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Assortative Mating and Education Gradients within and across Generations[a]

Paul Bingley[b] Lorenzo Cappellari[c] Konstantinos Tatsiramos[d]

June 2026

Abstract

We study how assortative mating shapes the composition of education–outcome gradients and how these gradients relate to intergenerational transmission. Using Danish administrative data on family quartets, we decompose own gradients in long-run earnings, disposable income, assets, and wealth into jointly transmitted parental factors, parent-specific transmission, non-parental shared influences, and individual-specific heterogeneity. Earnings and income gradients mainly reflect jointly transmitted parental factors and individual-specific heterogeneity; assets and especially wealth mainly reflect parent-specific transmission. Comparing families facing different parental access to middle schools, we show that the composition of financial gradients varies by educational opportunity, while labor market gradients are largely invariant.

Keywords: Assortative mating, Education gradients, Intergenerational mobility.

JEL Classification: J62; D31; J12; I24; E21; J24

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1 Introduction

Education is strongly linked to later-life economic outcomes, from earnings and income to assets and wealth. For labor market outcomes, this relationship is central to the literature on returns to schooling (Card, 1999; Heckman et al., 2006), while for financial outcomes, it relates to work on education and wealth returns (Fagereng et al., 2026). Observed education–outcome gradients can reflect a mix of parental resources and behaviors, other aspects of family background, and individual-specific determinants, rather than a single pathway linking education to outcomes. A central question, therefore, is not only how steep education–outcome gradients are, but also what they capture, since gradients that are similar in size may reflect very different sources of family advantage and individual heterogeneity, with different implications for inequality and intergenerational mobility (Black and Devereux, 2011; Mogstad and Torsvik, 2021).

To interpret the family-related components of these gradients, it is important to understand how parental advantage is transmitted. Positive assortative mating on education and correlated traits can shape the transmission of advantage from parents to children by concentrating resources, skills, and preferences within families. The literature has emphasized both sorting in the offspring generation, which can affect intergenerational mobility through the formation of new households (Chadwick and Solon, 2002; Ermisch et al., 2006; Holmlund, 2022), and sorting in the parental generation, which can shape socioeconomic outcomes in the offspring generation and intergenerational mobility (Kremer, 1997; Fernández and Rogerson, 2001; de la Croix and Doepke, 2003). Yet parental influences are not necessarily transmitted in the same way within the family: some may operate jointly through shared family resources and environments, while others remain parent-specific. With rising educational assortative mating and widening inequality (Greenwood et al., 2014; Doepke and Zilibotti, 2017; Eika et al., 2019), distinguishing between joint and parent-specific transmission becomes increasingly important.

In this paper, we use Danish administrative data on family quartets consisting of two parents and their first two children to develop and estimate a model that decomposes the own education–outcome gradient into different components: (i) parental factors transmitted jointly, (ii) parent-specific factors transmitted separately, (iii) non-parental influences shared within the family, and (iv) individual-specific variation. Sibling information is essential for this decomposition because it allows us to separate parental transmission from other shared within-family influences and from individual-specific factors. We also study the intergenerational education gradient linking parental schooling to children's economic outcomes, which allows us to isolate the parental-transmission margin and distinguish between its joint and parent-specific components. We implement these decompositions for four long-run outcomes, earnings, disposable income, assets, and wealth, allowing the balance of components to differ across labor market and financial domains.[1]

The composition of education–outcome gradients differs systematically across outcomes. For earnings and disposable income, own-education gradients are accounted for by jointly transmitted parental factors alongside a substantial individual-specific component. The corresponding intergenerational gradients are driven primarily by jointly transmitted parental factors. For assets and wealth, by contrast, both own and intergenerational gradients are accounted for mainly by parent-specific transmission, with jointly transmitted factors contributing much less. labor market gradients therefore have a large jointly transmitted component, whereas financial gradients have a large parent-specific component, consistent with evidence on wealth transmission across generations (Charles and Hurst, 2003; Boserup et al., 2016; Adermon et al., 2018; Fagereng et al., 2021).

One interpretation of this contrast is that labor market and financial outcomes reflect different forms of family advantage. Earnings and disposable income depend largely on human capital, work-related preferences, and labor market orientation, factors that assortative mating may align across spouses and that parents may reinforce jointly within the household. Assets and wealth, by contrast, reflect cumulative stocks shaped by inheritances, transfers, portfolio choices, and debt, which may be more closely related to one parental line and therefore appear as father- or mother-specific transmission. Although the decomposition does not identify these mechanisms directly, it

[1] A related decomposition approach is developed by Björkegren et al. (2026) in the context of adult health, where the parental education gradient is decomposed into pre-birth and post-birth components using Swedish adoptees. Our paper instead studies long-run economic outcomes and decomposes own and intergenerational gradients along the channels through which family advantage is transmitted, using family quartets in population-wide administrative data.

shows which form of family transmission is most consistent with the observed gradients in each domain.

We further use cohort-by-municipality variation in access to eighth and ninth grades associated with the gradual implementation of a school reform affecting the parental generation to examine whether the composition of children's own education–outcome gradients differs with parental educational opportunity. Because the reform changed the context in which parents acquired schooling, parental access to middle schools may be related to the family inputs embedded in children's education–outcome gradients: under more constrained access, gradients may be more closely tied to parent-specific family resources and advantages, whereas broader access may make jointly transmitted family inputs more salient. We find that for assets and wealth, gradients in higher-access families contain a larger jointly transmitted component and smaller parent-specific components than gradients in lower-access families, whereas the composition of earnings and income gradients is largely invariant to parental educational opportunity. We interpret these findings as heterogeneity across parental schooling-access environments rather than as the causal effect of the reform.

This paper contributes to two strands of literature. First, it speaks to the interplay between assortative mating and intergenerational mobility. While a large literature studies how sorting in the parental generation shapes inequality and persistence in the next generation, the closest studies to ours are those that use family-based information to distinguish assortative and intergenerational components of transmission. Bingley et al. (2022) develop a joint-versus-parent-specific framework for the intergenerational transmission of schooling and study how its components evolve over time, while Collado et al. (2023) estimate assortative and intergenerational processes in extended family data with a focus on educational attainment.

We contribute to this literature by applying the distinction between jointly transmitted and parent-specific components to multiple long-run economic outcomes and by showing how educational matching in the parental generation shapes the composition of education-outcome gradients both within and across generations. The analysis reveals variation in the composition of gradients across economic domains and by parental educational opportunity that is not apparent from focusing on schooling alone. This interpretation also relates to recent work on intergenerational mobility estimates, which emphasizes that conventional mobility measures can combine multiple sources of persistence (Del Pizzo et al., 2026).

Second, the paper connects to a large literature on the relationship between schooling and later-life outcomes. For earnings and income, the relevant literature studies earnings functions and returns to schooling (e.g., Card, 2001), while for financial outcomes, it examines how education relates to wealth returns (Fagereng et al., 2026). We contribute to this literature by providing an interpretation of observed education–outcome gradients that separates family transmission correlated with education from individual-specific variation. This distinction helps clarify how far observed education gradients, especially across labor market and financial domains, reflect family transmission rather than individual-specific determinants.

The remainder of the paper proceeds as follows. Section 2 describes the data and presents the key education–outcome associations for earnings, income, assets, and wealth. Section 3 outlines the empirical model and its identification. Section 4 reports the main estimates and decompositions, along with robustness checks and heterogeneity analyses based on variation in parental access to middle schools. Section 5 concludes.

2 Data

We use Danish administrative data to construct family quartets consisting of two parents and their first two children, as recorded in the civil register. While sibling information is not required to document education–outcome associations or intergenerational correlations, it is essential for our decomposition because it allows us to distinguish individual-specific variation from influences shared within the family, and to separate parental transmission from other non-parental shared influences.

2.1 Data Sources and Sample Construction

Our dataset comprises all families residing in Denmark between 1980 and 2018, with individuals linked across registers via unique personal identification numbers. We identify families in which both parents were born between 1935 and 1954 and in which children were born between 1955 and 1973. Cohort 1955 is the first for which parent–child links are complete (Pedersen, 2011). Cohort 1973 is the latest for which we observe outcomes up to age 45 and can therefore construct long-run outcome measures, given that our data extend through 2018. We select families with the two first-born children observed in this window, yielding 122,532 families. We then link individual-level data on educational attainment and labor earnings, disposable income, assets, and wealth to this sample.

2.2 Variable Definitions

We link educational data to each family member using qualifications recorded in the education register. To calculate educational attainment, we use the Ministry of Education's norms, which specify the shortest expected duration to complete each qualification (Jensen and Rasmussen, 2011). An individual's highest level of education is determined based on the qualification with the longest normed duration as of October 31 in the year they turn 29.

Annual pre-tax labor earnings are sourced from income tax returns, with employers reporting directly to tax authorities, who then send statements to employees each March for verification of the previous calendar year's earnings. Using the Statistics Denmark Income Statistics Register (Baadsgaard and Quitzau, 2011), we compute total annual earnings from all employment between 1980 and 2018. Disposable income is calculated as personal gross income plus transfers minus taxes.[2]

[2]Registered disposable income has been revised several times. In 1984, imputed rent for owner-occupied housing and several tax-free transfers (disability supplements, child and family benefits, housing benefits) were added. In 1990–1994, rehabilitation benefits, cash assistance, and public pensions were grossed up, and the labor market contribution on wages and self-employment income was introduced. Since 1994, imputed rent has been based on the property register, and since 2002, tax-free cash assistance, heating subsidies, and the tax-free part of child support (allocated to the child) have been included.

We analyze two related measures of financial resources: assets and total wealth. Asset values are drawn from the income register and defined as the sum of financial and non-financial assets, excluding liabilities.[3] High real estate leverage can generate near-zero net wealth even for households with substantial asset holdings. We therefore separately analyze gross assets, excluding liabilities, to capture access to resources independent of leverage decisions. Our wealth measure, in contrast, includes both assets and liabilities, capturing total net worth.[4] For consistency over time, we exclude defined contribution pension plans, which were only registered for the population starting in 2012.

Monetary outcomes are expressed in thousands of Danish kroner (DKK) in 2018 prices and winsorized at the top and bottom 0.5 percent by year. For the offspring generation, we construct long-run outcome measures over ages 31–45 by averaging annual outcomes across this window, requiring at least five annual observations per individual for each outcome.

2.3 Descriptive Statistics and Empirical Correlations

Table 1 presents descriptive statistics for the variables in our analysis. Panel A summarizes demographic characteristics and educational attainment for parents and children. Parents in our sample are born, on average, in the early 1940s, while their children are born in the mid-1960s. Fathers have slightly more schooling than mothers (11.9 versus 10.9 years), while children exceed both parents with an average of 13.4 years of education.

Panel B summarizes children's long-run outcomes over ages 31–45. Mean labor earnings and

[3] Total non-pension assets at year-end, including property, bank deposits, bonds, shares, mortgage deeds, cars, boats, cooperative apartment shares, and business shares. In 1980–1982, assets for married couples are recorded under the husband, and we distribute them equally between spouses; since 1983, assets, liabilities, and capital income are split equally between spouses unless otherwise specified. From 1987–1996, the equity of self-employed businesses was calculated separately and added to assets. From 1997, asset measures have been based almost exclusively on third-party reports from financial institutions, as vehicles, boats, cooperative and business shares are excluded.

[4] Liabilities are total year-end debt, including mortgage debt, bank loans, credit card debt, mortgage deeds held in custody, student loans, and debts to mortgage banks, finance companies, municipalities, and other creditors. In 1980–1982, debts for married couples were recorded under the husband, and we distributed them evenly between spouses. Since 1983, liabilities have generally been split evenly between spouses unless otherwise specified. Since 1987, most major debts and associated interest have been pre-printed on the tax return. Between 1987 and 1996, debt related to self-employment was excluded from this liability measure and instead entered the separate equity-in-self-employment variable that is added to assets.

disposable income are 385 and 254 (thousand DKK), respectively, while mean assets and wealth are 896 and 200 (thousand DKK). Dispersion is substantially larger for assets and wealth than for labor market outcomes, reflecting the greater heterogeneity of balance-sheet positions.[5]

Table 2 reports sample correlations between education and long-run outcome ranks, where outcomes are measured as average percentile ranks over ages 31–45. Three patterns stand out. First, own education–outcome correlations are larger than the corresponding intergenerational correlations, suggesting that own gradients partly reflect individual-specific factors beyond the parental-transmission components captured by parental schooling. Second, education gradients are steeper for labor market outcomes than for financial outcomes: both own and intergenerational correlations are stronger for earnings and income than for assets and wealth. Third, cross-sibling education–outcome correlations are smaller than own correlations and broadly similar in magnitude to the intergenerational correlations.[6] Across all comparisons, wealth exhibits the weakest link with education.

3 Empirical Model

This section presents an empirical model for decomposing education–outcome gradients. The model builds on the joint-versus-parent-specific transmission framework of Bingley et al. (2022), and extends it to own and intergenerational gradients linking education to long-run economic outcomes rather than to schooling transmission alone. We begin by modeling the components of education in the parental generation and then describe how these components are transmitted to the offspring generation and shape their long-run outcomes.

[5] After constructing the family quartets, we retain families with incomplete education or child-outcome information: education may be missing for some family members, and child outcomes may be missing in some years. Consequently, the number of observations differs across variables and outcomes in Table 1. Estimation for each gradient uses the available non-missing observations for the education variables and child outcome measure entering that gradient.

[6] The cross-sibling correlation is used in Section 3 to separate individual-specific variation correlated with education from non-parental influences shared within the family.

3.1 Parental Generation

Families consist of four members: father (F), mother (M), and the first two children (C_1 and C_2). Let s_{Pj} denote the years of education of parent $P \in \{F, M\}$ in family j. Education is modeled as the sum of four orthogonal latent components, each with a zero mean:

$$s_{Pj} = \gamma_{Aj} + \gamma_{Pj} + \mu_j + a_{Pj} \tag{1}$$

The components γ_{Aj} and γ_{Pj} represent the factors transmitted across generations. The first term, γ_{Aj}, captures traits shared between parents which are jointly transmitted to their children. These may include shared skills, resources, or preferences, for example, attitudes toward education, parenting styles, or work ethic, and capture the margin through which assortative mating can concentrate transmissible characteristics within families. The second term, γ_{Pj}, reflects attributes transmitted individually by each parent P, for example, personal abilities or behavioral traits, which are not shared with the co-parent.

The remaining terms represent components that are not transmitted to the next generation. The term μ_j, which accounts for the intragenerational component of assortative mating, captures characteristics that parents share but do not transmit (e.g., specific shared interests or habits without intergenerational spillover). Finally, the term a_{Pj} captures parent-specific factors that are neither shared nor transmitted, for example, idiosyncratic ability or shocks.

3.2 Offspring Generation

For the offspring generation, let s_{kj} denote the years of education of child $k \in \{C_1, C_2\}$ in family j. We model this as:

$$s_{kj} = \gamma_{Aj} + \gamma_{Mj} + \gamma_{Fj} + \theta_j + a_{kj} \tag{2}$$

As in the parental generation, education is expressed as the sum of orthogonal, zero-mean latent components. The terms γ_{Aj}, γ_{Mj}, and γ_{Fj} represent factors transmitted across generations:

γ_{Aj} captures shared traits jointly transmitted by both parents, while γ_{Mj} and γ_{Fj} reflect parent-specific factors transmitted independently by the mother and the father, respectively. The remaining components are not transmitted by parents: θ_j captures sibling-shared environmental factors, such as common school or neighborhood environments, and a_{kj} reflects child-specific factors, including individual ability and idiosyncratic shocks.[7]

For offspring long-run economic outcomes, let y_{kjt} denote the outcome for child k in family j at age t. As described in Section 2, we compute annual percentiles of these outcomes and average them over time to isolate the permanent component. Let p_{kj} denote this average percentile, which we model as:

$$p_{kj} = \delta_{Aj} + \delta_{Mj} + \delta_{Fj} + \phi_j + b_{kj} \tag{3}$$

Each term in Equation (3) mirrors the structure in the education model: δ_{Aj} captures jointly transmitted parental factors, δ_{Mj} and δ_{Fj} represent parent-specific transmission, ϕ_j captures sibling-shared influences independent of parental factors, and b_{kj} reflects idiosyncratic factors.

3.3 Estimation

We assume that each of the zero-mean latent factors in Equations (1) to (3) has variance σ_s^2, where $s \in \{\gamma_A, \gamma_F, \gamma_M, \mu, \theta, a, \delta_A, \delta_F, \delta_M, \phi, b\}$. While the latent factors are orthogonal within each equation, we allow for cross-equation correlations between similar components, reflecting common underlying influences across education and long-term outcomes. For example, the idiosyncratic components of education (a_{kj}) and economic outcomes (b_{kj}) are allowed to be correlated, with parameter σ_{ab}. Similarly, the intergenerational factors for education (γ_{Aj}, γ_{Mj}, and γ_{Fj}) and outcomes (δ_{Aj}, δ_{Mj}, δ_{Fj}) are allowed to be correlated, with parameter $\sigma_{\gamma\delta X}$ (for $X = A, M, F$). Additionally, sibling-specific factors in education (θ_j) and outcomes (ϕ_j) may also be correlated, with the parameter $\sigma_{\theta\phi}$.

We estimate the contributions of these factors to education–outcome gradients, distinguishing

[7] The assumption that sibling-shared factors are orthogonal to those transmitted by parents implies no family sorting across neighborhoods or schools. Bingley et al. (2021) show that this restriction may overstate the role of sibling-shared influences.

among intergenerational, sibling, and own-education gradients. The intergenerational gradients identify the parental-transmission margin, while the sibling and own gradients add the non-parental shared and individual-specific components. The model parameters are estimated using an Equally Weighted Minimum Distance estimator, matching the observed correlations in education and economic outcomes to their model-implied counterparts, and using the inverse sample variances of the moments to correct standard errors post-estimation. Because our empirical analysis focuses on gradients, we only discuss identification and estimate parameters that contribute to the gradients and not other parameters of the model. Since we match empirical correlations, gradients are expressed as correlations and the estimated parameters can be interpreted as contributions to correlations, rather than as components of variances or covariances.

3.4 Moment Restrictions – Education Gradients

The intergenerational gradients, which measure the correlations between parental education and child outcomes, capture the factors transmitted jointly ($\sigma_{\gamma\delta A}$), and parent-specific factors ($\sigma_{\gamma\delta F}, \sigma_{\gamma\delta M}$). For fathers, the education–outcome (EO) gradient is:

$$\rho_{FC}^{EO} = \sigma_{\gamma\delta A} + \sigma_{\gamma\delta F}, \tag{4}$$

and for mothers, the gradient is:

$$\rho_{MC}^{EO} = \sigma_{\gamma\delta A} + \sigma_{\gamma\delta M}. \tag{5}$$

The sibling education–outcome gradient, ρ_{CC}^{EO}, which measures the correlation between one sibling's education and the other sibling's outcome is:

$$\rho_{CC}^{EO} = \sigma_{\gamma\delta A} + \sigma_{\gamma\delta F} + \sigma_{\gamma\delta M} + \sigma_{\theta\phi}. \tag{6}$$

This gradient depends on the parental transmission components ($\sigma_{\gamma\delta A}, \sigma_{\gamma\delta F}, \sigma_{\gamma\delta M}$) and on sibling-specific factors ($\sigma_{\theta\phi}$), which capture non-parental influences shared by siblings. Equation (6) then isolates the sibling-specific component, $\sigma_{\theta\phi}$, by netting out the parental transmission terms identified by ρ_{FC}^{EO} in Equation (4), and ρ_{MC}^{EO} in Equation (5), from the sibling correlation ρ_{CC}^{EO}.

Finally, the own education–outcome gradient, denoted ρ^{EO}, is:

$$\rho^{EO} = \sigma_{\gamma\delta A} + \sigma_{\gamma\delta F} + \sigma_{\gamma\delta M} + \sigma_{\theta\phi} + \sigma_{ab}, \tag{7}$$

reflecting parental factors $(\sigma_{\gamma\delta A}, \sigma_{\gamma\delta F}, \sigma_{\gamma\delta M})$, sibling-specific factors $(\sigma_{\theta\phi})$, and the correlation between idiosyncratic factors in education and long-term outcomes (σ_{ab}). Given the components identified from Equations (4)–(6), Equation (7) then identifies σ_{ab} as the residual component unique to the own education–outcome correlation, capturing individual-specific variation correlated with education.

Equations (4)–(7) provide the set of moments needed for the analysis of education gradients. These gradients depend on five parameters, but we only have four moment restrictions, so an additional restriction is required for identification. We achieve identification by normalizing the independent sibling-shared component $(\sigma_{\theta\phi})$ to zero for mixed-gender sibling pairs, such that for these pairs the gradient becomes:

$$\rho_{CC}^{EO} = \sigma_{\gamma\delta A} + \sigma_{\gamma\delta F} + \sigma_{\gamma\delta M}. \tag{6'}$$

Under this normalization, $(\sigma_{\theta\phi})$ identifies the *excess* environmental similarity specific to same-gender pairs relative to mixed-gender pairs (e.g., gender-specific peer effects or role modeling).

The assumption that same-gender siblings share more than mixed-gender pairs is consistent with evidence that sibling spillovers in educational specialization or major choice are often stronger within same-gender pairs than across genders (Dahl et al., 2024), though evidence from postsecondary choice is more mixed (Altmejd et al., 2021). It is also consistent with evidence that children's peer interactions are strongly gender-segregated (Martin and Fabes, 2001). Some studies further suggests that the salience and consequences of parental differential treatment vary with sibling gender composition (Jensen et al., 2013). Nevertheless, to the extent that mixed-gender siblings also share non-parental influences relevant for education–outcome gradients, the baseline normalization attributes those influences to parental transmission. The estimated parental transmission components should therefore be interpreted as upper bounds.[8]

4 Results

We begin by presenting parameter estimates in Section 4.1. Section 4.2 then decomposes the education–outcome gradients, and Section 4.3 reports sensitivity analyses. Section 4.4 compares the decomposition of education–outcome gradients across groups defined by parental educational opportunity, measured by access to middle schools. Finally, Section 4.5 presents additional results on intergenerational and sibling correlations in long-run economic outcomes.

4.1 Parameter Estimates

Table 3 reports the estimated parameters for earnings and disposable income ranks in Columns 1 and 2. For both outcomes, the joint parental component ($\sigma_{\gamma\delta A}$) is large and statistically significant, while the parent-specific components ($\sigma_{\gamma\delta F}$ and $\sigma_{\gamma\delta M}$) are close to zero. The correlation between individual-specific determinants of education and labor market outcomes (σ_{ab}) is also sizeable, indicating that the education–earnings and education–income gradients combine jointly transmitted parental factors with individual-specific heterogeneity.

Columns 3 and 4 of Table 3 show a different pattern for financial outcomes. For assets and wealth, the combined parent-specific components account for most of the transmitted part of the gradient, while the jointly transmitted component is comparatively small. This pattern indicates that the financial-outcome gradients reflect less joint transmission of traits shared within the family and more parent-specific behaviors and resources, for example, saving choices, and separate inheritances or gifts. The correlation between individual-specific determinants of education and outcomes (σ_{ab})

[8] In Section 4.3, we assess the sensitivity of the results by calibrating the mixed-gender sibling-shared component to one-half of the corresponding same-gender estimate. This calibration lies between the baseline normalization, in which the mixed-gender component is zero, and the case in which the mixed-gender and same-gender components are equal.

is also much weaker for financial outcomes, implying that the individual-specific determinants of educational attainment are only weakly related to the determinants of asset and wealth accumulation.

Finally, we estimate the parameter $\sigma_{\theta\phi}$, which captures the correlation between sibling-shared non-parental factors in education and outcomes. This correlation is statistically significant for earnings, income, and assets but not for wealth. The estimates are modest in magnitude, suggesting that non-parental influences shared by siblings, for example, schools, neighborhoods, or community environments, contribute less to the observed education–outcome associations than parental transmission.

4.2 Decomposition of Education–Outcome Gradients

Using the estimated parameters, we decompose education–outcome gradients in Table 4. We begin with the own-education gradient, which links an individual's schooling to their own outcomes, and then turn to the intergenerational education gradient, which links parental schooling to children's economic outcomes.[9]

Figure 1 examines own-education gradients (own education–own outcome correlations). The composition of these gradients differs markedly across outcome domains. The labor market gradients contain substantial jointly transmitted and individual-specific components, while the financial gradients are dominated by father- and mother-specific components.

For earnings and disposable income, jointly transmitted parental factors account for a substantial share of the gradient, consistent with assortative mating concentrating family-level advantages that are correlated with both schooling and labor market success (e.g., Ermisch et al., 2006; Eika et al., 2019). Individual-specific factors correlated with education also explain a large proportion, indicating that both family-related transmission and individual heterogeneity contribute to the education–earnings and education–income associations.

For assets and wealth, jointly transmitted factors account for only a small proportion of the

[9] Table 4 also reports sibling gradients, which link one sibling's schooling to the other sibling's outcomes. These gradients are included for identification of the full set of parameters underlying the decompositions and for completeness.

financial gradients, while parent-specific transmission accounts for the majority. This pattern is consistent with evidence that bequests, gifts, and financial behaviors are central to wealth transmission (e.g., Boserup et al., 2016; Adermon et al., 2018; Fagereng et al., 2021).

Figure 2 shows the intergenerational education gradients (parental education–child outcome correlations). The intergenerational decompositions mirror the pattern for the own gradients. For earnings and income, these gradients are accounted for primarily by jointly transmitted parental factors. For assets and wealth, the pattern reverses: the intergenerational gradients are accounted for mainly by parent-specific transmission, and the jointly transmitted component is comparatively small.

4.3 Robustness: Alternative Identification of the Sibling-Shared Component

We next assess the sensitivity of the baseline decomposition to the identification of the sibling-shared component. In the baseline specification, the education–outcome correlation attributable to non-parental sibling-shared influences is normalized to zero for mixed-gender sibling pairs, so that same-gender pairs identify the excess sibling-shared component. Table A1 reports a sensitivity analysis that relaxes this normalization by assigning the mixed-gender sibling-shared component an intermediate value, equal to one-half of the corresponding same-gender estimate.

The resulting parameter estimates are very close to the baseline estimates in Table 3. For earnings and income, the jointly transmitted and individual-specific components remain substantial, while parent-specific components remain close to zero. For assets and wealth, the qualitative pattern is also unchanged: the jointly transmitted component remains small relative to the parent-specific components, and the individual-specific component remains modest, especially for wealth. This sensitivity analysis indicates that the main decomposition results are not driven by the particular normalization used to identify the sibling-shared component.

4.4 Own Education–Outcome Gradients by Parental Educational Opportunity

We extend the gradient analysis using variation in educational opportunities associated with a 1937 school reform that expanded access to eighth and ninth grades in the parental generation. We use this variation to ask whether the composition of children's own education–outcome gradients differs with parental educational opportunity, since similar gradients may still mask different underlying compositions. The reform required municipalities to expand access to middle school, but implementation was gradual and uneven. The pace of implementation varied with local resources, school infrastructure, and administrative capacity, generating substantial heterogeneity in access to post-compulsory schooling across municipalities and across cohorts within the same municipality. Indeed, many municipalities had not fully implemented the reform by 1958, when a second reform mandated universal access.[10]

We partition families according to parental access to middle schools. Using linked register information on each parent's parish and year of birth, we measure distance to the nearest middle school when the mother and the father were 14, the typical age of entry into eighth grade.[11] We then construct a family-level access measure by averaging the two parental distances. Families whose average parental distance is below the median of all parental distances are classified as higher-access families, while families whose average parental distance is above the median are classified as lower-access families. Because eighth- and ninth-grade provision expanded gradually across middle schools over time, the variation comes not only from differences across locations, but also from changes in grade availability across cohorts within location. We interpret the resulting comparison descriptively, as heterogeneity across parental educational-opportunity groups rather than as the causal effect of the reform. We then estimate the baseline model separately on the

[10] Individuals born before August 1957 faced 7 years of compulsory schooling. A 1972 reform made those born on or after August 1957 formally subject to 9 years of schooling. The 1972 reform essentially codified the fact that almost all cohorts born from the mid-1950s onward were already enrolled in 8th grade and often 9th grade. See Arendt et al. (2021) for an analysis of the effects of maternal schooling on child health using this compulsory schooling reform as an instrument.

[11] Since addresses were only registered from 1968, we assume the parents resided in their parish of birth until age 14.

two resulting family-level partitions of the data. The corresponding parameter estimates are used to decompose the children's own education–outcome gradients within higher- and lower-access families, allowing the full decomposition to differ across groups.[12]

Table 5 and Figure 3 report predicted own education–outcome gradients, defined as correlations between own education and own outcomes, and their decomposition by parental access to middle schools. We find contrasting patterns for labor market and financial outcomes. Earnings and income gradients are very similar across access groups, and their decomposition is also generally unchanged: in both higher- and lower-access families, these gradients are split evenly between the jointly transmitted parental component and individual-specific factors, with small contributions from parent-specific transmission and non-parental shared influences within the family.

Assets and wealth display substantial heterogeneity in their decomposition across access groups. For wealth, jointly transmitted parental factors account for a large proportion of the gradient in higher-access families, while father- and mother-specific transmission contribute less. In lower-access families, by contrast, the jointly transmitted component is negligible and parent-specific transmission dominates. A similar, though more moderate, pattern emerges for assets: higher-access families exhibit a substantial jointly transmitted component, whereas the lower-access decomposition attributes most of the education–asset gradient to parent-specific transmission.

One possible interpretation of these contrasting patterns is that when access to post-compulsory schooling was limited, additional schooling may have been more selective with respect to parent-specific resources that also predicted children's later asset and wealth accumulation. As access to middle school broadened, education may have become more closely associated with inputs shared by both parents, consistent with the larger jointly transmitted component in financial gradients among higher-access families.

Our access-based decomposition is also robust to using alternative thresholds to define parental access to middle schools. Tables A2 and A3 reproduce the analysis by defining higher-access

[12]Parental access to middle schools is associated with higher parental schooling. Average years of education are 12.2 for fathers and 11.2 for mothers in higher-access families, compared with 11.5 for fathers and 10.5 for mothers in lower-access families.

families as those whose average parental distance to the nearest middle school is below the 40th or 60th percentile of all parental distances. The qualitative pattern is unchanged.

4.5 Additional Results: Decomposing Intergenerational and Sibling Correlations

While our main analysis focuses on education gradients, the empirical mobility literature often summarizes persistence using intergenerational correlations (IGCs) and sibling correlations in long-run economic outcomes (e.g., Solon, 1999; Björklund and Jäntti, 2012; Mazumder, 2008). Decomposing these conventional measures is useful because they capture persistence directly in outcomes and therefore reflect transmissible family influences that may not be fully summarized by parental education alone. We view the results in this section as supplementary and more model-dependent than the baseline education-gradient decompositions, since identification of the parameters governing outcome persistence requires an extra parametric restriction.

The sibling correlation in long-run outcomes, denoted ρ_{CC}^{OO}, is the correlation between one sibling's outcome and the other sibling's outcome. Implied by Equation (3), the sibling outcome correlation is given by the sum of four components:

$$\rho_{CC}^{OO} = \sigma_{\delta A}^2 + \sigma_{\delta F}^2 + \sigma_{\delta M}^2 + \sigma_{\phi}^2, \tag{8}$$

where $\sigma_{\delta A}^2$ captures jointly transmitted parental factors, $\sigma_{\delta F}^2$ and $\sigma_{\delta M}^2$ capture father- and mother-specific transmission, and σ_{ϕ}^2 captures non-parental shared influences within the family. While the non-parental shared component (σ_{ϕ}^2) can be identified using variation in sibling gender composition, the three parental transmitted components in long-run outcomes ($\sigma_{\delta A}^2, \sigma_{\delta F}^2, \sigma_{\delta M}^2$) cannot be separately recovered without an additional restriction.

To proceed, we impose a proportionality restriction linking the transmitted components of long-run outcomes to the corresponding education–outcome cross-moments. Specifically, for each transmission component, we assume that the variance contribution in long-run outcomes is proportional to the corresponding education–outcome covariance:

$$\sigma^2_{\delta A} = \lambda\sigma_{\gamma\delta A}, \quad \sigma^2_{\delta F} = \lambda\sigma_{\gamma\delta F}, \quad \sigma^2_{\delta M} = \lambda\sigma_{\gamma\delta M}, \tag{9}$$

where λ is a proportionality parameter that is common across the jointly transmitted, father-specific, and mother-specific components within a given outcome, but allowed to vary across outcomes. The proportionality parameter is then identified using the sibling-correlation moment of Equation (8).

The proportionality restriction of Equation (9) implies that, within a given outcome, the relative size of the joint and parent-specific components in outcome persistence mirrors their relative size in the education–outcome associations. The components may differ in the amount of transmitted advantage they carry, but not in the rate at which this advantage is converted into long-run outcomes, since the same λ applies to all transmitted components within an outcome.

Conditional on this assumption, we can recover the implied intergenerational correlations in long-run outcomes as the sum of the jointly transmitted component and the relevant parent-specific component:

$$\rho^{OO}_{FC} = \sigma^2_{\delta A} + \sigma^2_{\delta F}, \qquad \rho^{OO}_{MC} = \sigma^2_{\delta A} + \sigma^2_{\delta M}. \tag{10}$$

Table 6 reports the predicted correlations and the resulting decompositions. Predicted intergenerational correlations are larger for earnings and income than for assets and wealth, while sibling correlations are larger still and remain sizeable across all outcomes. The estimated proportionality parameter is higher for financial outcomes than for labor market outcomes, suggesting a stronger mapping from transmitted advantage into persistence in assets and wealth than in earnings and income in our setting.

The decomposition reveals a clear contrast across domains that mirrors the results of the education-gradient analysis. For earnings and income, persistence is driven predominantly by jointly transmitted parental factors, accounting for roughly three-quarters of the sibling correlation, whereas parent-specific components are small. By contrast, for assets and wealth, parent-specific transmission becomes much more important. In the intergenerational correlations (Figure 4), the parent-specific share exceeds two-thirds for assets and wealth, and in the sibling correlations (Figure 5) the combined contribution of father- and mother-specific components dominates the jointly transmitted component. Non-parental shared influences within the family (σ_{ϕ}^2) account for a substantial proportion of sibling persistence in earnings and income, but a considerably smaller proportion in assets and wealth.

Overall, these findings are closely aligned with the baseline education-gradient decompositions: labor-income persistence is associated primarily with jointly transmitted parental factors, whereas for the transmission of assets and wealth, parent-specific factors are more important. The similarity between these patterns and those obtained from the education-gradient analysis is consistent with the conclusion that the mechanisms underlying persistence differ systematically between labor market and financial domains.

Two caveats are important. First, the proportionality restriction of Equation (9) is not directly testable in our setting. Because parental long-run outcomes are not observed at comparable life-cycle stages to those of their offspring, the transmitted components of outcome persistence cannot be separately identified from the available moments without this proportionality restriction. Second, the restriction may be more demanding for wealth than for labor market outcomes if joint and parent-specific factors operate through qualitatively different mechanisms. For this reason, the decompositions reported in this section should be interpreted as suggestive and model-dependent. Nevertheless, the broad contrast they imply between labor market and financial outcomes is consistent with the main evidence from the education-gradient analysis.

5 Conclusion

Education–outcome gradients that appear similar in magnitude can reflect very different underlying mixes of family transmission. Using Danish administrative data on family quartets, we decompose education–outcome gradients for long-run earnings, disposable income, assets, and wealth into jointly transmitted parental factors, separately transmitted parent-specific factors, non-parental shared influences within the family, and individual-specific variation. Our main contribution is not only to decompose these gradients, but to show that their composition differs systematically across economic domains and with parental educational opportunity.

For earnings and disposable income, jointly transmitted parental factors account for a substantial proportion of the own education–outcome gradients, consistent with educational assortative mating concentrating family-level advantages that contribute to labor market success. At the same time, the own-education gradients for these outcomes contain a substantial individual-specific component, indicating that both family transmission and individual heterogeneity contribute to observed education–earnings and education–income associations. For assets and wealth, the balance shifts. Parent-specific components account for most of the association, consistent with financial outcomes reflecting more parent-specific behaviors and resources, for example, transfer decisions and financial choices, than the jointly transmitted factors that dominate labor market gradients.

Using variation in the availability of middle schools associated with the gradual implementation of a schooling reform, we also compare the decomposition of education–outcome gradients across groups defined by parental educational opportunity. Earnings and income gradients are similar in both magnitude and composition across access groups. For assets and wealth, by contrast, higher-access families exhibit a larger jointly transmitted component and smaller parent-specific components than lower-access families. We interpret these findings descriptively, as heterogeneity across schooling environments rather than as causal effects of the reform.

Our findings inform how education gradients should be interpreted and which policy levers are likely to matter across domains. For labor market outcomes, where education gradients reflect an important jointly transmitted component alongside individual-specific determinants, persistence in earnings and income is likely to depend in part on educational sorting and family-level resources. For assets and wealth, where parent-specific transmission is more prominent, persistence appears more closely tied to intergenerational transfers. Although these mechanisms are not separately identified by the decomposition, policies that act on gifts and bequests may therefore be especially relevant for shaping persistence in the financial domain.

Future research could apply our framework to other schooling policy changes, as well as to policy changes in inheritance taxation and saving incentives. Such applications could show whether interventions alter the composition of education–outcome gradients by weakening parent-specific financial transmission, amplifying jointly transmitted family advantages, or shifting the role of individual-specific components.

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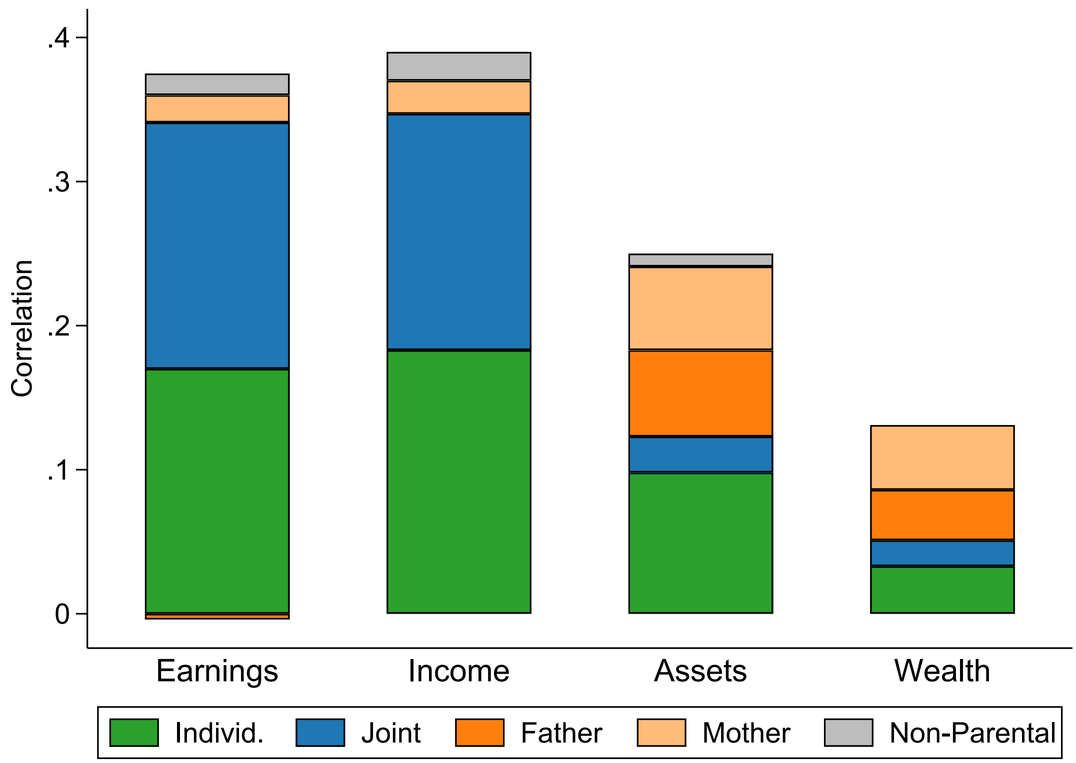
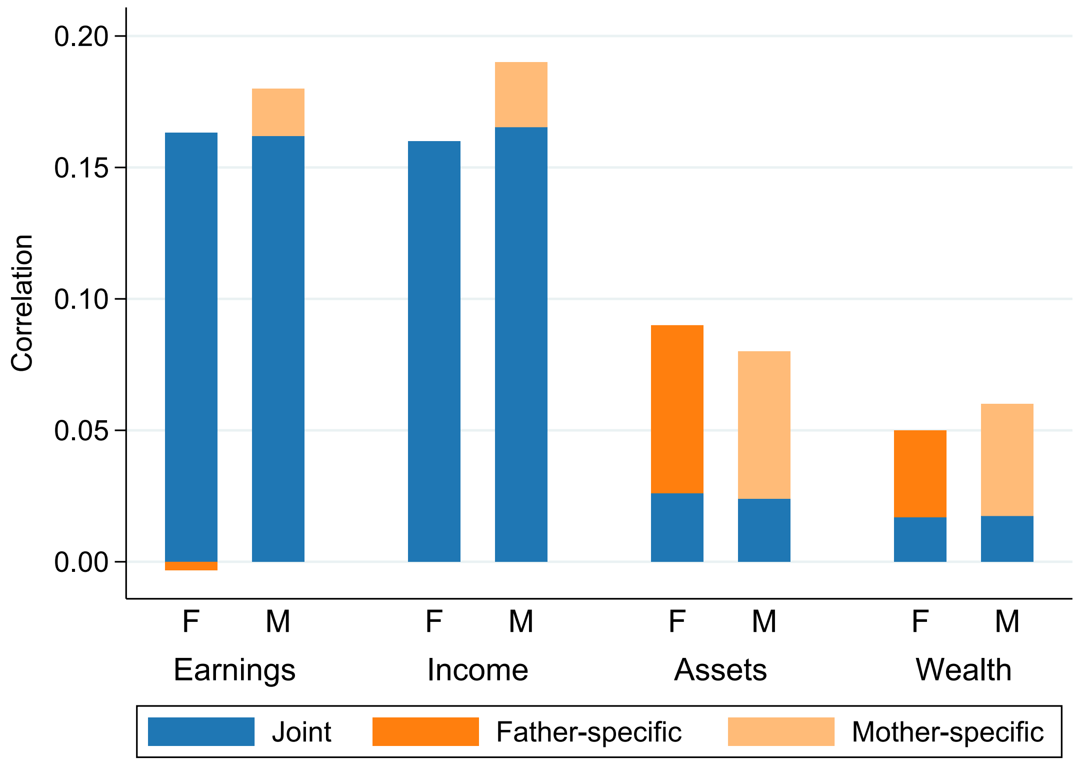
Figures

Figure 1: Estimated Decompositions of Own Education–Outcome Gradients



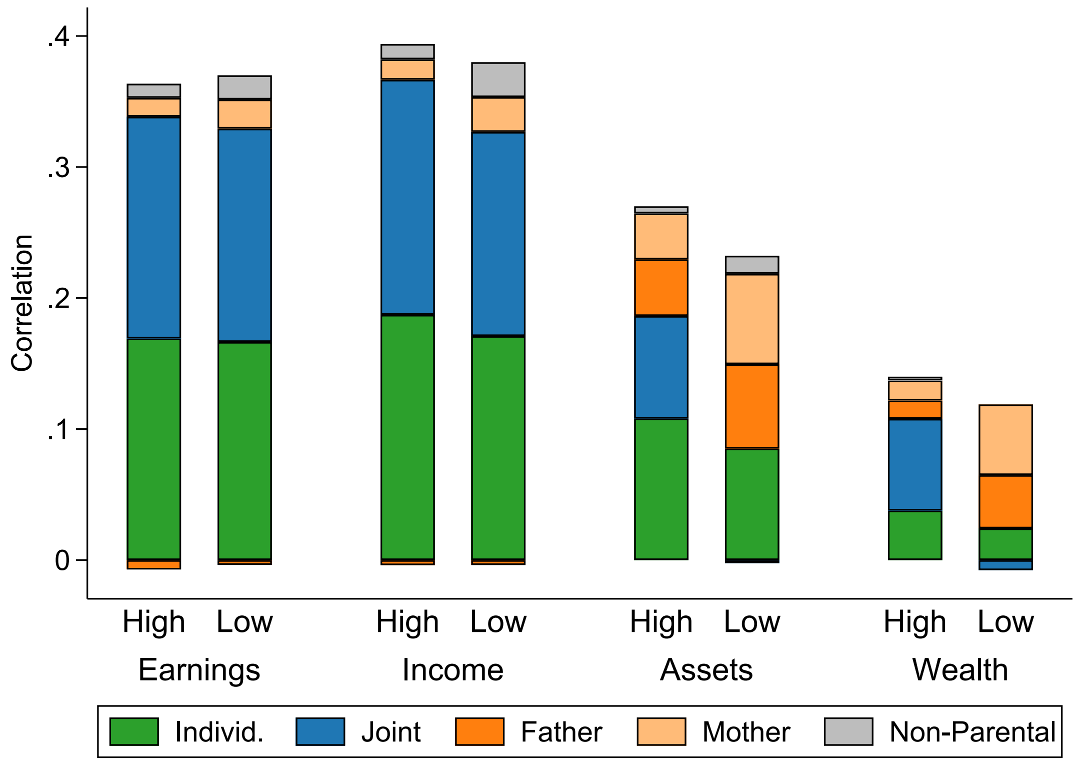
Note: The figure presents the decomposition of own education–outcome gradients in earnings, income, assets, and wealth into transmission components. Levels, proportions, and standard errors are presented in the upper panel of Table 4.

Figure 2: Estimated Decompositions of Intergenerational Education Gradients



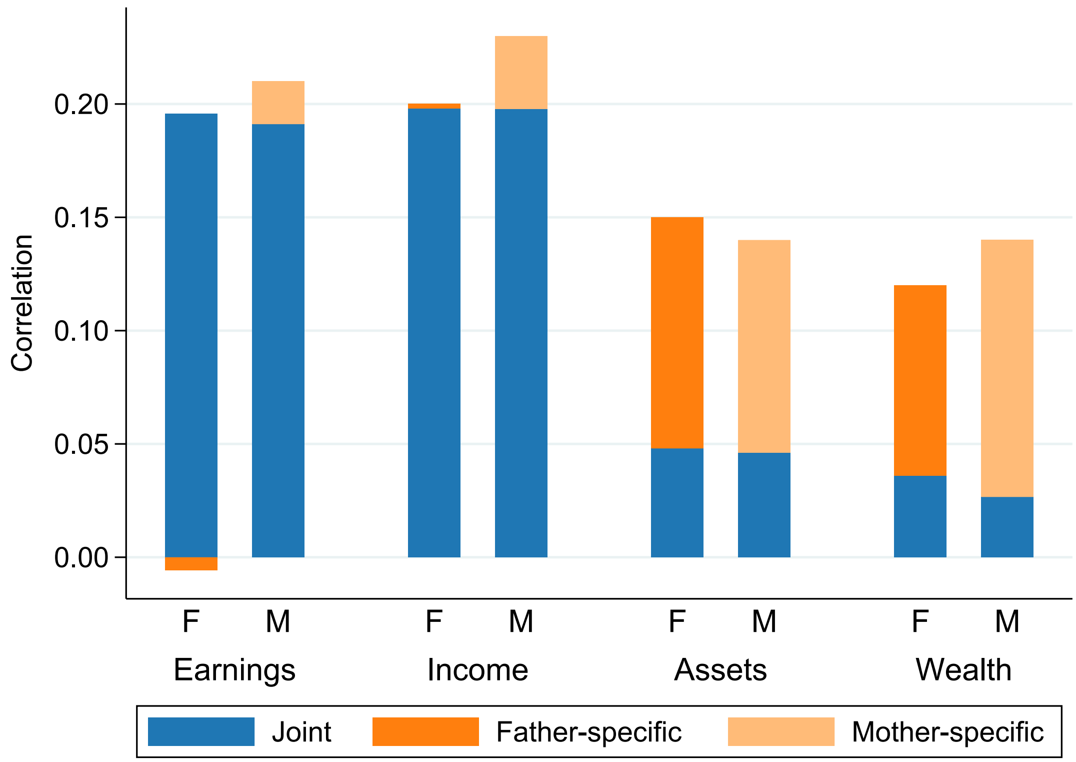
Note: The figure presents the decomposition of intergenerational education gradients, defined as correlations between parental education and child outcomes, separately for mothers and fathers. The corresponding levels, proportions, and standard errors are reported in the middle panel of Table 4.

Figure 3: Own Education–Outcome Gradient Decompositions by Parental Access to Middle School



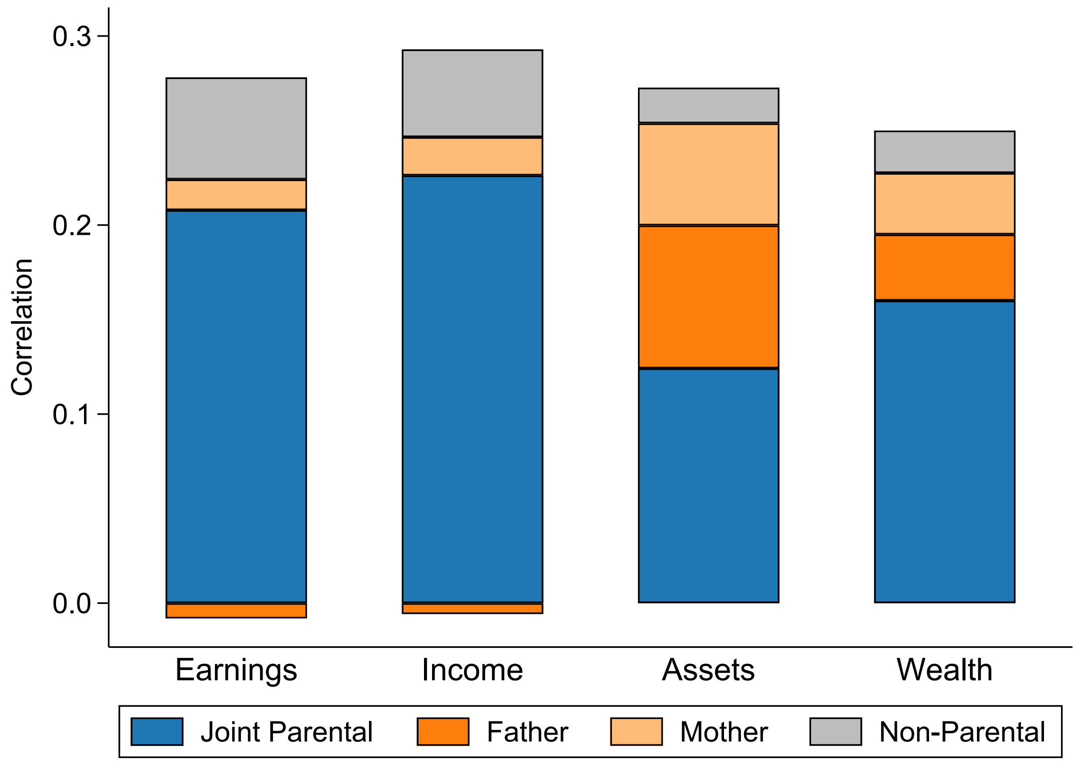
Note: The figure presents the decomposition of predicted children's own education–outcome gradients in earnings, income, assets, and wealth into: (i) individual-specific factors, (ii) jointly transmitted parental factors, (iii) father-specific transmission, (iv) mother-specific transmission, and (v) non-parental shared influences within the family. The figure splits the sample by parental access to middle schools. For each parent, access is measured by distance at age 14 to the nearest middle school offering eighth and ninth grades. The average parental distance is computed by averaging the mother's and father's distances within the family. Higher-access families (High) are those whose average parental distance is below the median of all parental distances; lower-access families (Low) are those whose average parental distance is above that median. Levels, proportions, and standard errors are reported in Table 5.

Figure 4: Estimated Decompositions of Intergenerational Outcome Correlations



Note: The figure presents the decomposition of intergenerational outcome correlations, defined as correlations between parental outcomes and child outcomes, in long-run earnings, disposable income, assets, and wealth. Decompositions are shown separately for fathers (F) and mothers (M) and distinguish jointly transmitted parental factors from the relevant parent-specific component. Levels, proportions, and standard errors are reported in the top panel of Table 6.

Figure 5: Estimated Decompositions of Sibling Outcome Correlations



Note: The figure presents the decomposition of sibling outcome correlations, defined as correlations between one sibling's long-run outcome and the other sibling's long-run outcome, in earnings, disposable income, assets, and wealth. Decompositions distinguish jointly transmitted parental factors, father-specific transmission, mother-specific transmission, and non-parental shared influences within the family. Levels, proportions, and standard errors are reported in the bottom panel of Table 6.

Tables

Table 1: Descriptive Statistics.

	Mean	SD	Obs.
A. Demographics			
Year of birth			
Father	1940.8	3.73	122,532
Mother	1942.9	3.79	122,532
Child 1	1965.4	3.35	122,532
Child 2	1968.7	3.29	122,532
Years of education			
Father	11.9	3.15	120,939
Mother	10.9	3.12	121,397
Children	13.4	2.30	243,564
B. Outcomes (ages 31–45)			
Labor earnings	385.7	233.4	3,051,808
Disposable income	254.7	205.2	3,465,458
Assets	896.1	1812.7	3,465,663
Wealth	200.4	1242.4	3,465,579

Notes: The table reports means, standard deviations, and the number of observations for parents and children in the estimation sample. After constructing family quartets, we retain families with incomplete education or child-outcome information: education may be missing for some family members, and child outcomes may be missing in some years. Consequently, the number of observations differs across variables and outcomes. Labor earnings, disposable income, assets, and wealth are measured in thousands of Danish kroner (DKK) in 2018 prices and averaged over ages 31–45 after winsorizing the top and bottom 0.5 percent by year.

Table 2: Empirical Education-Outcome Correlations.

	Earnings	Income	Assets	Wealth
Own education–own outcome	0.37	0.39	0.25	0.13
Mother's education–child outcome	0.18	0.19	0.08	0.06
Father's education–child outcome	0.16	0.16	0.09	0.05
Own education–sibling's outcome	0.20	0.21	0.16	0.10

Notes: The table reports sample correlations between education and long-term outcomes. The own education–sibling's outcome correlation is used to separate individual-specific variation correlated with education from non-parental influences shared within the family as discussed in Section 3.

Table 3: Parameter Estimates.

	Earnings		Income		Assets		Wealth	
	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.
$\sigma_{\gamma\delta A}$	0.17	0.01	0.16	0.00	0.03	0.01	0.02	0.00
$\sigma_{\gamma\delta F}$	0.00	0.00	0.00	0.00	0.06	0.01	0.03	0.00
$\sigma_{\gamma\delta M}$	0.02	0.00	0.02	0.00	0.06	0.01	0.04	0.00
$\sigma_{\theta\phi}$	0.02	0.01	0.02	0.01	0.01	0.01	0.00	0.01
σ_{ab}	0.17	0.01	0.18	0.00	0.10	0.00	0.03	0.01

Notes: The table reports estimated model parameters for each outcome and their standard errors. The parameters describe how education–outcome gradients are related to jointly transmitted parental factors, parent-specific transmission, sibling-shared non-parental influences, and the correlation between individual-specific determinants of education and outcomes.

Table 4: Decompositions of Predicted Education-Outcome Gradients.

	Earnings		Income		Assets		Wealth	
	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.
Own education-outcome gradients (own education-own outcome)	0.37	0.00	0.39	0.00	0.25	0.00	0.13	0.00
Proportion due to individual specific factors	0.46	0.01	0.47	0.01	0.39	0.02	0.25	0.04
Proportion due to joint parental transmission	0.46	0.02	0.42	0.01	0.10	0.02	0.14	0.04
Proportion due to father-specific transmission	-0.01	0.01	-0.00	0.01	0.24	0.02	0.27	0.03
Proportion due to mother-specific transmission	0.05	0.01	0.06	0.01	0.23	0.02	0.34	0.04
Proportion due to sibling-shared non-parental factors	0.04	0.02	0.05	0.00	0.04	0.02	0.01	0.05
Intergenerational gradients (parent education-child outcome)								
Father education-child outcome gradient	0.16	0.00	0.16	0.00	0.09	0.00	0.05	0.00
Proportion due to joint parental transmission	1.00	0.03	1.00	0.03	0.29	0.06	0.34	0.09
Proportion due to father-specific transmission	0.00	0.03	0.00	0.03	0.71	0.06	0.66	0.09
Mother education–child outcome gradient	0.18	0.00	0.19	0.00	0.08	0.00	0.06	0.00
Proportion due to joint parental transmission	0.90	0.03	0.87	0.02	0.30	0.06	0.29	0.08
Proportion due to mother-specific transmission	0.10	0.03	0.13	0.02	0.70	0.06	0.71	0.08
Sibling gradients (one sibling's education-other sibling's outcome)	0.20	0.00	0.21	0.00	0.16	0.00	0.10	0.00
Proportion due to jointly transmitted factors	0.85	0.03	0.79	0.03	0.16	0.04	0.18	0.05
Proportion due to father-specific factors	-0.02	0.02	-0.00	0.02	0.39	0.03	0.36	0.05
Proportion due to mother-specific factors	0.09	0.02	0.12	0.02	0.38	0.03	0.45	0.05
Proportion due to sibling-shared non-parental factors	0.08	0.03	0.09	0.03	0.06	0.04	0.01	0.06

Notes: The table reports predicted education-outcome gradients and their decompositions. The top panel reports own education-outcome gradients, defined as correlations between own education and own outcomes. The middle panel reports intergenerational education gradients, defined as correlations between parental education and child outcomes. The bottom panel reports sibling education–outcome gradients, defined as correlations between one sibling's education and the other sibling's outcome. The sibling gradients are reported because they are used to identify the full set of parameters underlying the decompositions. Own gradients are decomposed into proportions due to individual-specific factors, jointly transmitted parental factors, father-specific transmission, mother-specific transmission, and sibling-shared non-parental factors. Intergenerational gradients are decomposed into the jointly transmitted component and the relevant parent-specific component. Sibling gradients are decomposed into jointly transmitted parental factors, father-specific transmission, mother-specific transmission, and sibling-shared non-parental factors.

Table 5: Decompositions of Predicted Own Education-Outcome Gradients by Parental Access to Middle School.

	Earnings		Income		Assets		Wealth	
	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.
Panel A: Higher Access								
Own education-outcome gradients (own education-own outcome)	0.36	0.00	0.39	0.00	0.27	0.00	0.14	0.00
Proportion due to individual-specific factors	0.47	0.02	0.48	0.02	0.40	0.02	0.27	0.05
Proportion due to jointly transmitted parental factors	0.47	0.02	0.46	0.02	0.29	0.03	0.50	0.05
Proportion due to father-specific transmission	-0.02	0.02	-0.01	0.02	0.16	0.03	0.10	0.04
Proportion due to mother-specific transmission	0.04	0.02	0.04	0.02	0.13	0.03	0.11	0.04
Proportion due to non-parental shared influences within the family	0.03	0.03	0.03	0.02	0.02	0.03	0.02	0.06
Panel B: Lower Access								
Own education-outcome gradients (own education-own outcome)	0.37	0.00	0.38	0.00	0.23	0.00	0.11	0.00
Proportion due to individual-specific factors	0.45	0.02	0.45	0.02	0.37	0.03	0.22	0.05
Proportion due to jointly transmitted parental factors	0.44	0.02	0.41	0.02	-0.01	0.03	-0.07	0.06
Proportion due to father-specific transmission	-0.01	0.02	-0.01	0.02	0.28	0.03	0.37	0.05
Proportion due to mother-specific transmission	0.06	0.02	0.07	0.02	0.30	0.03	0.49	0.05
Proportion due to non-parental shared influences within the family	0.05	0.02	0.07	0.02	0.06	0.04	-0.00	0.06

Notes: The table reports predicted children's own education–outcome gradients, defined as correlations between own education and own outcomes, and their decomposition into: (i) individual-specific factors, (ii) jointly transmitted parental factors, (iii) father-specific transmission, (iv) mother-specific transmission, and (v) non-parental shared influences within the family. Panels split the sample by parental access to middle schools. For each parent, access is measured by distance at age 14 to the nearest middle school offering eighth and ninth grades. The average parental distance is computed by averaging the mother's and father's distances within the family. Higher-access families are those whose average parental distance is below the median of all parental distances; lower-access families are those whose average parental distance is above that median.

Table 6: Decompositions of Predicted Intergenerational and Sibling Correlations.

	Earnings		Income		Assets		Wealth	
	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.
Intergenerational correlations (parent outcome-child outcome)								
Father–child correlation	0.19	0.01	0.20	0.01	0.15	0.01	0.12	0.01
Proportion due to joint parental transmission	1.00	0.02	0.99	0.02	0.32	0.04	0.30	0.07
Proportion due to father-specific transmission	0.00	0.02	0.01	0.02	0.68	0.04	0.70	0.07
Mother–child correlation	0.21	0.01	0.23	0.01	0.14	0.01	0.14	0.01
Proportion due to joint parental transmission	0.91	0.02	0.86	0.02	0.33	0.04	0.19	0.06
Proportion due to mother-specific transmission	0.09	0.02	0.14	0.02	0.67	0.04	0.81	0.06
Sibling correlations (one sibling's outcome-other sibling's outcome)	0.27	0.01	0.29	0.01	0.27	0.01	0.25	0.01
Proportion due to jointly transmitted factors	0.77	0.07	0.78	0.05	0.46	0.07	0.64	0.09
Proportion due to father-specific factors	-0.03	0.04	-0.02	0.03	0.28	0.04	0.14	0.06
Proportion due to mother-specific factors	0.06	0.03	0.07	0.02	0.20	0.04	0.13	0.05
Proportion due to non-parental shared influences within the family	0.20	0.03	0.16	0.02	0.07	0.03	0.09	0.03

Notes: The table reports predicted intergenerational outcome correlations and sibling outcome correlations in long-run earnings, disposable income, assets, and wealth, together with their decompositions. Intergenerational outcome correlations are defined as correlations between parental outcomes and child outcomes and are reported separately for fathers and mothers. Sibling outcome correlations are defined as correlations between one sibling's long-run outcome and the other sibling's long-run outcome. Father–child and mother–child correlations are decomposed into jointly transmitted parental factors and the relevant parent-specific component. Sibling correlations are decomposed into jointly transmitted parental factors, father-specific transmission, mother-specific transmission, and non-parental influences shared within the family. The decompositions use the proportionality restriction described in Section 4.5.

Appendix

Table A1: Parameter Estimates – Sensitivity to Identification Assumption.

	Earnings		Income		Assets		Wealth	
	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.
$\sigma_{\gamma\delta A}$	0.17	0.00	0.17	0.00	0.03	0.01	0.02	0.01
$\sigma_{\gamma\delta F}$	0.00	0.00	0.00	0.00	0.05	0.01	0.03	0.01
$\sigma_{\gamma\delta M}$	0.00	0.00	0.00	0.00	0.05	0.01	0.04	0.00
$\sigma_{\theta\phi}$	0.02	0.01	0.03	0.00	0.02	0.01	0.00	0.01
σ_{ab}	0.17	0.00	0.18	0.00	0.10	0.01	0.03	0.01

Notes: The table reports parameter estimates for each outcome under the alternative calibration of the sibling-shared non-parental component. The mixed-gender sibling-shared component $\sigma_{\theta\phi}$ is set to one-half of the corresponding same-gender component, rather than normalized to zero as in the baseline specification.

Table A2: Decompositions of Predicted Own Education-Outcome Gradients by Parental Access to Middle School (4th decile).

	Earnings		Income		Assets		Wealth	
	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.
Panel A: Higher Access								
Own education-outcome gradients (own education-own outcome)	0.37	0.00	0.39	0.00	0.28	0.00	0.14	0.00
Proportion due to individual-specific factors	0.49	0.02	0.49	0.02	0.40	0.03	0.31	0.06
Proportion due to jointly transmitted parental factors	0.47	0.02	0.46	0.02	0.31	0.03	0.54	0.06
Proportion due to father-specific transmission	-0.01	0.02	-0.01	0.02	0.15	0.03	0.07	0.06
Proportion due to mother-specific transmission	0.05	0.01	0.05	0.02	0.11	0.03	0.08	0.06
Proportion due to non-parental shared influences within the family	0.04	0.02	0.02	0.02	0.03	0.03	-0.01	0.07
Panel B: Lower Access								
Own education-outcome gradients (own education-own outcome)	0.36	0.00	0.38	0.00	0.24	0.00	0.12	0.00
Proportion due to individual-specific factors	0.45	0.02	0.45	0.02	0.38	0.03	0.20	0.05
Proportion due to jointly transmitted parental factors	0.46	0.02	0.42	0.02	0.01	0.03	-0.02	0.06
Proportion due to father-specific transmission	-0.02	0.01	-0.01	0.02	0.28	0.03	0.36	0.05
Proportion due to mother-specific transmission	0.04	0.01	0.06	0.02	0.29	0.03	0.45	0.05
Proportion due to non-parental shared influences within the family	0.06	0.02	0.07	0.02	0.04	0.04	0.01	0.07

Notes: The table reports predicted own education–outcome gradients, defined as correlations between own education and own outcomes, and their decomposition into: (i) individual-specific factors, (ii) jointly transmitted parental factors, (iii) father-specific transmission, (iv) mother-specific transmission, and (v) non-parental shared influences within the family. Panels split the sample by parental access to middle schools. For each parent, access is measured by distance at age 14 to the nearest middle school offering eighth and ninth grades. The average parental distance is computed by averaging the mother's and father's distances within the family. Higher-access families are those whose average parental distance is below the 40th percentile of all parental distances; lower-access families are those whose average parental distance is above that threshold.

Table A3: Decompositions of Predicted Own Education-Outcome Gradients by Parental Access to Middle School (6th decile).

	Earnings		Income		Assets		Wealth	
	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.
Panel A: Higher Access								
Own education-outcome gradients (own education-own outcome)	0.36	0.00	0.39	0.00	0.27	0.00	0.14	0.00
Proportion due to individual-specific factors	0.47	0.02	0.48	0.01	0.39	0.02	0.25	0.04
Proportion due to jointly transmitted parental factors	0.47	0.02	0.42	0.01	0.27	0.02	0.47	0.04
Proportion due to father-specific transmission	-0.01	0.02	-0.00	0.01	0.17	0.02	0.11	0.04
Proportion due to mother-specific transmission	0.04	0.02	0.06	0.01	0.14	0.02	0.13	0.04
Proportion due to non-parental shared influences within the family	0.04	0.02	0.05	0.02	0.03	0.02	0.04	0.05
Panel B: Lower Access								
Own education-outcome gradients (own education-own outcome)	0.38	0.00	0.39	0.00	0.23	0.00	0.11	0.00
Proportion due to individual-specific factors	0.45	0.02	0.45	0.02	0.38	0.03	0.25	0.07
Proportion due to jointly transmitted parental factors	0.42	0.02	0.40	0.02	-0.00	0.04	-0.13	0.07
Proportion due to father-specific transmission	0.00	0.02	-0.01	0.02	0.27	0.03	0.40	0.07
Proportion due to mother-specific transmission	0.07	0.02	0.08	0.02	0.29	0.03	0.54	0.07
Proportion due to non-parental shared influences within the family	0.05	0.02	0.08	0.02	0.06	0.04	-0.06	0.09

Notes: The table reports predicted own education–outcome gradients, defined as correlations between own education and own outcomes, and their decomposition into: (i) individual-specific factors, (ii) jointly transmitted parental factors, (iii) father-specific transmission, (iv) mother-specific transmission, and (v) non-parental shared influences within the family. Panels split the sample by parental access to middle schools. For each parent, access is measured by distance at age 14 to the nearest middle school offering eighth and ninth grades. The average parental distance is computed by averaging the mother's and father's distances within the family. Higher-access families are those whose average parental distance is below the 60th percentile of all parental distances; lower-access families are those whose average parental distance is above that threshold.