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Assortative Mating and Education Gradients within and across Generations

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Abstract

We develop a model that links education–outcome gradients to intergenerational transmission, distinguishing joint from parent-specific channels under assortative mating. Using Danish administrative data on family quartets, we estimate the own education–outcome gradient and, in addition, intergenerational gradients in long-run earnings, disposable income, assets, and wealth. Gradients differ sharply across domains: for earnings and income, joint transmission matters alongside individual-specific heterogeneity; for assets and especially wealth, gradients are dominated by parent-specific channels. Exploiting Danish schooling reforms, we show that the composition of financial gradients varies with access to schooling.

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

Keywords: Assortative mating, Education gradients, Intergenerational mobility.

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1 Introduction

Education–outcome associations are central objects in research and policy debates because they summarize how differences in schooling line up with differences in economic advantage later in life. Individuals with more schooling typically have higher earnings, a relationship routinely documented in Mincer-type earnings regressions and the returns-to-schooling literature (Card, 1999; Heckman et al., 2006). Education is also positively associated with wealth-related outcomes, including higher returns to net worth (Fagereng et al., 2026). At the same time, the observed education-outcome associations compress many mechanisms, including abilities and preferences, parental resources and behaviors, and other aspects of family background, into a single relationship between education and outcomes. A natural question, therefore, is not only how steep education–outcome gradients are but also what they measure, in a way that is directly relevant to inequality and mobility (Black and Devereux, 2011; Mogstad and Torsvik, 2021).

A key part of the answer concerns how family background is transmitted. Parents exhibit positive assortative mating on education and correlated traits (Chadwick and Solon, 2002; Ermisch et al., 2006; Holmlund et al., 2011; Guell et al., 2015), thereby concentrating resources, skills, and preferences within households and shaping what can be transmitted to children. With rising educational assortative mating and widening inequality, this concentration mechanism has become increasingly important (Greenwood et al., 2014; Doepke and Zilibotti, 2017; Eika et al., 2019), making it informative to distinguish parental factors transmitted jointly by parents from parent-specific transmission when interpreting education–outcome associations.[1]

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 four components: (i) parental factors transmitted jointly, (ii) parent-specific transmission, (iii) non-parental shared influences within the family, and (iv) individual-specific variation. The own-education gradient links an individual's education to their adult outcomes and provides

[1] Related work emphasizes how assortative mating on education shapes inequality in schooling (e.g., Bingley et al., 2022; Collado et al., 2023).

a benchmark for the relative importance of individual-specific determinants versus family-related factors correlated with schooling. We additionally study the intergenerational education gradient linking parental schooling to children's economic outcomes, which allows us to characterize how family transmission operates through jointly transmitted versus parent-specific channels. We implement these decompositions for four long-run outcomes—earnings, disposable income, assets, and wealth—allowing the balance of channels to differ across labor-market and financial domains.[2]

Our results show that education–outcome gradients differ markedly across outcome domains, both in magnitude and in composition. For the own-education gradient, education is most strongly associated with labor-market outcomes, and the gradients for earnings and income reflect an important role for jointly transmitted parental factors alongside individual-specific determinants. For wealth, by contrast, the own education–wealth gradient is dominated by parent-specific transmission, with a comparatively limited role for jointly transmitted factors. Intergenerational gradients exhibit a similar contrast: parental education is linked to offspring earnings and income primarily through jointly transmitted factors, whereas links to assets and wealth operate mainly through parent-specific channels.

Exploiting cohort-by-municipality variation in access to eighth and ninth grades induced by a middle-school reform, we further show that the decomposition of financial gradients varies with educational opportunity: among cohorts more exposed to expanded schooling access, asset and wealth gradients shift toward the jointly transmitted component, whereas among less exposed cohorts they are dominated by parent-specific transmission; by contrast, the composition of earnings and income gradients is similar across exposure groups.

This paper contributes to two strands of literature. First, it speaks to the interplay between assortative mating and intergenerational mobility by showing how educational matching in the parental generation shapes the composition of education gradients. By separating jointly transmitted parental factors from parent-specific transmission, consistently across own-education and intergenerational gradients, we clarify when assortative mating primarily operates through the

[2] Björkegren et al. (2024) decompose the intergenerational education gradient in adult health using Swedish adoptees, distinguishing pre-birth factors from post-birth influences.

joint transmission of advantages and when persistence is better characterized by distinct parental pathways. We show that the balance between joint and parent-specific transmission is strongly outcome-dependent: jointly transmitted factors are central for earnings and income, whereas for assets and wealth, parent-specific pathways dominate, consistent with evidence that bequests, gifts, and financial behaviors are central to wealth transmission (Charles and Hurst, 2003; Boserup et al., 2016; Adermon et al., 2018; Fagereng et al., 2021).

Second, the paper connects to work that uses education–outcome gradients as summary measures of the link between schooling and later-life outcomes by providing an interpretation that separates inherited advantage correlated with education from individual-specific variation. This distinction helps assess how far observed education gradients, especially in labor-market versus financial outcomes, reflect family transmission mechanisms 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 education, earnings, income, assets, and wealth. Section 3 outlines the empirical model and its identification. Section 4 reports the main estimates and decompositions of the education gradients across outcomes. 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 standard intergenerational correlations, it is central to our analysis 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 1953 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.[3]

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.[4]

We analyze two related measures of financial resources: assets and total wealth. Asset values are drawn from the wealth register and defined as the sum of financial and non-financial assets,

[3] The data used in this article are administrative registers from Statistics Denmark. Due to confidentiality restrictions, the authors are not permitted to share the microdata. However, the data can be accessed by researchers who obtain the necessary approvals from Statistics Denmark and the Danish Data Protection Agency. We provide the Stata code used to perform the analysis to facilitate replication.

[4] 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.

excluding liabilities.[5] High real estate leverage often leads to near-zero net wealth despite high consumption. We therefore separately analyze gross assets (excluding liabilities) to capture resource access independent of leverage decisions. Our wealth measure, in contrast, includes both assets and liabilities, capturing total net worth.[6] For consistency over time, we exclude defined contribution pension plans, which were only recorded in the registers 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 children, 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

Table 1 presents descriptive statistics for the key 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 disposable income are 385 and 254 (thousand DKK), respectively, while mean assets and wealth are 896 and 200. Dispersion is substantially larger for assets and wealth than for labor-market outcomes, reflecting the greater heterogeneity of balance-sheet positions.

[5] 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.

[6] 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.

2.4 Empirical Correlations

Table 2 reports sample correlations between education and long-run outcomes (measured as average percentile ranks over ages 31–45) for earnings, income, assets, and wealth. The first row reports own education–outcome correlations: 0.37 for earnings, 0.39 for income, 0.25 for assets, and 0.13 for wealth. The next two rows report intergenerational education–outcome correlations, relating parents' schooling to children's economic outcomes. These intergenerational correlations are uniformly smaller than the corresponding own education–outcome correlations and are stronger for labor-market outcomes than for financial outcomes. For mothers' education, the correlations are 0.18 for earnings and 0.19 for income, compared with 0.08 for assets and 0.06 for wealth; the corresponding correlations for fathers' education are 0.16, 0.16, 0.09, and 0.05.

The final row reports the cross-sibling education–outcome correlation, defined as the correlation between one sibling's education and the other sibling's long-run outcome.[7] These cross-sibling correlations are smaller (0.20, 0.21, 0.16, and 0.10) and broadly comparable to the intergenerational correlations. Education shows the weakest association with wealth.

3 Empirical Model

This section presents an empirical model for education–outcome gradients that relates own and parental education to long-run economic outcomes. 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.

3.1 Parental Generation

Families consists 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

[7] 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.

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, such as attitudes toward education, parenting styles, or work ethic, and reflect the role of assortative mating in concentrating transmissible characteristics within families. The second term, γ_{Pj}, reflects attributes transmitted individually by each parent P, such as 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, such as 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.[8]

For the offspring's long-run economic outcomes (earnings, income, assets, or wealth), 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 (δ_j) and outcomes (ϕ_j) may also be correlated, with the parameter $\sigma_{\theta\phi}$.

We estimate the contributions of these factors to educational gradients, distinguishing among intergenerational, sibling, and own-education gradients. The model parameters are estimated using an Equally Weighted Minimum Distance estimator, matching the observed correlations in education

[8] 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), using Danish data, show that this restriction may overstate the role of sibling-shared influences. Accordingly, our estimates for the sibling-shared factors should be interpreted as upper bounds.

and economic outcomes to their model-implied counterparts, and using the inverse sample variances of the moments to correct standard errors post-estimation. Since we leverage gradients we only identify and estimate parameters that contribute to the gradients and not other parameters of the model, which we do not need for the purpose of the main gradient analysis.[9]

Because 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. Focusing on correlations implies that we can identify only those parameters that affect cross-person and/or cross-outcome correlations. By contrast, the variances of the idiosyncratic terms affect only marginal outcome variances and are therefore not identified. Accordingly, they are excluded from the theoretical moment restrictions and from the set of parameters used to evaluate the Minimum Distance criterion.

3.4 Moment Restrictions - Education Gradients

The parental education gradients in long-term outcomes measure the correlations between parental education and child outcomes, which capture the channels transmitted jointly ($\sigma_{\gamma\delta A}$), and parent-specific channels ($\sigma_{\gamma\delta F}, \sigma_{\gamma\delta M}$). For fathers, the gradient ρ_{FC}^{EO} is:

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

and for mothers, the gradient ρ_{MC}^{EO} is:

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

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

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

[9] We return to identification and estimation in Section 4.6 where we extend the analysis to intergenerational and sibling correlations.

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^{EO}_{FC} in equation (4), and ρ^{EO}_{MC} in equation (5), from the sibling correlation ρ^{EO}_{CC}.

Finally, the correlations between own education and own outcomes, denoted ρ^{EO}, are:

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

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.

These equations provide the set of moments needed for the analysis of education gradients. These gradients depend on 5 parameters, but we have only have 4 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:

$$\rho^{EO}_{CC} = \sigma_{\gamma\delta A} + \sigma_{\gamma\delta F} + \sigma_{\gamma\delta M}. \tag{8}$$

The parameter ($\sigma_{\theta\phi}$), therefore, identifies the *excess* environmental similarity specific to same-gender pairs relative to mixed-gender pairs (e.g., gender-specific peer effects or role modeling). This interpretation implies that our estimates of parental transmission represent an upper bound of parental influence.

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 work further suggests that the salience and consequences of parental differential treatment vary with sibling gender composition (Jensen et al., 2013).

4 Results

In Sections 4.1-4.3, we present parameter estimates organized by outcome domain, which highlights that the relative importance of jointly transmitted and parent-specific components differs sharply between labor-market outcomes and financial outcomes. In Section 4.4, we decompose the education gradients, in Section 4.5, we extend the gradient analysis by exploiting variation in educational opportunities through a schooling reform, and in Section 4.6, we decompose intergenerational and sibling correlations in long-run economic outcomes.

4.1 The Transmission of Labor Market Outcomes: Earnings, and Income

Table 3 (Columns 1 and 2) report the estimated parameters for earnings and income, which suggest that transmission in earnings and income is dominated by *jointly transmitted parental factors*. For both earnings and disposable income, the joint parental component ($\sigma_{\gamma\delta A}$) is large and statistically significant (0.165 and 0.160, respectively), while the parent-specific components ($\sigma_{\gamma\delta F}$ and $\sigma_{\gamma\delta M}$) are very small. We also estimate the correlation between idiosyncratic factors in education and these two outcomes (σ_{ab}). This parameter is statistically significant and relatively large (0.17), indicating that individual-specific determinants associated with educational attainment are also strongly related to labor market success.

4.2 The Transmission of Financial Outcomes: Assets and Wealth

In contrast to labor-market outcomes, the estimates for financial-related outcomes (Table 3, Columns 3 and 4) point to a markedly different transmission pattern. *Parent-specific components* account for most of the transmitted variation, while the jointly transmitted component is relatively small. For assets and wealth, the jointly transmitted components are 0.03 and 0.01, respectively, whereas the components associated with parent-specific transmission are larger. The father- and mother-specific parameters are of similar magnitude, ranging from 0.05 to 0.06. This similarity is consistent with wealth transmission operating through mechanisms that are less reliant on characteristics shared within the parental household and more related to parent-specific behaviors and decisions, such as saving choices, risk preferences, and the timing and composition of inter vivos transfers.

We also find that the correlations between idiosyncratic determinants of education and outcomes (σ_{ab}) are substantially smaller for financial outcomes. These correlations are moderate for assets (0.10) but fall to 0.03 for wealth, implying that the individual-specific determinants of educational attainment are only weakly related to the determinants of wealth accumulation.

4.3 The Role of Sibling-Shared Non-Parental Environments

We also estimate the parameter $\sigma_{\theta\phi}$, which captures the correlation between sibling-specific factors in education and outcomes. This correlation is statistically significant for earnings, income, and assets but not for wealth, further reinforcing the disconnect between educational and financial pathways for wealth accumulation.

These low estimates imply that broad environmental factors beyond the family unit, such as neighborhood characteristics, local school systems, or community-level shocks, play a secondary role in generating sibling similarity compared to the direct transmission of parental traits and resources. Notably, this family-over-neighborhood finding holds true regardless of whether the outcome is human capital or financial wealth.

4.4 Decomposition of Education Gradients

Using the estimated parameters, we decompose education–outcome gradients. 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. The decompositions in Table 4 show that the balance between jointly transmitted and parent-specific channels differs sharply across labor-market and financial outcomes.[10]

Figure 1 examines own-education gradients (own education–own outcome correlations). The composition of these gradients differs markedly across outcome domains. For earnings and disposable income, jointly transmitted parental factors account for a substantial share of the gradient, consistent with assortative mating concentrating household-level advantages that are correlated with both schooling and labor-market success (Ermisch et al., 2006; Eika et al., 2019). Individual-specific factors correlated with education also explain an important share, indicating that both family-related transmission and individual heterogeneity contribute to the education–earnings and education–income associations.

For wealth, the gradient reflects a different mix of channels. Jointly transmitted factors account for only a small share of the education–wealth gradient, while parent-specific transmission accounts for the majority. This pattern implies that, in the wealth domain, education is more strongly correlated with channels operating through parents individually than with the jointly transmitted factors that dominate education gradients in labor-market outcomes, consistent with evidence that bequests, gifts, and financial behaviors are central to wealth transmission (Charles and Hurst, 2003; 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, with only a limited role for parent-specific transmission. 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. This contrast indicates that the association between parental schooling and children's labor-market outcomes is closely tied to jointly transmitted parental inputs, whereas the association with children's financial outcomes reflects more strongly parent-specific channels.

[10]Table 4 also reports cross-sibling education–outcome associations, which link one sibling's schooling to the other sibling's outcomes. These associations are included for identification of the full set of parameters underlying the decompositions and for completeness; the main qualitative contrasts across outcome domains are already apparent in the own and intergenerational gradients, so we do not discuss the cross-sibling associations further.

4.5 Decomposition of Own Education Gradient by Reform Exposure

We extend the gradient analysis by exploiting quasi-experimental variation in educational opportunities generated by a 1937 schooling reform.[11] The reform required municipalities to expand access to eighth and ninth grades, but implementation was gradual and uneven. Many municipalities had not complied by 1958, when a second reform mandated universal access. The pace of implementation varied with local resources, school infrastructure, and administrative capacity, creating substantial across-municipality and across-cohort differences in access to post-compulsory schooling.

To exploit this variation, we classify individuals as "treated" or "non-treated" based on whether they had access to a school offering eighth and ninth grades at age 14, the typical age of eighth-grade entry. Using linked register information on parish and year of birth, we measure distance to the nearest school offering these grades and define exposure as being below the cohort-specific median distance at age 14. This procedure generates a treated group with comparatively better local access to post-compulsory schooling, and an untreated group with more limited access. We then re-estimate and decompose the own education gradient separately by treatment status, allowing the decomposition between jointly transmitted parental factors, parent-specific transmission, non-parental shared influences within the family, and individual-specific variation to differ across groups.

Table 5 and Figure 3 report predicted individual gradients (correlations between own education and own outcomes) and their decomposition by treatment status for earnings, disposable income, assets, and wealth. We find two contrasting patterns for labor market and financial outcomes. First, labor-market gradients are remarkably stable across treatment groups. The earnings and income gradients are very similar for treated and non-treated individuals. The decomposition is also broadly unchanged: in both groups, the gradient is split roughly evenly between the jointly

[11] 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 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.

transmitted parental component and individual-specific factors, with small contributions from parent-specific transmission and non-parental shared influences within the family. This stability suggests that expanding access to eighth and ninth grades, at least as captured by our treatment measure, does not alter the underlying mix of family and individual components mapping education into labor-market outcomes.

The second pattern is that the reform changes the decomposition of assets and wealth. For the treated group, both gradients place substantially more weight on the jointly transmitted parental component than in the non-treated group. The contrast is sharpest for wealth: among treated individuals, jointly transmitted parental factors account for half of the gradient, while father- and mother-specific transmission are comparatively small (0.10 and 0.11). Among non-treated individuals, the jointly transmitted component is essentially absent, whereas parent-specific transmission dominates (father-specific: 0.37; mother-specific: 0.49). A similar, though more moderate, pattern appears for assets: treated individuals exhibit a substantial jointly transmitted component (0.29), whereas the non-treated decomposition assigns essentially none of the education-asset gradient to joint transmission and attributes most of it to parent-specific components (0.28 father-specific; 0.30 mother-specific).

This treatment heterogeneity is informative about what education is proxying for in the financial domain. When post-compulsory schooling is more accessible, education appears more tightly linked to jointly transmitted family inputs, consistent with a stronger role for shared household resources, coordinated investments, and common parental traits in shaping both educational attainment and longer-run financial accumulation. When access is more constrained, the education–assets and education–wealth gradients are instead accounted for primarily by parent-specific transmission. This pattern is consistent with financial accumulation reflecting mechanisms that need not be jointly coordinated within the parental household, such as parent-specific transfer practices and heterogeneous financial behaviors. Finally, non-parental shared influences within the family remain modest in both groups.

This evidence indicates that the reform variation primarily operates through parental transmission: for assets, and especially wealth, greater access to schooling shifts weight away from parent-specific transmission toward the jointly transmitted component.

4.6 Extension to Decomposing Intergenerational and Sibling Correlations

While our main analysis focuses on education gradients, the empirical mobility literature typically summarizes persistence using intergenerational correlations (IGC) and sibling correlations in long-run economic outcomes (e.g., Solon, 1999; Björklund and Jäntti, 2012; Mazumder, 2008). Decomposing these conventional measures serves two purposes. First, it facilitates direct comparison with the broader literature on intergenerational mobility. Second, outcome-based correlations capture persistence directly in earnings, income, assets, and wealth, and therefore reflect transmissible family influences that may not be fully summarized by parental education alone, such as entrepreneurial ability, financial attitudes, or other family-specific traits and resources.

The sibling correlation in long-run outcomes implied by Equation (3) is:

$$\rho^{O}_{CC} = \sigma^2_{\delta A} + \sigma^2_{\delta F} + \sigma^2_{\delta M} + \sigma^2_{\phi}, \tag{9}$$

where $\sigma^2_{\delta A}$ captures jointly transmitted parental factors, $\sigma^2_{\delta F}$ and $\sigma^2_{\delta M}$ capture father- and mother-specific transmission, and σ^2_{ϕ} captures non-parental shared influences within the family. This equation provides a single empirical moment but depends on four parameters. While σ^2_{ϕ} can be identified using variation in sibling gender composition, we identify the three transmitted components by imposing a proportionality restriction linking the transmitted components of long-run outcomes to the corresponding education–outcome cross-moments. Specifically, for each transmitted factor we assume:

$$\sigma^2_{\delta A} = \lambda \sigma_{\gamma \delta A}, \quad \sigma^2_{\delta F} = \lambda \sigma_{\gamma \delta F}, \quad \sigma^2_{\delta M} = \lambda \sigma_{\gamma \delta M}, \tag{10}$$

where λ is a proportionality parameter. This restriction implies that the relative importance of jointly transmitted and parent-specific components in shaping outcome persistence mirrors their relative importance in the education–outcome cross-moments, up to a common scaling factor.

Economically, the restriction can be interpreted as assuming that the transmitted components capture different manifestations of a common underlying family advantage that is already revealed through education. Long-run outcomes may load differently on this underlying advantage across domains (earnings, income, assets, wealth), but do so symmetrically across jointly transmitted and parent-specific components. Imposing a common λ is therefore a parsimonious homogeneity restriction that allows identification while preserving the relative contributions of the transmitted channels implied by the education–outcome associations. The parameter λ is then identified using the sibling-correlation moment.

Conditional on this assumption, we can recover the implied intergenerational correlations in long-run outcomes:

$$\rho^{O}_{FC} = \sigma^2_{\delta A} + \sigma^2_{\delta F}, \qquad \rho^{O}_{MC} = \sigma^2_{\delta A} + \sigma^2_{\delta M}. \tag{11}$$

Table 6 reports the predicted correlations and the resulting decompositions. Predicted intergenerational correlations are 0.2 for earnings and income, and somewhat lower for assets and wealth (0.12–0.15). Sibling correlations are larger and remain sizeable across outcomes (0.25–0.29).[12]

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^2_{ϕ}) account for a meaningful proportion of sibling persistence in earnings and income (16–20%), but a considerably smaller share in assets and wealth (7–9%). Overall, these findings confirm that labor-income persistence is primarily associated with jointly transmitted parental factors, whereas the intergenerational transmission of

[12] The estimated proportionality parameter λ is 2.44 (s.e. 0.10) for wealth, 1.63 (0.06) for assets, 1.26 (0.03) for income, and 1.15 (0.04) for earnings.

assets and wealth relies much more heavily on parent-specific channels. The similarity between these decompositions and those obtained from education gradients reinforces the conclusion that the mechanisms underlying persistence differ systematically between labor-market and financial outcomes.

5 Conclusion

This paper studies what education–outcome gradients reveal about the transmission of advantage when parents assortatively mate on education and correlated traits. Using Danish administrative data on family quartets, we estimate a model that decomposes the own education–outcome gradient for long-run earnings, disposable income, assets, and wealth into jointly transmitted parental factors, parent-specific transmission, non-parental influences shared by siblings, and individual-specific heterogeneity. We also apply the framework to intergenerational education gradients, linking parental schooling to children's economic outcomes, to characterize how family transmission operates through joint versus parent-specific channels.

The results show sharp outcome dependence in the composition of education gradients. 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 household-level advantages that are closely tied to labor-market success. At the same time, the own-education gradients for these outcomes contain a sizable 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. Joint parental transmission plays a limited role, while parent-specific components account for most of the association, consistent with financial outcomes depending more on parent-specific behaviors and resources, such as transfer decisions and financial choices, than on the jointly transmitted factors that dominate labor-market gradients. Non-parental sibling-shared influences are modest throughout.

Exploiting cohort-by-municipality variation in access to eighth and ninth grades induced by a schooling reform, we further show that the composition of financial gradients varies with educational opportunity: among cohorts more exposed to expanded access to eighth and ninth grades, asset and wealth gradients shift toward a larger jointly transmitted component and a smaller parent-specific component. This evidence suggests that educational opportunity can change not only the magnitude of financial gradients, but also their composition, shifting weight from parent-specific to jointly transmitted channels.

These 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, forces that shape educational sorting and household-level resources are central for understanding persistence in earnings and income. For assets and wealth, where parent-specific transmission is central in our baseline decompositions, policies that act directly on asset accumulation and intergenerational transfers, such as taxation of gifts and bequests or asset-building policies, are likely to play a first-order role. Consistent with the reform evidence, expanding educational opportunity can also shift the composition of financial gradients toward factors jointly transmitted.

More broadly, our contribution is to treat education–outcome gradients as informative descriptive objects and to use them as diagnostics of family transmission. Gradients that appear similar in magnitude can mask very different underlying mixes of joint parental transmission, parent-specific pathways, and individual-specific determinants, with distinct implications for welfare analysis and for the design of feasible interventions. Applying similar decompositions across cohorts and institutional settings, and examining how the composition of gradients responds to policy variation, offers a tractable way to connect rich administrative data to the question of which aspects of family background policy can realistically be expected to change.

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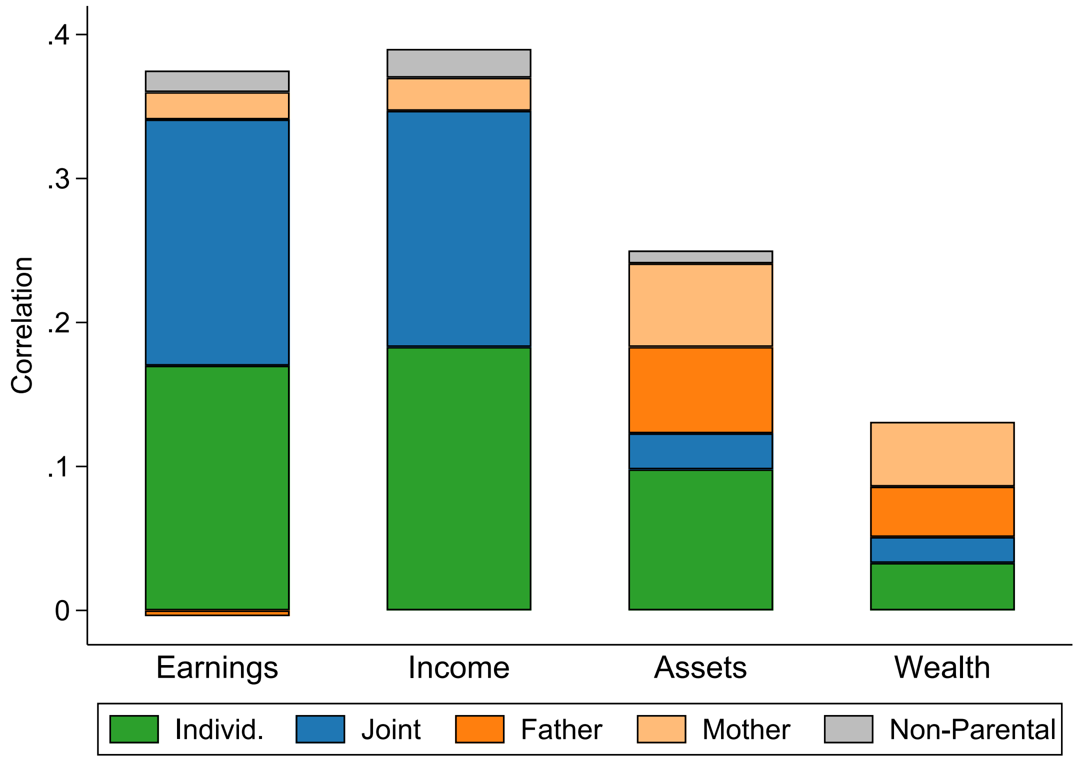
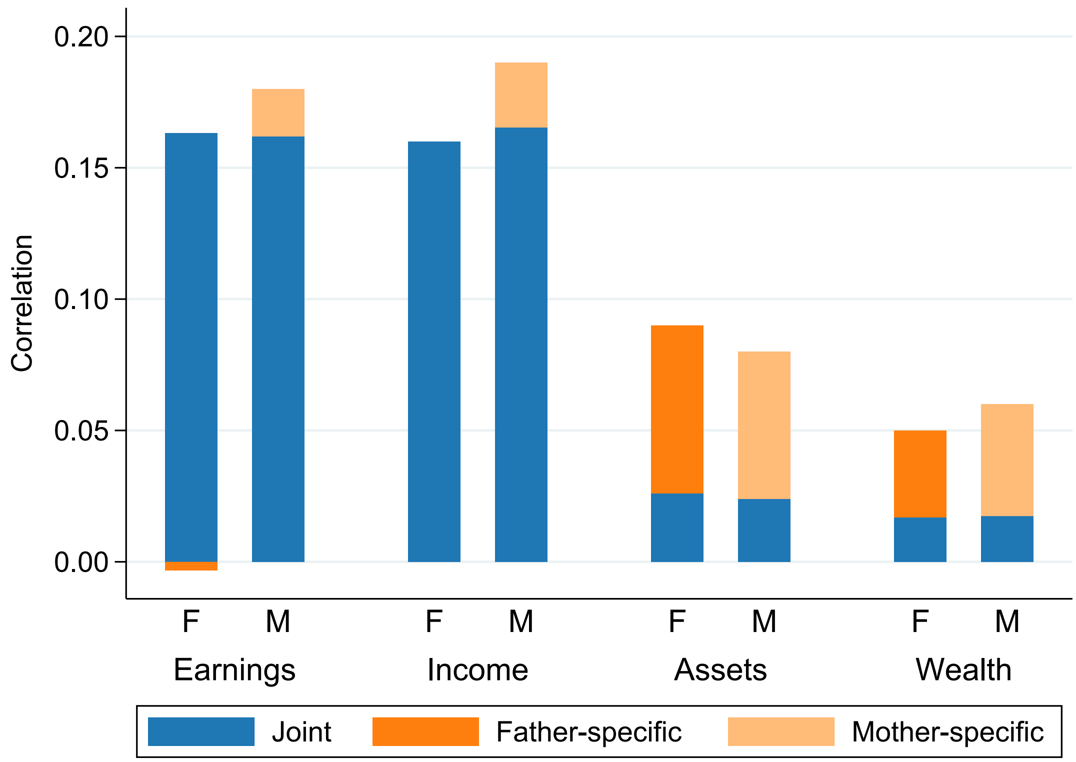
Figure 1. Estimated Decompositions of Individual Gradients



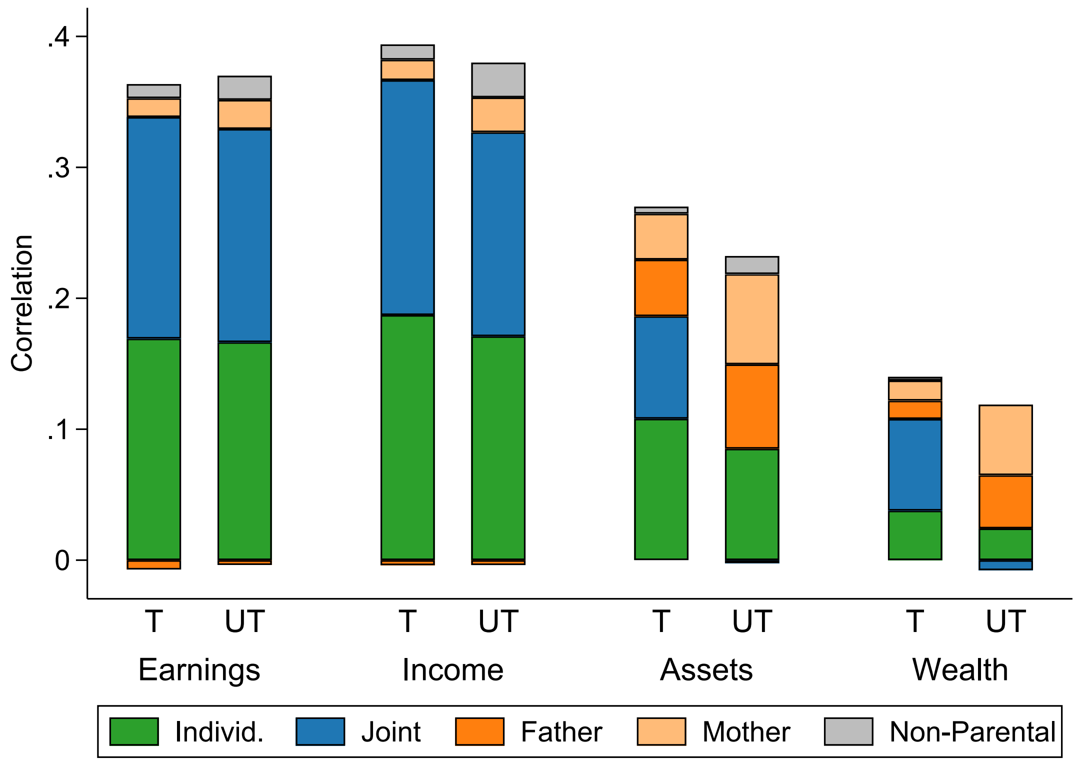
Note: The figure presents the decomposition of individual gradients (own education gradient in earnings, income, assets, and wealth) into transmission components. Levels, shares, and standard errors are presented in the upper panel of Table 4.

Figure 2. Estimated Decomposition of Intergenerational Gradients



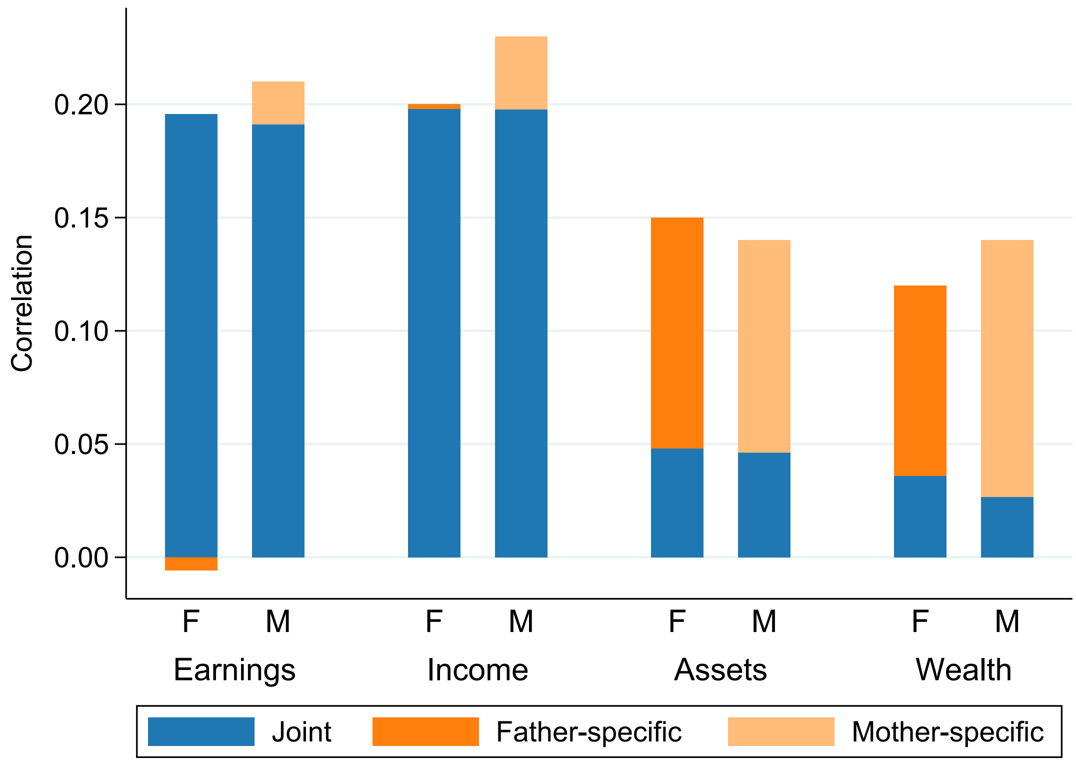
Note: The figure presents the decomposition of the correlation between parental education and child outcome (income, earnings, assets, wealth) separately for mothers and fathers. The corresponding levels, shares, and standard errors are reported in the middle panel of Table 4.

FIGURE 3. Estimated Decompositions of Individual Education Gradients by School Reform Treatment Status



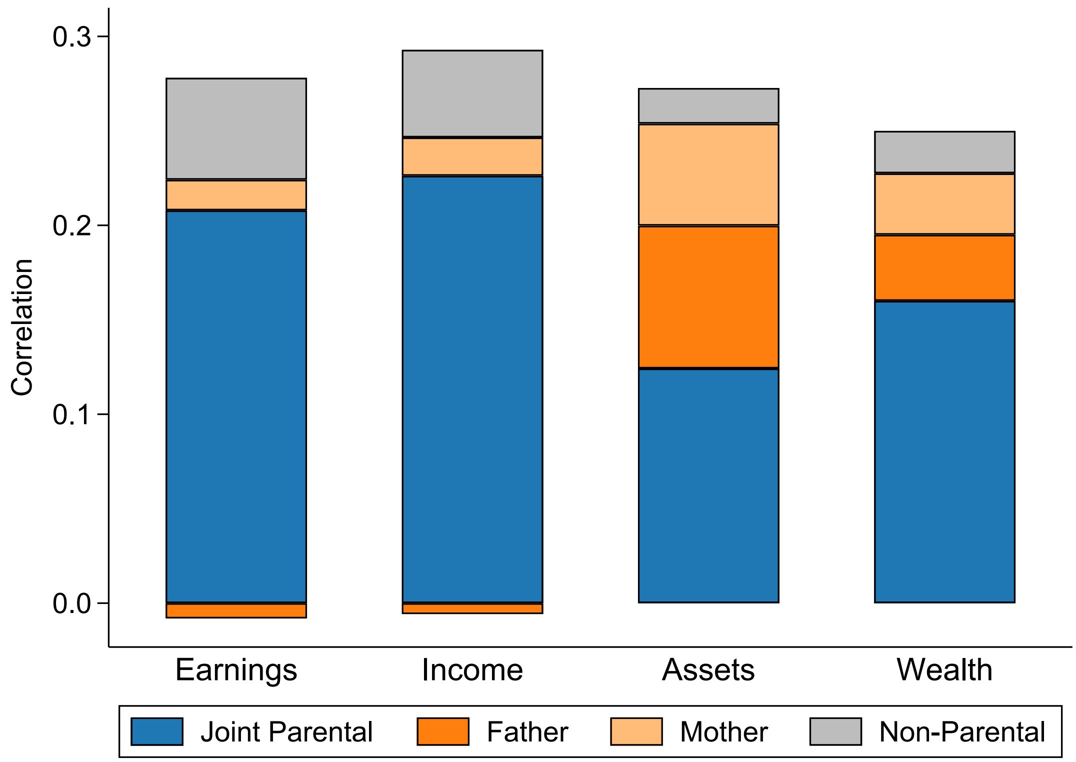
Note: The figure presents the decomposition of individual education gradients in earnings, income, assets, and wealth into transmission components, split by middle school expansion treatment status: T indicates treated, UT indicates un-treated. Levels, shares, and standard errors are presented in Table 5.

Figure 4. Estimated Decompositions of Intergenerational Correlations



Note: The figure presents the decomposition of intergenerational correlations in earnings, income, assets, and wealth into transmission components for (F)ather and (M)other. Levels, shares, and standard errors are presented in the top panel of Table 6.

FIGURE 5. Estimated Decompositions of Sibling Correlations



Note: The figure presents the decomposition of sibling correlations in earnings, income, assets, and wealth (one sibling's education with the other sibling's outcomes) into transmission components. Levels, shares, and standard errors are presented in the bottom panel of Table 6.

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)			
Labour 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. Labour earnings, disposable income, assets, and wealth are measured in thousands of Danish kroner (DKK) in 2018 prices, averaged over ages 31–45 after winsorizing the top and bottom 0.5 percent by year.

TABLE 2—Empirical 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[a]	0.20	0.21	0.16	0.10

Notes: The table reports sample correlations between education and long-term outcomes. Education–outcome correlations are presented for (i) own education with own outcomes, (ii) parental education with child outcomes, and (iii) own education with sibling's outcome, defined as the correlation between one sibling's education and the other sibling's long-term outcomes.
[a] The cross-sibling correlation is used to separate individual-specific variation correlated with education from non-parental influences shared within the family; see 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 parameter estimates from the model for each outcome.

Table 4—Decompositions of Predicted Education Gradients.

	Earnings		Income		Assets		Wealth	
	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.
Individual gradients (own education–own outcome)	0.37	0.00	0.39	0.00	0.25	0.00	0.13	0.00
Share due to individual specific factors	0.46	0.01	0.47	0.01	0.39	0.02	0.25	0.04
Share due to joint parental transmission	0.46	0.02	0.42	0.01	0.10	0.02	0.14	0.04
Share due to father-specific transmission	-0.01	0.01	-0.00	0.01	0.24	0.02	0.27	0.03
Share due to mother-specific transmission	0.05	0.01	0.06	0.01	0.23	0.02	0.34	0.04
Share 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
Share due to father-specific transmission	-0.02	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
Share due to mother-specific transmission	0.10	0.03	0.13	0.02	0.70	0.06	0.71	0.08
Sibling gradients (own education–sibling outcome)	0.20	0.00	0.21	0.00	0.16	0.00	0.10	0.00
Share due to jointly transmitted factors	0.85	0.03	0.79	0.03	0.16	0.04	0.18	0.05
Share due to father-specific factors	-0.02	0.02	-0.00	0.02	0.39	0.03	0.36	0.05
Share due to mother-specific factors	0.09	0.02	0.12	0.02	0.38	0.03	0.45	0.05
Share 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 individual gradients (own education–own outcome), the middle panel reports intergenerational gradients (parent education–child outcome), and the bottom panel reports sibling gradients (own education–sibling outcome). Individual gradients are decomposed into shares 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. Standard errors are in parentheses.

Table 5—Decompositions of Predicted Individual Education Gradients by Reform Exposure.

	Earnings		Income		Assets		Wealth	
	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.
Panel A: Treated								
Individual gradients (own education–own outcome)	0.36	0.00	0.39	0.00	0.27	0.00	0.14	0.00
Share due to individual-specific factors	0.47	0.02	0.48	0.02	0.40	0.02	0.27	0.05
Share due to jointly transmitted parental factors	0.47	0.02	0.46	0.02	0.29	0.03	0.50	0.05
Share due to father-specific transmission	-0.02	0.02	-0.01	0.02	0.16	0.03	0.10	0.04
Share due to mother-specific transmission	0.04	0.02	0.04	0.02	0.13	0.03	0.11	0.04
Share 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: Untreated								
Individual gradients (own education–own outcome)	0.37	0.00	0.38	0.00	0.23	0.00	0.11	0.00
Share due to individual-specific factors	0.45	0.02	0.45	0.02	0.37	0.03	0.22	0.05
Share due to jointly transmitted parental factors	0.44	0.02	0.41	0.02	-0.01	0.03	-0.07	0.06
Share due to father-specific transmission	-0.01	0.02	-0.01	0.02	0.28	0.03	0.37	0.05
Share due to mother-specific transmission	0.06	0.02	0.07	0.02	0.30	0.03	0.49	0.05
Share 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 individual education–outcome gradients (own education–own outcome) and their decomposition into: (i) individual-specific factors, (ii) jointly transmitted parental factors (linked to assortative mating), (iii) father-specific transmission, (iv) mother-specific transmission, and (v) non-parental shared influences within the family. Standard errors are in parentheses. Panels split the sample by reform exposure (treated vs. untreated).

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–child outcome)								
Father–child correlation	0.19	0.01	0.20	0.01	0.15	0.01	0.12	0.01
Share due to father-specific transmission	-0.03	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
Share due to mother-specific transmission	0.09	0.02	0.14	0.02	0.67	0.04	0.81	0.06
Sibling correlations	0.27	0.01	0.29	0.01	0.27	0.01	0.25	0.01
Share due to jointly transmitted factors	0.77	0.07	0.78	0.05	0.46	0.07	0.64	0.09
Share due to father-specific factors	-0.03	0.04	-0.02	0.03	0.28	0.04	0.14	0.06
Share due to mother-specific factors	0.06	0.03	0.07	0.02	0.20	0.04	0.13	0.05
Share 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 and sibling correlations and their decompositions.

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