H(i) = F, M \tag{1}$$

that is, they are factored into the sum of four orthogonal zero mean components. The first term, a_{ij}, represents sources of human capital, such as idiosyncratic ability or luck, that are specific to parent i and are not shared with other family members.

The second and third terms denote human capital-generating factors that are passed across generations. We distinguish two such factors. The first factor of intergenerational transmission denoted as γ_{Aj}, is shared between parents and represents the contribution of parents' assortative mating to intergenerational transmission. This term captures the existence of transferable skills, attitudes, or values shared between parents that are relevant for the acquisition of education and are transmitted to the children. For example, both parents are proficient in math and jointly transfer their proficiency to the children, or both are patient and exhibit self-control. The second factor of intergenerational transmission denoted as $\gamma_{H(i)j}$, is parent-specific and, therefore, it is not shared between parents. This factor captures the existence of skills, attitudes, and values that each parent transmits to the children independently from the co-parent.

Finally, the fourth term μ_j, represents determinants of human capital that are shared between parents, but are not passed on to the children, i.e., a purely intragenerational component of parental assortative mating. For example, parents may share traits or behaviors that can hamper human capital (say smoking) that they do not want to pass to the children. More generally, there may be frictions in the transmission process such that not all factors shared by the parents are passed on to the next generation.

In the offspring generation, years of education of child i are given by

$$y_{ij} = a_{ij} + \gamma_{Aj} + \gamma_{Mj} + \gamma_{Fj} + \gamma_{Mj}\gamma_{Fj} + \theta_j, \quad H(i) = C_1, C_2 \qquad (2)$$

that is, they are factored into the sum of the following orthogonal components: (i) idiosyncratic factors, a_{ij}, such as ability and luck, that are specific to child i and are not shared with other family members; (ii) all factors that are received from the parent generation (i.e. the shared factors – γ_{Aj} – the parent-specific factors from the mother – γ_{Mj} – and the father – γ_{Fj} – and their interaction – $\gamma_{Mj}\gamma_{Fj}$ – to allow for complementarity between the parent-specific components); and (iii) other intra-generational influences, θ_j, such as school or community factors that siblings share independently from their parents.

By assuming orthogonality across the components of equation (2), and in particular between each of the γ terms and θ, we are effectively ruling out sorting of families across schools and communities. In Bingley, Cappellari and Tatsiramos (2021) we show how sorting can be identified in models of the sibling correlation by exploiting the timing of families' mobility across communities; results for Denmark indicate that community-related effects tend to be overestimated when ignoring sorting. Therefore, the intra-generational term θ_j in equation (2) must be seen as an upper bound on the relevance of these influences that siblings share independently from their parents within the overall sibling correlation of education.

We assume that each of the zero mean human capital generating factors described above has variance σ_s^2 with $s \in \{a, \gamma_A, \gamma_F, \gamma_M, \mu, \theta\}$. We estimate the contributions of these factors to educational correlations within the family by matching moment restrictions generated by the model to the empirical correlations estimated from the data. Because these correlations capture similarities in education between family members, they will be functions only of the variances of shared factors and not of idiosyncratic factors, and only the former can be estimated from the empirical correlations.

Starting from the parents, their correlation of educational attainment implied by the model is given by

$$\rho_{MF} = \sigma_{\gamma A}^2 + \sigma_\mu^2. \qquad (3)$$

The parameter ρ_{MF} is our measure of parental assortative mating and is the sum of the variances of two factors: those that are shared between parents and are transmitted to the children ($\sigma_{\gamma A}^2$), and those that are shared between parents but are not transmitted to the children (σ_μ^2). In contrast, parent-specific determinants of the intergenerational transmission of human capital do not contribute to parental assortative mating.

Looking across generations, the intergenerational correlation of education between each parent and each child is given by

$$\rho_{PC} = \sigma_{\gamma A}^2 + \sigma_{\gamma P}^2, \quad P = M, F \qquad (4)$$

which is the sum of the variances of the factors that are shared between parents and are transmitted to the children ($\sigma_{\gamma A}^2$), and the parent-specific factors transmitted by each parent to each of the children ($\sigma_{\gamma P}^2$) independently from the co-parent. Note that the three parameters of intergenerational transmission $\sigma_{\gamma A}^2$, $\sigma_{\gamma M}^2$ and $\sigma_{\gamma F}^2$ can also be used to derive a measure of *total* intergenerational correlation, that is the one that originates from all the factors that the parents pass on to each child, either jointly or individually: $\rho_{MFC} = \sigma_{\gamma A}^2 + \sigma_{\gamma M}^2 + \sigma_{\gamma F}^2 + \sigma_{\gamma M}^2 \sigma_{\gamma F}^2$, where the last term is the variance of $\gamma_{Mj}\gamma_{Fj}$, which equals the product of the variances because γ_{Mj} and γ_{Fj} are zero mean independent random variables. This correlation has no empirical counterpart and therefore is not a moment that we can use in estimation, but is a statistic that we can compute post-estimation.

The sibling correlation, based on the model assumptions, is given by

$$\rho_{C_1C_2} = \sigma_{\gamma A}^2 + \sigma_{\gamma M}^2 + \sigma_{\gamma F}^2 + \sigma_{\gamma M}^2\sigma_{\gamma F}^2 + \sigma_{\theta}^2, \qquad (5)$$

which is the sum of the variances of all the factors transmitted intergenerationally (i.e., the total intergenerational correlation ρ_{MFC}) and the intragenerational factors that siblings share independently from the parents (σ_{θ}^2).

It is important to emphasize that this is a system of four equations (two intragenerational equations – (3) and (5) – and two intergenerational equations – (4), one for each parent) in five parameters ($\sigma_{\gamma A}^2, \sigma_{\gamma M}^2, \sigma_{\gamma F}^2, \sigma_{\mu}^2, \sigma_{\theta}^2$), and it is not identified. For identification, therefore, we need an additional restriction.

To solve the indeterminacy, we exploit variation in the gender composition of the children and restrict mixed-gender children to share only factors stemming from the family environment, while same-gender children share influences originating both from within the family as well as outside the family. That is, we restrict

$$\theta_j = 0 \;\; if\; g_{ij} \neq g_{i'j};\;\; H(i) = C_1,\; H(i') = C_2 \qquad (6)$$

where g is a gender indicator. The rationale for this restriction is that, particularly at young ages, interactions independent from the family environment occur predominantly among same-gender peers (e.g., Martin and Fabes, 2001; Fabes et al., 2003). The evidence shown in Section 2 of lower educational correlations for mixed-gender children, compared to those of the same gender, provides some corroboration suggesting that shared influences among same-gender children may represent an upper bound on the values of the parameter for mixed-gender children. Under restriction (6), the difference in educational correlations between same-gender and mixed-gender children identifies the parameter σ_{θ}^2. To operationalize this idea, we compute the empirical correlations by family type based on the gender composition of the children (mixed, all sons, all daughters) and use the empirical correlations of all family types jointly in estimation.

We estimate the model by Minimum Distance and match the empirical educational correlations with their counterparts predicted by the model on the basis of model parameters, using bootstrapped standard errors of the correlations to weight the minimization problem. The correlation function implied by the model for members H and H' is given by:

$$f(\omega)_{HH'} = \sigma_{\gamma A}^2[I(H = M)I(H' = F) + I(H = P)I(H' = C) + I(H = C_1)I(H' = C_2)] \quad (7)$$
$$+ \sigma_{\mu}^2 I(H = M)I(H' = F)$$
$$+ \sigma_{\gamma M}^2[I(H = M)I(H' = C) + I(H = C_1)I(H' = C_2)]$$
$$+ \sigma_{\gamma F}^2[I(H = F)I(H' = C) + I(H = C_1)I(H' = C_2)]$$
$$+ \sigma_{\gamma M}^2\sigma_{\gamma F}^2 I(H = C_1)I(H' = C_2) + \sigma_{\theta}^2 I(H = C_1)I(H' = C_2)I(g_{C_1} = g_{C_2})$$

where $I(.)$ is an indicator function, ω is the vector collecting all model parameters, $P \in \{M, F\}$, $C \in \{C_1, C_2\}$, the regression weights are given by $(var(r_{HH'}))^{-1/2}$, and the regression does not include a constant such that estimated parameters can be interpreted as levels (of the components) of correlation coefficients.

4. Results

We start the discussion of results by providing some benchmark estimates from intergenerational OLS regressions of years of education in Table 3. We consider both children of each family in each regression and cluster standard errors at the family level. All variables are measured as deviations from generational means, so the regressions do not include a constant. In Column (1), the regression coefficient of child years of education on father's years of education is equal to 0.2, indicating that an additional year of father's education is associated with an increase of child's education of about two and a half months. Rescaling the regression coefficient with the ratio of the standard deviations of years of education for fathers and children (which is equal to 1.4), the implied intergenerational correlation of years of education is 0.28. This is very close to the estimate of Table 2 obtained by averaging correlations across cohorts, after excluding cells with fewer than 100 pairs. Similarly, in Column (2), the regression coefficient for mother's education is equal to 0.21 and the implied intergenerational correlation is equal to 0.29.

As noted by Holmlund, Lindahl and Plug (2011), regressing child outcomes on each parent's outcome in isolation from their spouse, delivers estimates that are a convolution of the direct effect of that parent and the impact of parental assortative mating. As a way of netting out the latter, they suggest including the outcomes of both parents in the intergenerational regressions. This is done in Column (3) of Table 3, showing that the direct effect for each parent is indeed lower (by about a third) relative to the corresponding coefficients in Columns 1 and 2. These estimates suggest that assortative mating indeed plays a role in shaping intergenerational transmission; however, they do not provide any measure of this effect, which is instead the aim of the model we propose and estimate in this paper.

In a final set of benchmark estimates, we extend the OLS specification by including the interaction between father's and mother's education in order to capture any complementarity of parental inputs. Column (4) of Table 3 shows the regression coefficient on the interaction is positive and statistically significant, which suggests that there is complementarity, although its magnitude is negligible compared with the baseline effects.

In what follows, we report and discuss Minimum Distance estimates for the baseline model in Section 4.1, by gender of the children in Section 4.2 and over time in Section 4.3.

4.1 Baseline estimates

The baseline estimates of Panel (A) in Table 4 suggest a correlation of educational attainment between parents of about 0.48, which is the sum of the component of parental assortative mating that is transmitted intergenerationally to the children ($\sigma_{\gamma A}^2$ = 0.2403, s.e. = 0.0048) and the component that is not transmitted and instead remains within the generation of the parents (σ_{μ}^2 = 0.2418, s.e. =

0.0054). That is, on average across birth cohorts and family types, about half of the factors shared by parents are transmitted intergenerationally.

Panel (A) of Table 4 also reports the parent-specific factors ($\sigma_{\gamma M}^2, \sigma_{\gamma F}^2$) that each parent transmits independently to their children. Combining the joint ($\sigma_{\gamma A}^2$) with the parent-specific factors, we obtain an intergenerational correlation of education which is equal to 0.2755 for mothers (0.2403 + 0.0352) and 0.2790 for fathers (0.2403 + 0.0387). Thus, parent-specific contributions to intergenerational transmission appear to be of modest size, each about one sixth of the size of the joint parental contribution, and very similar for mothers and fathers. The complementarity effect is given by the product of parent-specific factors and is equal to 0.0013 (s.e. = 0.0003), which is negligible compared to the joint and parent-specific contributions.

With these estimates we can compute the *total* intergenerational correlation, which measures transmission from both parents (either joint or parent-specific) to a child; as shown in Section 3, this total correlation is not directly observed in the data, but it is estimated by the model. Total intergenerational correlation is equal to 0.3155 (= 0.2403 + 0.0352 + 0.0387 + 0.0013). This sum implies that about 75 percent of the intergenerational correlation in education is driven by the joint parental contribution (0.2403/0.3155), suggesting a major role of parental assortative mating in accounting for intergenerational transmission. Our model – based on the direct estimation of the share of parental assortative mating within the intergenerational correlation – points to a greater role of parental assortative mating compared with the one implicit in the indirect assessment of Table 3 based on the contrast of OLS regressions with different conditioning sets.

Finally, Panel (A) of Table 4 reports the estimate of the intragenerational factors that siblings share independently from their parents ($\sigma_{\theta}^2 = 0.0431$, s.e. = 0.0050), which is small and accounts for about 12 percent of the overall sibling correlation. The latter is equal to 0.3586 (calculated as the sum of all factors transmitted intergenerationally – shared – $\sigma_{\gamma A}^2$ – and parent-specific – $\sigma_{\gamma M}^2$, $\sigma_{\gamma F}^2$ and their product– plus the intragenerational factors that children share independently from their parents

$-\ \sigma_\theta^2$).[6] As all these estimates are derived under the restriction that mixed-gender children share only influences within the family, the relatively small estimates of the residual sibling effect σ_θ^2 from same-gender children – that can be thought of as upper bounds for the mixed-gender estimates – suggest that the assumption of zero independent correlation for mixed-gender children is reasonable.

4.2 Heterogeneity of educational correlations

The finding that, compared to the joint contributions, the independent parental contributions to intergenerational transmission are of second order importance, may miss part of the parental effect if each parent's ability to influence their children's educational attainment depends on the family environment. For example, fathers could have greater influence in a mostly male environment, while mothers in a mostly female environment. To investigate whether child gender matters for the magnitude of each parent's independent influences, we extend the model by allowing parameters to differ according to the gender mix of the children.

In particular, we interact family type with the three intergenerational parameters $\sigma_{\gamma A}^2$, $\sigma_{\gamma M}^2$ and $\sigma_{\gamma F}^2$, which are the ones needed to decompose the intergenerational correlation into parental assortative mating and parent-specific transmission and are central to our research question. We also interact family type with the residual sibling correlation σ_θ^2, which in the baseline model is effectively already family-type-specific, being zero for families with mixed-gender children. It is worth noting that we cannot interact family type with *all* the parameters of the baseline model because a saturated interaction would re-introduce the under-identification problem (discussed in Section 3) within each family type. To avoid this issue, we restrict the intragenerational assortative mating parameter σ_μ^2 to be constant across family types.

[6] Using a model of sibling correlations and intergenerational transmission from the father only, Bingley and Cappellari (2019) obtain that the share of brothers' correlation in education accounted for by factors that the siblings share independently of the father is about 26 percent (see their Table 4). Because that model does not consider mothers, its residual sibling correlation includes the mother specific-intergenerational transmission and the complementarity between parent-specific components. The sum of mother-specific intergenerational transmission, complementarity and residual sibling correlation in our model accounts for about 24 percent of the total sibling correlation.

The results, reported in Panel B of Table 4, show evidence that gender matters for intergenerational transmission. For mothers, we find that the mother-specific contribution to the intergenerational correlation is about a quarter larger when both children are daughters ($\sigma^2_{\gamma M\_GG}$), compared to when both children are sons ($\sigma^2_{\gamma M\_BB}$), but the difference is not statistically significant. For fathers, we find that the father-specific contribution to the intergenerational correlation is about twice as large when both children are sons ($\sigma^2_{\gamma F\_BB}$)rather than daughters ($\sigma^2_{\gamma F\_GG}$), while father-specific transmission with mixed-gender children ($\sigma^2_{\gamma F\_MX}$) is in-between the same-gender estimates, and all differences are statistically significant (at the 10% level for mixed vs. all-daughters, or lower). Together with the finding that the intergenerational component of assortative mating is rather stable across family types, these estimates show only modest differences in parental assortative mating between family types in shaping *total* intergenerational transmission, which varies between 72 percent for families with all sons and 78 percent for all daughters.

The remaining parameter that varies with family type in Panel B of Table 4 is the residual sibling correlation σ^2_{θ}, which is larger for daughters than for sons ($\sigma^2_{\theta\_GG} = 0.057$ vs. $\sigma^2_{\theta\_BB} = 0.030$), and the difference is significant at the 5 percent level.

4.3 Cohort analysis

We extend the analysis by exploiting the cohort structure of the empirical moments to estimate the evolution in the components of assortative mating and intergenerational transmission over time. As reported in Figure 1, there is a marked decline in parental assortative mating between the cohorts born in the mid-1920s and those born in the mid-1950s, while the evolution of intergenerational correlations is also declining, albeit at a more modest pace. As discussed in Section 2, the different trends in assortative mating and in intergenerational transmission are compatible with two possible explanations. According to the first explanation, there is a decline in the joint intergenerational transmission from both parents, which is mostly compensated by an increase in parent-specific intergenerational transmission. According to the second explanation, the decline in parental assortative mating is only driven by a decline over time in the component of parental assortative mating that is not transmitted from parents to children.

By exploiting the cohort structure within our model, we are able to offer new insights regarding the evolution of parental assortative mating and intergenerational transmission over time. In particular, we interact each of the model parameters with a linear trend in the birth cohort. For all parameters that involve the parents, that is, the parameters of parental assortative mating and intergenerational transmission, the trend is fitted using the cohort of the elder parent. For child correlations, we use the cohort of the elder sibling. We fit simple linear trends which, as Figure 1 suggests, should not be overly restrictive.

The estimates are reported in Panel C of Table 4 and are summarized in Figures 2 to 4. Figure 2, which is the counterpart of Figure 1 predicted from the model, displays an overall marked decline of parental assortative mating and only a minor reduction over time of intergenerational transmission from each parent. Also, the parent-specific estimates are very close between parents and not statistically different, resulting in closely overlapping plots in Figure 2. Figure 3 decomposes the trend of parental assortative mating into its intra- and inter-generational components, showing that the sharp observed decline of parental assortative mating over time is due to both components, with a prevalence of the intragenerational component. Figure 4 decomposes *total* intergenerational transmission (the sum of all intergenerational factors) into the part due to assortative mating and the part due to parent-specific transmission, showing that, while the total effect is stable, its components have followed quite distinct trends. The contribution of parental assortative mating has declined by a third (from 0.3 to 0.2) between the 1921 and the 1951 cohort. In contrast, there is an increase of the parent-specific components from virtually zero in the 1921 cohort to about 0.05 among the most recent parental cohort. Consequently, a similar increasing pattern characterizes the complementarity of parent-specific factors.[7] These findings suggest a change in the nature of intergenerational transmission over time, with an increasing importance of one-to-one parent-child relationships.

5. Conclusion

In this paper we study the importance of parental educational similarity in shaping the intergenerational persistence of education by transmitting factors shared by both parents to the children, relative to influences transmitted by each parent separately. We develop an empirical model of educational correlations within families composed of two parents and two children. We estimate the model using educational attainment from Danish population-based administrative data for over 400,000 families.

We find that about 75 percent of the intergenerational correlation in education is driven by the joint contribution of the parents, which points towards a strong role of shared parental inputs in producing the human capital of children. Parent-specific contributions to intergenerational transmission of education are each about a sixth of the size of the joint parental contribution, with father-specific transmission being larger for sons, and mother-specific transmission being larger for daughters.

Considering the evolution of parental assortative mating and intergenerational transmission over time, we document a sizeable secular decline of parental assortative mating in education, which results in a decline of the joint intergenerational transmission from both parents. We show that this decline in joint transmission is compensated by an increase in parent-specific intergenerational transmission, leaving intergenerational persistence unaffected. This shift from joint to parent-specific transmission implies a reduction in the importance of parental assortative mating for intergenerational transmission over time, with an increase in the importance of one-to-one parent-child relationships.

[7] Estimating the time trends of intergenerational transmission by OLS, we found an increase of the mother-specific coefficient over time and of the father-mother interaction, while we found the father-specific coefficient declines over time.

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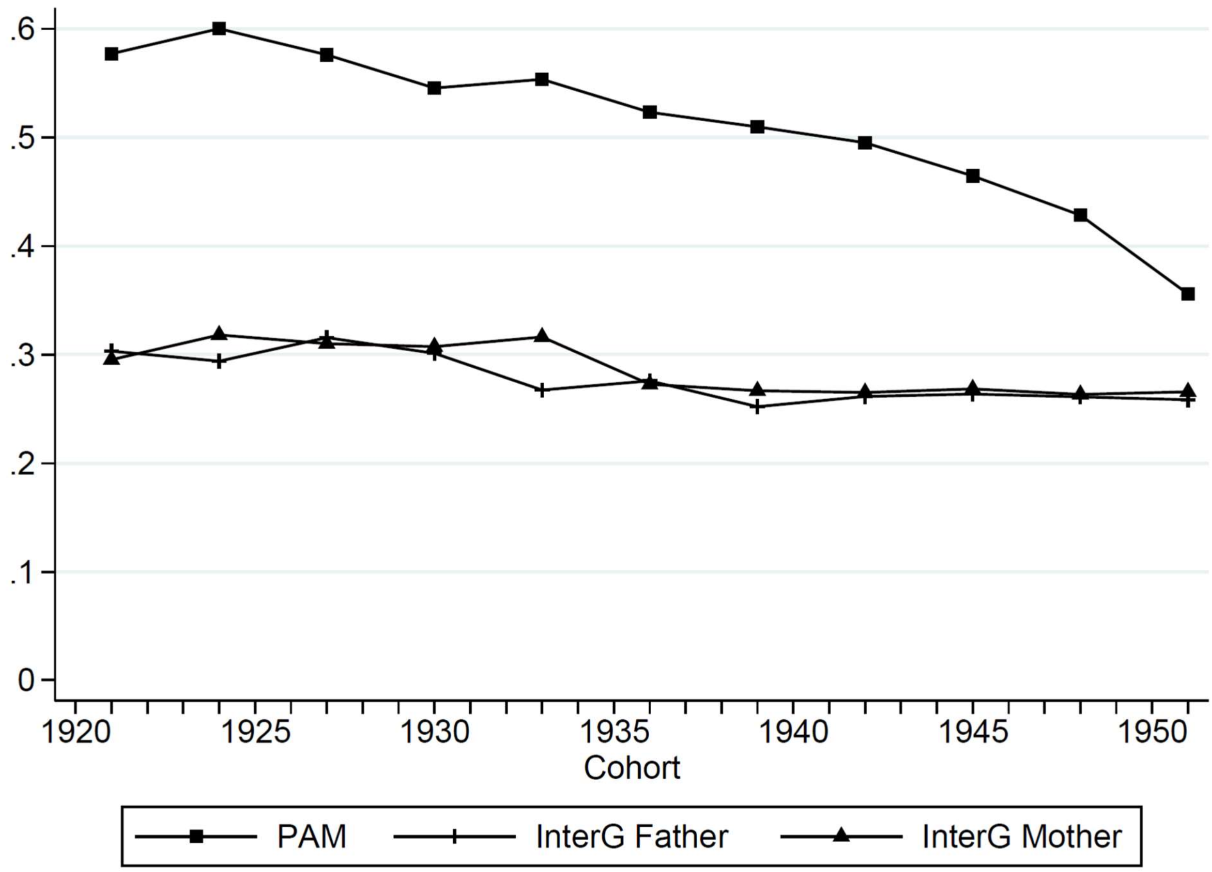
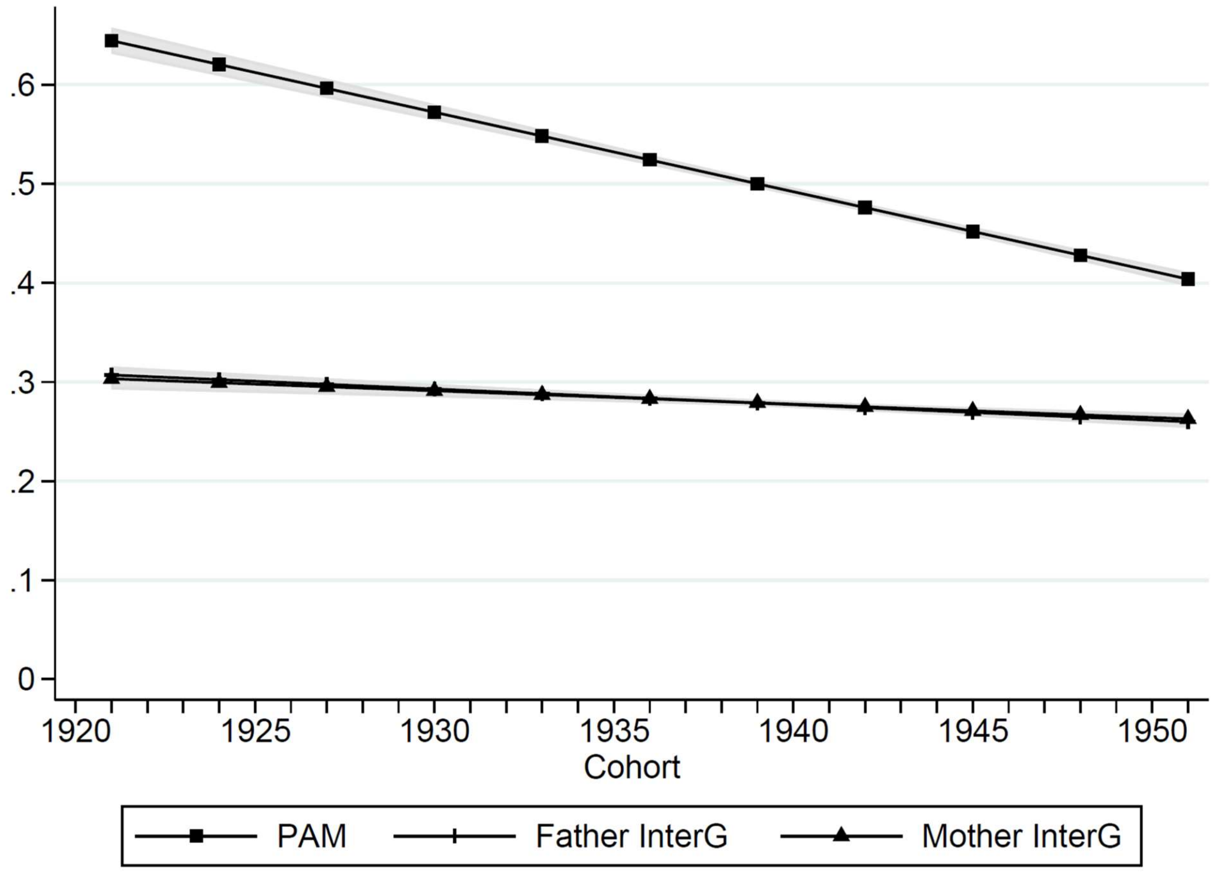
Figure 1

Parental assortative mating and intergenerational transmission. Raw correlations



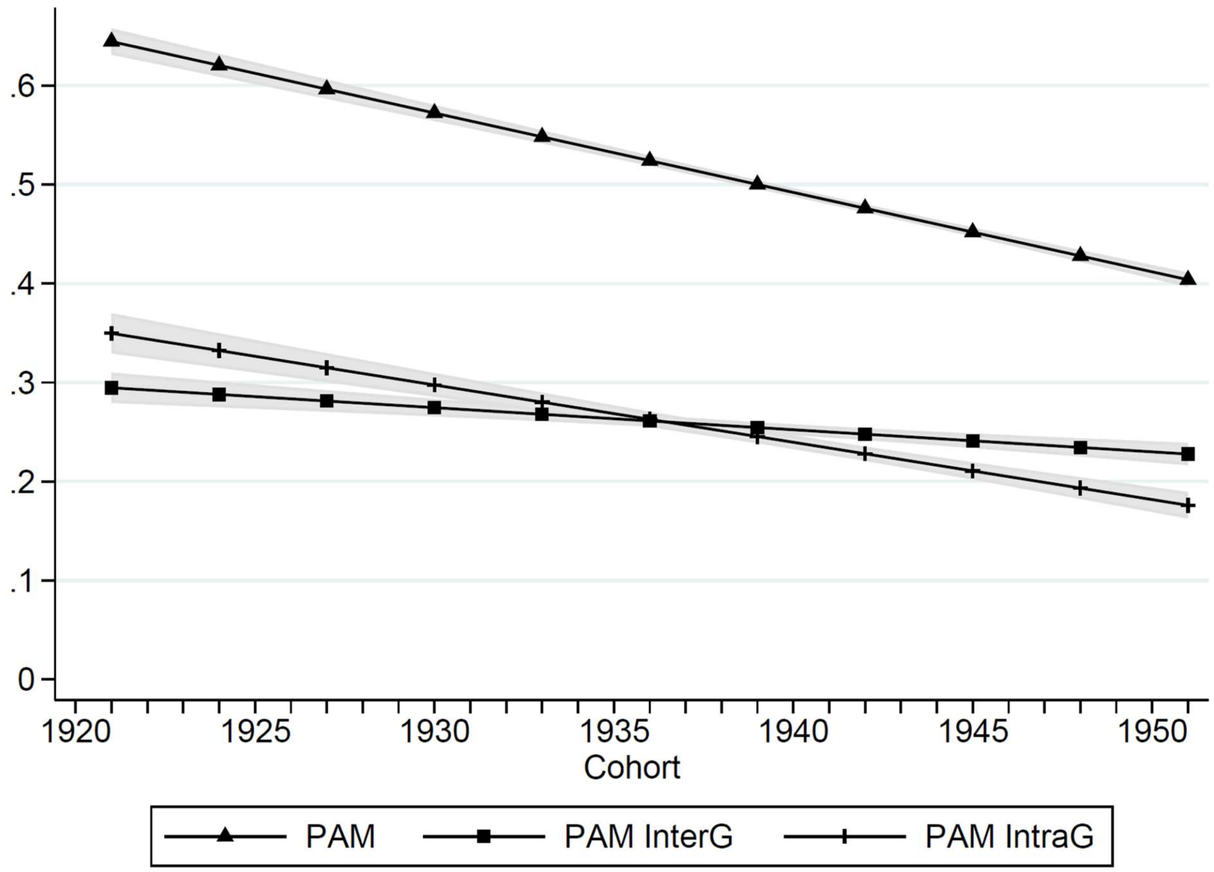
Note: The graph plots empirical correlation coefficients of years of education between family members. The line labelled PAM shows the correlation between parents; the line labelled InterG Father shows the father-child correlation; the line labelled InterG Mother shows the mother-child correlation. Correlations are computed after residualizing years of school on year-of-birth dummies and are estimated for each combination of birth cohorts of the family members, after excluding cells with fewer than 100 pairs. Correlations are plotted by birth cohort of the oldest member in the pair.

Figure 2
Parental assortative mating and intergenerational transmission.
Predicted correlations



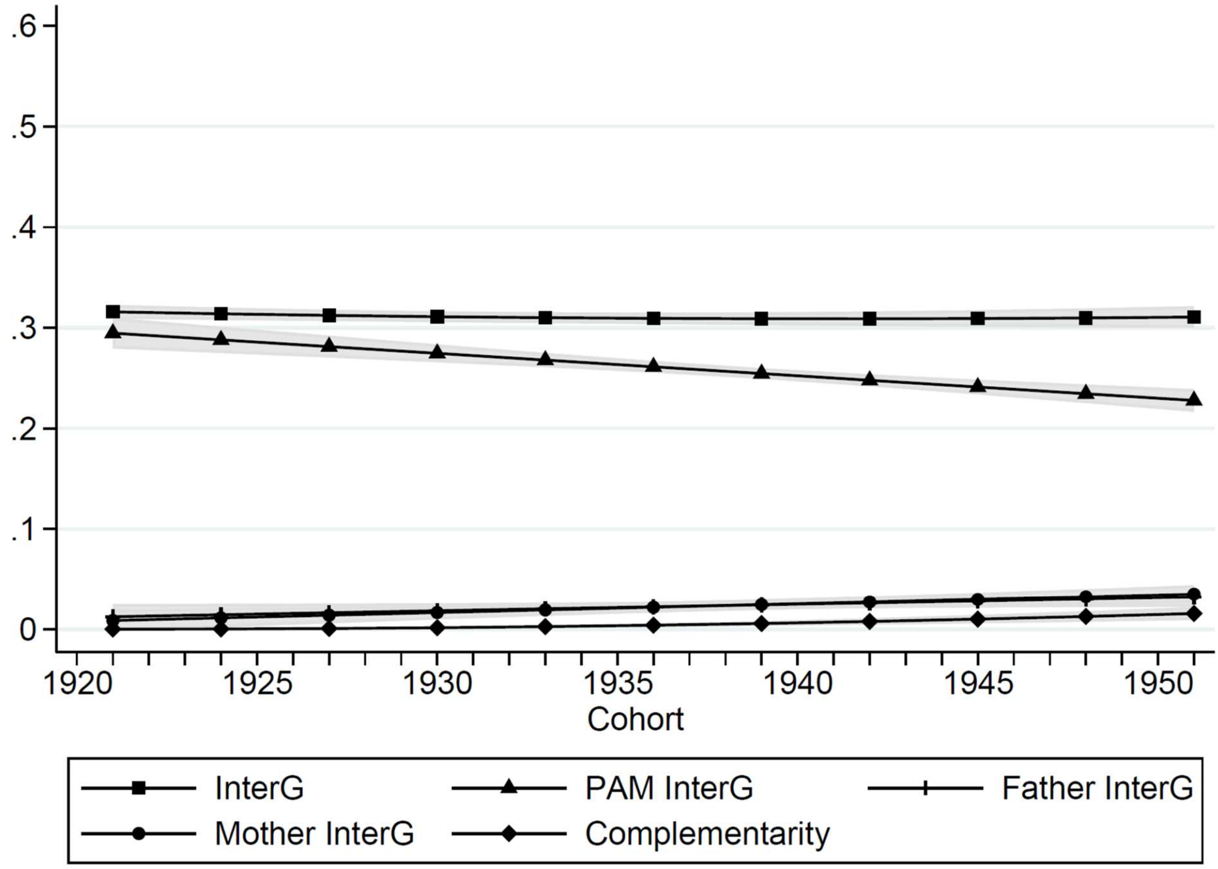
Note: The graph plots predicted correlation coefficients of years of education between family members. The shaded areas are the 95% confidence intervals of the predictions. The line labelled PAM shows the correlation between parents; the line labelled Father InterG shows the father-child correlation; the line labelled Mother InterG shows the mother-child correlation. Correlations are estimated from the model with cohort trends of Section 4.3.

Figure 3
Predicted decomposition of parental assortative mating.



Note: The graph plots predicted correlation coefficients of years of education between parents and their decomposition into the factors that are transmitted to children and the factors that are not transmitted. The shaded areas are the 95% confidence intervals of the predictions. The line labelled PAM shows the correlation between parents; the line labelled PAM InterG shows the factors that are transmitted to children; the line labelled PAM IntraG shows the factors that are not transmitted. Correlations are estimated from the model with cohort trends of Section 4.3.

Figure 4
Predicted decomposition of intergenerational transmission.



Note: The graph plots predicted correlation coefficients of years of education between parents and children and their decomposition into the factors that are transmitted jointly by both parents and the factors that are transmitted individually by each parent. The shaded areas are the 95% confidence intervals of the predictions. The line labelled InterG shows the total intergenerational correlation resulting from the sum of all the factors that are passed from parents to children; the line labelled PAM InterG shows the factors that are transmitted jointly by the parents; the line labelled Father InterG shows the factors that are transmitted only by the father; the line labelled Mother InterG shows the factors that are transmitted only by the mother. The line labelled Complementarity shows the product of the father and mother-specific factors. Correlations are estimated from the model with cohort trends of Section 4.3.

Table 1
Descriptive statistics.

	(1) Number of persons					(2) Years of education	
	By role in the family				Total	Mean	S.D.
	Mother	Father	Child 1	Child 2			
All birth cohorts	417,746				1,670,984	12.30	3.04
Birth cohort							
1921	648	5,171			5,819	9.91	3.54
1924	3,033	12,009			15,042	9.99	3.53
1927	7,983	20,358			28,341	10.27	3.53
1930	17,036	31,801			48,837	10.53	3.48
1933	30,931	43,452			74,383	10.67	3.39
1936	47,842	52,290			100,132	10.73	3.35
1939	57,374	56,593			113,967	10.92	3.33
1942	65,529	62,880			128,409	11.28	3.27
1945	75,491	68,291			143,782	11.69	3.14
1948	64,877	47,036			111,913	11.98	2.99
1951	47,002	17,865			64,867	12.09	2.80
1957			55,998	8,243	64,241	12.86	2.41
1960			61,203	42,109	103,312	12.87	2.32
1963			65,902	60,513	126,415	13.03	2.25
1966			71,126	67,655	138,781	13.22	2.22
1969			62,321	62,802	125,123	13.37	2.28
1972			55,689	65,454	121,143	13.69	2.29
1975			35,078	56,036	91,114	14.02	2.24
1978			10,429	37,077	47,506	14.28	2.22
1981			0	14,826	14,826	14.38	2.26
1984			0	2,691	2,691	14.39	2.32
1987			0	340	340	14.56	2.28

Note: The left panel of the table reports the number of individuals in the estimating sample, their role in the family and birth cohort, where the cohorts are defined as non-overlapping groups of individuals who are born over three consecutive years. The table indicates each cohort by its central year. The right panel of the table reports summary statistics for the distribution of years of education by birth cohort.

Table 2
Raw correlations in years of education among family members, by gender composition of the children.

	Sibling composition			
	Two boys	Two girls	Mixed	All families
Parents	0.50	0.50	0.50	0.50
Children	0.34	0.34	0.31	0.33
Mother-child	0.28	0.27	0.28	0.28
Father-child	0.29	0.26	0.27	0.28

Note: The table reports empirical correlation coefficients of years of education between family members. Correlations are computed after residualizing years of school on year-of-birth dummies and are estimated for each combination of birth cohorts of the family members, after excluding cells with fewer than 100 pairs. Reported correlations are averaged over birth cohorts.

Table 3
OLS intergenerational regressions.

	(1)		(2)		(3)		(4)	
	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
Years of education of								
Father	0.201	0.001			0.129	0.001	0.130	0.001
Mother			0.217	0.001	0.153	0.001	0.149	0.001
Father×Mother							0.010	0.0003

Note: The table reports coefficients from OLS regression of child years of education on parental years of education with robust standard errors clustered at the level of the family. Each regression is run on 835,492 observations.

Table 4
Parameter estimates of educational correlations model.

	Coeff.	S.E
(A) Baseline		
Intragenerational Parental Assortative Mating σ_{μ}^{2}	0.2418	0.0054
Intergenerational Parental Assortative Mating $\sigma_{\gamma A}^{2}$	0.2403	0.0048
Intergenerational Mother-specific $\sigma_{\gamma M}^{2}$	0.0352	0.0043
Intergenerational Father-specific $\sigma_{\gamma F}^{2}$	0.0387	0.0043
Residual sibling σ_{θ}^{2}	0.0431	0.0058
(B) Heterogeneity by family type		
Intragenerational Parental Assortative Mating σ_{μ}^{2}	0.2421	0.0065
Intergenerational Parental Assortative Mating $\sigma_{\gamma A\_MX}^{2}$	0.2414	0.0055
Intergenerational Parental Assortative Mating $\sigma_{\gamma A\_BB}^{2}$	0.2396	0.0081
Intergenerational Parental Assortative Mating $\sigma_{\gamma A\_GG}^{2}$	0.2376	0.0083
Intergenerational Mother-specific $\sigma_{\gamma M\_MX}^{2}$	0.0357	0.0047
Intergenerational Mother-specific $\sigma_{\gamma M\_BB}^{2}$	0.0316	0.0090
Intergenerational Mother-specific $\sigma_{\gamma M\_GG}^{2}$	0.0392	0.0093
Intergenerational Father-specific $\sigma_{\gamma F\_MX}^{2}$	0.0370	0.0047
Intergenerational Father-specific $\sigma_{\gamma F\_BB}^{2}$	0.0556	0.0090
Intergenerational Father-specific $\sigma_{\gamma F\_GG}^{2}$	0.0237	0.0093
Residual sibling $\sigma_{\theta\_BB}^{2}$	0.0298	0.0119
Residual sibling $\sigma_{\theta\_GG}^{2}$	0.0575	0.0122
(C) Cohort trends		
Intragenerational Parental Assortative Mating σ_{μ}^{2} - Intercept (c. 1921)	0.3496	0.0103
Intragenerational Parental Assortative Mating σ_{μ}^{2} – Cohort trend	-0.0058	0.0005
Intergenerational Parental Assortative Mating $\sigma_{\gamma A}^{2}$- Intercept (c.1921)	0.2947	0.0078
Intergenerational Parental Assortative Mating $\sigma_{\gamma A}^{2}$– Cohort trend	-0.0022	0.0004
Intergenerational Mother-specific $\sigma_{\gamma M}^{2}$- Intercept (c. 1921)	0.0086	0.0056
Intergenerational Mother-specific $\sigma_{\gamma M}^{2}$– Cohort trend	0.0009	0.0003
Intergenerational Father-specific- Intercept (c. 1921)	0.0124	0.0065
Intergenerational Father-specific– Cohort trend	0.0007	0.0003
Residual sibling σ_{θ}^{2}- Intercept (c. 1957)	0.0431	0.0070
Residual sibling σ_{θ}^{2}– Cohort trend	0.0001	0.0006

Note: The table reports parameter estimates obtained by Minimum Distance. Robust standard errors are obtained by weighting the minimization problem with the inverse of the bootstrapped variance of empirical moments. In the model with heterogeneity by family types in Panel (B), MX denotes families with mixed-gender siblings, BB denotes families with two sons and GG denotes families with two daughters. The number of persons is equal to 1,670,984 and the number of moments is equal to 1,297.

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