

CORRELATION OF BROTHERS' EARNINGS AND INTERGENERATIONAL TRANSMISSION

Paul Bingley and Lorenzo Cappellari*

Abstract—We estimate sibling correlations and intergenerational transmission of life cycle earnings within a unified framework that nests previous models. Using data on the Danish population of father/first-son/second-son triads we find that intergenerational effects account for 72% of sibling correlations. This share is higher than in previous studies because we allow for heterogeneous intergenerational transmission between families. For the first time, we show significant U-shaped life cycle variation in sibling correlations, consistent with human capital models. Estimates of intergenerational mobility are of greater value than previously thought for understanding the role of the family in explaining earnings inequality.

I. Introduction

EXPLAINING inequality of individual incomes on the basis of family background is the subject of a vast literature. The theoretical background for the analysis of family effects dates back to the contributions of Becker and Tomes (1979). In their model, parents care about the lifetime earnings of children and maximize utility by choosing between their own consumption and their investment in the earnings capacity of their children. Offspring outcomes also depend on other productive endowments that parents transfer to children. As a result, lifetime earnings are transmitted between generations, through parental investments and productive endowments. Solon (1999), Björklund and Jäntti (2009), and Black and Devereux (2011) document the progress of economists in this field, illustrating various angles from which one can study the importance of family background. Among these, intergenerational and sibling studies are two prominent research approaches: the first explicitly considers parent-child transmission, and the second provides an omnibus measure of family and community influences on offspring outcomes.

How much of the correlation in sibling earnings is due to intergenerational persistence? Answering this question is key for understanding the channels through which outcomes are transmitted within the family and the importance of shared community factors. Existing evidence suggests that parent-

child transmission is not the main driver of sibling correlations, implying that the resemblance of siblings' earnings stems largely from factors that the siblings share independent of their parents (Solon, 1999; Björklund, Lindahl, & Lindquist, 2010; Björklund & Jäntti, 2012). However, the share of sibling correlation due to intergenerational persistence has never been estimated directly, but rather by means of calibrations derived under restrictive assumptions. In this paper, we develop a more general model of intergenerational transmission and sibling correlations and show that existing evidence substantially underestimates the importance of intergenerational persistence.

Our contribution is introducing a unified framework for analyzing sibling correlations and intergenerational transmission in life cycle earnings. We draw data from administrative registers of the Danish population and use a novel research design based on father/first-son/second-son triads. Using these triads identifies intergenerational effects separately from other factors shared by siblings within the overall sibling correlation, without requiring calibrations. Our model nests the models of previous research. We show that other studies miss much of the relevance of intergenerational persistence because their calibrations assume homogeneous intergenerational transmission between families. Relaxing this assumption, we find that intergenerational transmission accounts for a substantively larger share of sibling correlations than previously thought.

We model multiperson earnings dynamics combining insights from the sibling and intergenerational literatures with the literature on individual earnings dynamics. The seminal work of Lillard and Willis (1978), Lillard and Weiss (1979), Hause (1980), and MaCurdy (1982) initiated a long tradition of studies of individual earnings dynamics, surveyed in Meghir and Pistaferri (2011). Moffitt and Gottschalk (1995) pioneered the use of these models for analyzing earnings inequality, opening up a stream of empirical research on the evolution of permanent and transitory components of earnings inequality and their impacts on earnings mobility. For the first time, we apply this approach to the analysis of the joint earnings dynamics of fathers, sons, and brothers.¹

We estimate a sibling correlation of 0.22 on average over the life cycle and find that a predominant share of the correlation, 72%, originates from intergenerational transmission. This large share is in stark contrast to evidence from previous studies, which estimate intergenerational effects to account for only 6% of the sibling correlation of permanent earnings

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*Bingley: VIVE Copenhagen; Cappellari: Università Cattolica Milano.

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¹The one study of multiperson earnings dynamics is Ostrovsky (2012), who analyzes spouses' earnings in Canada. He builds on the work of Hyslop (2001), who modeled the covariance structure of spouses' earnings in the United States but without allowing for life cycle effects.

in Denmark. We show that this difference is due to our model allowing for heterogeneity in intergenerational transmission between families.

We find that sibling correlations vary considerably over the life cycle, being about 0.5 at age 25, dropping to 0.15 by the mid-30s, and then rising again to 0.25 by age 51. The U-shaped life cycle pattern of sibling correlations reflects Mincerian cross-overs of earnings profiles within birth cohorts: there is a negative association between starting earnings and earnings growth between individuals, so that the intragenerational distribution of permanent earnings first shrinks and then fans out over the working life (Mincer, 1958). Our results show that the compression/decompression occurs through the earnings component shared by siblings, generating a U-shaped pattern of sibling correlations. This finding is consistent with differences between families in human capital investments. We also find significant variation in the relative importance of intergenerational factors over the life cycle. At age 25, intergenerational transmission accounts for approximately half of the sibling correlation, but from the early 30s, intergenerational effects become predominant, and in the longer run, intergenerational transmission matters more than other shared factors for explaining similarities in the earnings profiles of brothers.

Our model encompasses the other models of sibling and intergenerational correlations used in the literature, and in the last section of the paper, we exploit this property to reconcile our findings with those of previous studies. We rule out data differences by applying the calibrated decomposition common in the literature to our data, finding an intergenerational share of 4% to 5% within the sibling correlation, which lines up with existing studies. Then, by relaxing the assumptions of the basic model, we approach our more general model and reconcile the differences in estimates.

II. Related Literatures

We draw on two strands of literature that have a long tradition: sibling correlations and earnings dynamics. Ours is a model of sibling correlations and intergenerational transmission in life cycle earnings.

A. Sibling Studies

Research on sibling correlations in outcomes is well established (see the reviews in Griliches, 1979; Solon, 1999; Björklund & Jäntti, 2009; Black & Devereux, 2011). Siblings are “more alike than a randomly selected pair of individuals on a variety of socioeconomic measurements” (Griliches, 1979, p. S38); sibling correlations of earnings or other outcomes have been used as a way of capturing many of the influences that siblings share. These influences may not only originate in the intergenerational transmission of outcomes, but may also stem from other factors passed from parents to children, factors (at least partly) independent of parental outcomes, such as values (Behrman, Pollak, & Taubman, 1982). In addition,

sibling effects capture influences that are shared by siblings but do not come from the parents, such as orthogonal school or community effects.

The prototypical model of sibling earnings specifies individual log earnings in deviation from the mean (w) as the sum of orthogonal permanent (y) and transitory (v) components,

$$w_{ijt} = y_{ij} + v_{ijt}, \quad v_{ijt} \sim (0, \sigma_v^2), \quad (1)$$

and factorizes the permanent component into individual-specific (a) and family-specific (f) parts:

$$y_{ij} = a_{ij} + f_j, \quad a_{ij} \sim (0, \sigma_a^2), \quad f_j \sim (0, \sigma_f^2), \quad (2)$$

where i indexes individuals, j indexes families, and t indexes time (see Solon, 1999, and Björklund et al., 2009). The transitory shock is typically assumed to be white noise. The individual-specific factor a_{ij} captures idiosyncratic components of permanent earnings, while the family-specific factor f_j absorbs all determinants of permanent earnings that are shared by siblings, including intergenerational persistence and all other sources of sibling similarities in earnings; we label all these other sources “residual sibling effects.” Residual sibling effects include family influences not captured by parental earnings and other community effects shared by siblings that are independent of the parents' earnings, such as school or friendship networks. We label the shared effects captured by f_j (intergenerational plus residual sibling) “overall sibling effects.” This model has been used to estimate the sibling correlation of permanent earnings (r_S) as the ratio between the variance of the overall sibling effect and the total variance of permanent earnings:

$$r_S = \frac{\sigma_f^2}{\sigma_a^2 + \sigma_f^2}. \quad (3)$$

After estimating y_{ij} as the individual average of w_{ijt} , r_S can be estimated using the variance of y_{ij} for $\sigma_a^2 + \sigma_f^2$ and its cross-sibling covariance for σ_f^2 . Equivalently, r_S can be obtained as the R^2 from a regression of y_{ij} on family fixed effects. The sibling correlation provides an omnibus measure of family and community effects, which is the share of inequality in permanent earnings accounted for by family and community background. Previous studies report estimates of the correlation in brothers' permanent incomes ranging from 0.4 to 0.5 in the United States (Solon et al., 1991; Altonji & Dunn, 1991; Solon, 1999; Mazumder, 2008) to a little over 0.3 in Sweden (Björklund et al., 2009) and about 0.2 for Norway and Denmark (Björklund & Jäntti, 2009). Thus, between one-fifth and one-half of the dispersion of permanent earnings is due to differences between sibling pairs in income-generating factors, and the remainder is due to idiosyncratic differences within sibling pairs.

Estimating how much of the sibling correlation is due to intergenerational transmission is important for both understanding the mechanisms behind between-family differences

in the distribution of outcomes and measuring the contribution of community factors. A formal characterization of the link between sibling income correlation and the intergenerational elasticity (IGE, the slope coefficient of a regression of sons' log incomes on fathers' log incomes) is provided by Corcoran et al. (1990) and Solon (1999). They start with the model of equation (2) and write the overall sibling effect as a linear function of fathers' permanent income through the IGE and an additive residual sibling effect orthogonal to fathers' income, capturing remaining shared factors independent of fathers' income,

$$f_j = \beta y_j^F + \mu_j^R, \quad \mu_j^R \sim (0, \sigma_{\mu R}^2), \quad (4)$$

where the IGE (β) is assumed constant between families, y_j^F denotes the log of fathers' permanent income in deviation from the mean, and μ_j^R denotes the residual sibling effect. Assuming stationarity in the distribution of permanent incomes between generations, the resulting decomposition of the sibling correlation is

$$r_S = \beta^2 + r_R, \quad (5)$$

where $r_R = \sigma_{\mu R}^2 / (\sigma_a^2 + \sigma_f^2)$. We label r_R "residual sibling correlation" because it measures the part of r_S that does not depend on fathers' permanent income.

Solon (1999) reports an IGE of 0.4 for the United States, which, when matched to a sibling correlation of about the same size, implies that 40% ($= 0.4^2 / 0.4$) of the sibling correlation can be ascribed to intergenerational persistence. Subsequent research has applied this decomposition indirectly as a calibration using sibling correlations and IGEs, which are sometimes estimated from different families and different samples. Intergenerational factors are generally found to have only a small effect. For Denmark, Björklund and Jäntti (2009) report an IGE of 0.12 and a brother correlation of 0.23, implying that the role of parental income is negligible, explaining 6% of the overall brother correlation.

By relaxing the assumption of stationarity, Björklund et al. (2010) obtain a decomposition analogous to equation (5) in terms of the intergenerational correlation (rather than elasticity) of permanent incomes,

$$r_S = \lambda^2 + r_R, \quad (5')$$

where λ denotes the intergenerational correlation (IGC). Björklund and Jäntti (2012) use Swedish register data and apply the sibling correlation model to a range of traits and outcomes such as IQ, noncognitive skills, height, schooling, and long-term earnings. Using the decomposition formula in equation (5'), they find that parental effects account for a small share of the overall sibling correlation, irrespective of the trait or outcome considered.

An alternative approach for assessing the role of parental incomes in shaping sibling correlations is provided by Mazumder (2008), who estimates the correlation before and after conditioning sibling earnings on family attributes in a

mixed-model framework. When family attributes are limited to fathers' permanent incomes, this approach is similar to the decomposition of equation (5'), with one difference being that mixed models are estimated via restricted maximum likelihood (REML) and assume that unobserved components of log income are normally distributed. Using this method on U.S. data, Mazumder reports that approximately one-third of the sibling correlation in long-run earnings is accounted for by paternal incomes. Applying this approach to Swedish data, Björklund et al. (2010) report a 13% reduction of the sibling correlation after controlling for fathers' income.

B. Estimation Issues and Models of Individual Earnings Dynamics

Estimating intrafamily income associations is complicated by two fundamental measurement issues. First, data on annual incomes are mixtures of long-term incomes and transitory income shocks, the latter being equivalent to classical measurement error (Solon, 1992; Zimmerman, 1992; Mazumder, 2005). Second, fathers' and sons' incomes are usually sampled at different phases of the life cycle, typically too early for sons and too late for fathers, when current measures under- and overestimate (respectively) long-term measures (see Jenkins, 1987; Haider & Solon, 2006; Böhlmark & Lindquist, 2006; Nybom & Stuhler, 2016). Haider and Solon (2006) show that if there is individual heterogeneity in life cycle earnings growth, then the relationship between current and lifetime earnings varies over the life cycle, and the bias incurred by using annual measures instead of lifetime measures is minimized in the age range of 30 to 40.

The strategies previous studies have used for coping with transitory shocks and life cycle biases conflict with each other. While transitory shocks are better dealt with using individual averages of long earnings strings, life cycle bias is minimized over a limited age range, between 30 and 40 years old. In this paper, we follow a different strategy—one that allows us to resolve this tension. We use tools from the earnings dynamics literature to model (rather than average out) the two sources of bias. We now review some relevant aspects of earnings dynamics models focusing on individuals and leaving aside family effects for a moment. In section IV, we return to siblings and introduce a model with family effects in earnings dynamics.

Models of individual earnings dynamics typically start from a permanent-transitory characterization of log earnings (in deviation from some central tendency) and pay considerable attention to the dynamic properties of earnings components. Transitory shocks are usually specified as low-order ARMA processes, thus allowing for some serial correlation. Permanent earnings are specified as either random growth (RG, also called heterogeneous income profile—HIP) or random walk (RW; also called restricted income profile; RIP) because there is no heterogeneity in earnings profiles processes. It is worth noting that in these models, permanent

earnings are not literally permanent but change over the life cycle due to permanent factors or shocks.

In the RG-HIP model, permanent earnings are assumed to evolve according to an individual-specific linear age (or experience) profile (see Lillard & Weiss, 1979; Hause, 1980; Baker, 1997; Haider, 2001; Guvenen, 2007; Gladden & Taber, 2009). Two factors generate permanent earnings differences across individuals: time-invariant heterogeneity and growth rate heterogeneity. The presence of growth rate heterogeneity makes the model particularly attractive for studying interpersonal dynamics as it enables controlling for the source of life cycle biases. Linearity in earnings levels implies a quadratic age profile of earnings variances. The RG-HIP model can be summarized as follows:

$$y_{it} = (m_i + g_i A_{it}) \pi_t; (m_i, g_i) \sim (0, 0; \sigma_m^2, \sigma_g^2, \sigma_{mg}), \quad (6)$$

where y_{it} is log permanent earnings (the counterpart of y_{ij} in equation [1] after ignoring family effects and allowing for time effects), m_i and g_i are idiosyncratic intercept and slope, A_{it} is age, and π_t is a time effect that avoids life cycle variation being confounded by secular trends of earnings inequality (Moffitt & Gottschalk, 2012). Heterogeneous profiles reflect heterogeneity in factors such as learning ability. Many studies have found a negative covariance between intercepts and slopes ($\sigma_{mg} < 0$), implying that individuals starting with low pay will see their earnings grow faster than initially higher-paid individuals (Gladden & Taber, 2009). As Baker and Solon (2003) pointed out, these different trajectories can be interpreted in a human capital framework. According to human capital theory, differential investments would generate heterogeneity of both initial earnings and earnings growth (Mincer, 1958; Ben-Porath, 1967). Moreover, heterogeneous investments induce a negative correlation between initial earnings and earnings growth because investors trade off lower initial earnings with higher earnings growth. In these circumstances, heterogeneous earnings profiles will converge at some point after labor market entry. Conventionally, the cross-over point of converging profiles can be computed as the age of minimum earnings variance: $A^* = -\sigma_{mg}/\sigma_g^2$ (Hause, 1980). Earnings inequality displays a U-shaped profile minimized at A^* . In principle, the covariance of intercepts and slopes may also be positive, indicating a complementarity between starting earnings and earnings growth; in that case, the life cycle profile of the variance would follow an ever increasing quadratic trend.

RW-RIP models assume earnings evolve through the arrival of permanent shocks (z),²

$$y_{it} = (y_{it-1} + z_{it}) \pi_t; y_{it(A_0)} \sim (0, \sigma_{y0}^2); z_{it} \sim (0, \sigma_z^2), \quad (7)$$

where A_0 is the starting age and $t(A_0)$ is the corresponding time period, so that $y_{it(A_0)}$ is the initial condition of the process. Examples of permanent shocks are promotions, dis-

placements, or chronic diseases. The accumulation of shocks and the model assumptions implies a constantly growing earnings variance that follows a linear trend over the life cycle. While most studies choose either the RG-HIP or RW-RIP model, there are examples of eclectic approaches using mixtures of the two, such as Baker and Solon (2003) and Moffitt and Gottschalk (2012). We use a combination of RG-HIP and RW-RIP in this paper.

III. Data Description

We use data from administrative registers of the Danish population. The civil registration system was established in 1968, and everyone resident in Denmark then and since has been registered with a unique personal identification number, which has subsequently been used in all national registers, enabling accurate linkage. Links from children to legal parents originate from municipal and parish records and are complete for births from 1955 onward. We sample fathers born from 1935 who have two sons with the same mother but drop fathers who were younger than 18 when their first son was born. For remaining fathers, we sample first and second sons but drop grandsons in the sense that no son is recycled as a father in the analysis. Subsequent sons are rare in the population (4%) and are ignored. Brothers born less than 12 months or more than 12 years apart are dropped from the sample. Boys changing legal parentage through adoption before age 18 are also dropped. In this way, we derive a sample of father/first-son/second-son triads. Women play no role in the main analysis after determining full brotherhood.³

We select fathers born between 1935 and 1961, first sons born between 1959 and 1985, and second sons born between 1962 and 1985. This selection is because of the completeness of registered parentage and the small number of first sons observed born before 1959. We group individuals into three-year birth cohorts, imputing the central age to each cohort group, and hereafter refer to cohort groups by this central age. Imposing a cohort structure on the data is fundamental for separating life cycle effects from calendar time, and this is the established practice of earnings dynamics studies (Baker & Solon, 2003).

We model annual pretax labor earnings, obtained from income tax returns. Each January, employers report earnings for each employee for the previous year to the tax authorities, and in March, the tax authorities send these returns to the employees themselves for verification. We use the sum of earnings from all employment during the year for the period 1980 to 2014 over which it is available in the Statistics Denmark Income Statistics Register (see Baadsgaard & Quitzau, 2011, for a detailed description of Danish income registers). In common with most of the earnings dynamics literature, we

³ Son birth order is determined irrespective of the presence of daughters. For example, we do not make any distinction for whether there is a daughter born between the two sons, before or after. We study men and do not consider mother/son, father/daughter, or brother/sister associations. Our results are robust to the presence of sisters.

² See, among others, MaCurdy (1982), Meghir and Pistaferri (2004), and Hryshko (2012).

TABLE 1.—DESCRIPTIVE STATISTICS

	(1) Sample without Earnings Selection			(2) Estimation Sample		
	Father	Son 1	Son 2	Father	Son 1	Son 2
Number of individuals	130,179	130,179	130,179	101,077	101,077	101,077
Number of observations	2,668,550	2,196,964	1,778,117	2,199,508	1,810,396	1,478,542
1990						
Mean earnings	368,261.83	287,404.81	269,512.06	367,051.03	291,035.22	273,920.64
SD earnings	204,049.4	136,741.16	126,391.34	166,440.55	124,137.25	118,698.83
Mean age; SD age	45.15; 5.81	27.97; 1.4	27; 0	45.42; 5.69	27.96; 1.4	27; 0
2000						
Mean earnings	394,533.93	340,160.29	312,005.92	390,018.13	341,237.57	314,185.53
SD earnings	243,685.03	192,990.43	167,521.24	189,596.6	162,519.18	146,926.77
Mean age; SD age	52.41; 4.48	31.56; 4.62	29.66; 3.82	52.65; 4.37	31.61; 4.58	29.66; 3.79
2010						
Mean earnings	404,648.26	434,923.86	382,454.54	397,140.46	429,654.23	383,240.54
SD earnings	288,662.28	325,866.69	263,048.95	207,137.93	216,977.35	194,144.27
Mean age; SD age	56.86; 2.49	39.39; 6.06	35.58; 6.08	56.97; 2.43	39.56; 5.94	35.71; 5.96

Annual earnings are reflated to 2012 Danish krone (1USD is worth about 7 DKK)

exclude zero earnings observations and assume that earnings are missing at random. It is also common to drop zeros in the sibling correlation literature (Björklund et al., 2009). In order to model life cycle dynamics, we need to observe individual earnings strings over time and conventionally set the start of the life cycle (A_0) at age 25 and its final point at age 60. Consequently, we observe fathers throughout this range 25 to 60, first sons 25 to 54 and second sons 25 to 51.⁴ Mean observed ages are 46.7, 35.1, and 33.4, respectively.

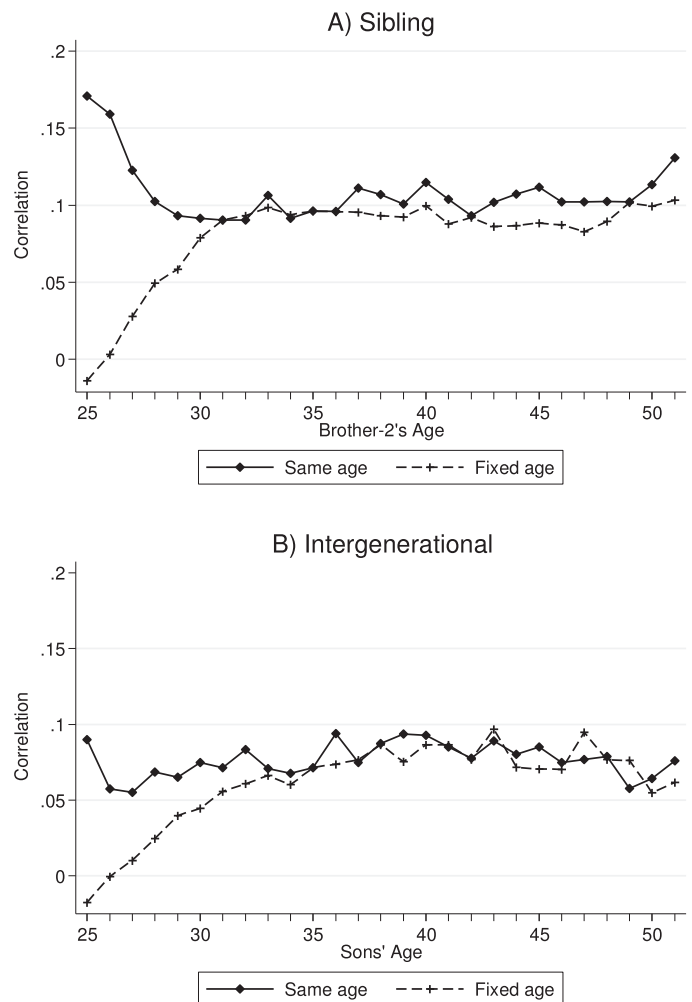
The combination of sample selection criteria generates the data set described in the left panel of table 1 for selected years in terms of first and second moments of the annual earnings and age distribution. For this sample, we apply two additional selections, which are typical in the earnings dynamics literature. First, we exclude outliers by dropping half a percentile on each tail of the earnings distribution of each year; since the analysis will exploit empirical earnings moments separately by family members, we perform the trimming within the distribution of each type of member.⁵ Second, in order to measure earnings profiles precisely, we require at least five consecutive positive earnings observations. This selection rule is intermediate between the one that Baker and Solon (2003) used of continuous positive earnings strings and Haider's (2001) approach, allowing individuals to move in and out of the sample, requiring only two positive but not necessarily consecutive earnings observations.

The right panel of table 1 describes the estimation sample after making these restrictions. Trimming outliers and imposing partially continuous earnings strings has an impact on sample size. There is also an impact on earnings dispersion, while average earnings are not much affected. In total, our sample consists of 303,231 men belonging to 101,077 families. Individuals are observed for 18.1 years on average (fathers 21.8 years, first sons 17.9 years, and second sons 14.6 years), giving 5,488,445 earnings observations in total.

⁴Various sensitivity checks show robustness of results to the age range analyzed.

⁵Findings are robust if we include or winsorize trimmed cases.

FIGURE 1.—INTERGENERATIONAL AND SIBLING CORRELATIONS OF RAW EARNINGS



Most observations (2,199,507) are for fathers' earnings, with 1,810,396 for first sons and 1,478,542 for second sons.

We begin describing patterns of earnings associations within the family in figure 1, which plots intergenerational

and brother correlations of log real annual earnings, adjusted for time and age effects by taking residuals of regressions for each birth cohort and type of family member on calendar year dummies and a quadratic age trend. We discard empirical second moments that are based on fewer than 100 cases throughout the analysis.⁶ The figure provides an overview of correlations in raw earnings, which reflect both permanent and transitory earnings components.

In panel A, we consider brother correlations. The fixed-age plot represents the average brother correlation by age of the younger brother, conditional on the age of the older brother being fixed at 35; the same-age plot is calculated from the average of correlations when brothers reach the same given age. There is a contrast between the two plots. The same-age plot displays a declining age profile, consistent with an underlying RG-HIP model of permanent earnings dynamics with Mincerian cross-overs, in which brothers share the determinants of their human capital investments. However, the fixed-age correlations are very low at young ages and converge to the level of same-age correlations at 30. This fixed-age pattern is consistent with life cycle bias: estimating brother correlations between brothers observed at different stages of the life cycle provides an underestimate of the correlation at the same stage. That we can observe this bias suggests our data provide an adequate basis for controlling the bias.⁷

In panel B of figure 1, we repeat the exercise for intergenerational correlations, obtained by averaging father-son correlations for both sons by sons' ages. Fixed-age correlations refer to fathers aged 35 and follow an increasing pattern similar to the fixed-age brother correlation, suggestive of life cycle bias. Same-age correlations are relatively flat and do not display the sharp initial decline that we observe for brother correlations. While this pattern might mean that the intergenerational component of permanent earnings is not generated by an RG-HIP model, it might also reflect much greater age spacing between fathers and sons than between brothers, making life cycle bias more severe and harder to control with same-age correlations, especially at young ages, when there is a larger measurement error from transitory shocks. The model of the next section features both age-dependent transitory shocks and RG-HIP permanent earnings, thus enabling us to test whether the intergenerational component of permanent earnings can be characterized as an RG-HIP process with Mincerian cross-overs.

IV. A Model of Earnings Dynamics for Fathers and Sons

We study earnings dynamics within the family and set up a multiperson model that contributes to the strands of litera-

ture reviewed in section II. First, we contribute to the sibling literature by decomposing the sibling correlation into intergenerational and residual sibling components using a novel research design based on father/first-son/second-son triads that allows for family heterogeneity in intergenerational transmission. Heterogeneous transmission can be rationalized in the Becker and Tomes (1979) framework as long as parental altruism, liquidity constraints, or the ability or willingness to transmit pre- or postbirth endowments are family specific. In contrast to our model, the calibration formula of equations (5) or (5') assumes that the IGE is constant between families.

Second, we contribute to the earnings dynamics literature because ours is a model of the joint earnings dynamics of three family members. This second key difference with existing models enables us to resolve the tension faced by previous studies on estimation biases when choosing the length of the income strings to analyze because we model both heterogeneous earnings growth and serially correlated transitory shocks. Moreover, for the first time, we can characterize the life cycle profile of the sibling correlation.

We focus on men and distinguish three types of family members: fathers (F), first-born sons (S_1), and second-born sons (S_2). For each family member, we consider individual log earnings in deviation from the mean (w), where the mean varies by year, birth cohort, and type of family member.⁸ Log earnings deviations from the mean consist of a permanent (long-term) component (y) and an orthogonal transitory (mean-reverting) shock (v). Orthogonality holds by definition of permanent and transitory components of earnings, and total earnings are written as the sum of the two orthogonal components:

$$w_{ijt} = y_{ijt} + v_{ijt}; \quad E(y_{ijt}, v_{ijt}) = 0. \quad (8)$$

A. Permanent Earnings

In order to highlight the differences between ours and previous models of sibling correlations, we discuss two alternative specifications. We begin with a simple model of permanent earnings featuring heterogeneous intergenerational transmission but without any dynamics. Next, we extend the model and introduce dynamics.

Constant permanent earnings. Equation (4) assumes that the intergenerational factor of the sibling effect (βy_j^F) is a fixed proportion (β) of fathers' log earnings, common across families. We relax this assumption and allow for an unrestricted intergenerational factor $\mu_j^I \sim (0, \sigma_{\mu I}^2)$, so that the family effect becomes $f_j = \mu_j^I + \mu_j^R$. Because there are no dynamics in this simple model, time indices on permanent

⁶There are 62,065 empirical moments in total, of which 6,324 are dropped because they are estimated on fewer than 100 cases. Our results are essentially unchanged if we set the threshold to 50 or 150 cases.

⁷Sensitivity checks show that these patterns are robust to the exclusion of late labor market entrants and the exclusion of closely spaced siblings who may share shocks at labor market entry.

⁸Considering earnings in deviation from yearly means by birth cohort is a flexible way of removing average age effects that may confound the estimation of individual life cycle profiles (see Baker & Solon, 2003).

earnings are redundant and sons' permanent earnings can be written as

$$y_{ij} = a_{ij} + \mu_j^I + \mu_j^R, \quad \forall i : h(i) = S_1 S_2, \quad (9)$$

where $h(i) \in \{F, S_1, S_2\}$ denotes the type of person i within the family. We allow for member-specific distributions of idiosyncratic nonshared factors: $a_{ij} \sim (0, \sigma_{ah}^2)$.

Fathers' earnings need to be modeled jointly with sons' earnings in order to identify an unrestricted intergenerational component within the overall sibling correlation. For fathers, there is no residual sibling component, and they share with sons only the intergenerational factor μ_j^I . Given these assumptions, the variances of shared components are identified by sibling ($\sigma_{\mu I}^2 + \sigma_{\mu R}^2$) or intergenerational ($\sigma_{\mu I}^2$) covariances in permanent earnings. The sibling correlation is given by

$$r_S = \frac{\sigma_{\mu I}^2 + \sigma_{\mu R}^2}{\sigma_{aS}^2 + \sigma_{\mu I}^2 + \sigma_{\mu R}^2} = r_I + r_R, \quad (10)$$

where the $\bar{S}$ subscript denotes the average of sibling-specific parameters, $r_I = \sigma_{\mu I}^2 / (\sigma_{aS}^2 + \sigma_{\mu I}^2 + \sigma_{\mu R}^2)$ is the intergenerational component of the sibling correlation, and $r_R = \sigma_{\mu R}^2 / (\sigma_{aS}^2 + \sigma_{\mu I}^2 + \sigma_{\mu R}^2)$ is the residual sibling correlation unrelated to fathers' earnings. The share of r_S accounted for by intergenerational factors can be estimated as

$$\frac{r_I}{r_S} = \frac{\sigma_{\mu I}^2}{\sigma_{\mu I}^2 + \sigma_{\mu R}^2}. \quad (10')$$

Comparing equation (10) with (5') immediately reveals that relaxing the assumption of homogeneous IGE results in a greater share of sibling correlation attributed to intergenerational transmission, because in our decomposition, the intergenerational component enters linearly, while in equation (5'), the IGC enters quadratically. Equation (5') uses the squared IGC because it derives it from a model with homogeneous IGE between families; the IGE turns out to be a multiplicative constant in the computation of the sibling covariance and is squared in the process, resulting in a squared IGC when stationarity is not assumed. The intuition is that while decompositions (5) or (5') parameterize intergenerational transmission as a linear function of father log earnings (βy_j^f), our model uses unrestricted family-specific effects (μ_j^I), resulting in greater explanatory power of the intergenerational component.⁹

⁹ Another difference between approaches is that the intergenerational component on the right-hand side of equation (10) is the ratio between the intergenerational earnings covariance and the variance of sons' permanent earnings. Instead equation (5') uses the IGC, which is equal to r_I divided by the ratio between the standard deviations of fathers' and sons' permanent earnings. In general, this ratio will be larger than unity if fathers are sampled at older ages than sons are. Using life cycle averages to measure permanent earnings, we find in our data that the ratio is equal to 1.2, and in practice, which of the two intergenerational parameters is used for the decomposition does not substantively affect the conclusions.

Life cycle permanent earnings. We now extend the model by introducing life cycle effects using the specifications reviewed in section II.B. We model earnings components shared between family members using the RG-HIP parameterization. This is motivated by the need to allow for heterogeneous earnings profiles in order to avoid life cycle biases. Also, in the previous section, we provided evidence that empirical brother correlations are U-shaped in age, consistent with a model of permanent earnings dynamics with Mincerian cross-overs in which brothers share the determinants of their human capital investments, a pattern that can be captured by an RG-HIP model and not by an RW-RIP. We maintain the RW-RIP specification for the idiosyncratic component of permanent earnings.¹⁰ Sons' earnings are written as

$$y_{ijt} = ((\mu_j^I + \mu_j^R) + (\gamma_j^I + \gamma_j^R) A_{it} + a_{ijt}) \pi_t, \\ a_{ijt} = a_{ijt-1} + \phi_{ijt}, \quad \forall i : h(i) = S_1, S_2. \quad (11)$$

The earnings profile is linear in age; intercepts (μ) and slopes (γ) of the RG-HIP model depend on family-specific effects and are factored into intergenerational and residual sibling components. The idiosyncratic component (a_{ijt}) is an RW-RIP process capturing persistent individual-specific deviations from the family effect, while π_t is a period-specific loading factor.

We specify a model for fathers' earnings similar to that of sons, with the exception of residual sibling effects that are shared by siblings only and do not feature in fathers' earnings. The model for fathers' earnings is

$$y_{ijt} = (\mu_j^I + \gamma_j^I A_{it} + a_{ijt}) \pi_t, \quad \forall i : h(i) = F. \quad (12)$$

Each individual- or family-specific parameter of the model is drawn from a zero mean unspecified distribution. RG-HIP intercepts and slopes are correlated within each dimension of family-specific heterogeneity (intergenerational and residual siblings) and are assumed to be independent between dimensions. RW-RIP parameters of idiosyncratic components are drawn from member-specific distributions. In sum, the distribution of permanent earnings is specified as follows:

$$(a_{ijt(A_0)}, \phi_{ijt}) \sim (0, 0; \sigma_{a0h}^2, \sigma_{\phi h}^2), \\ (\mu_j^I, \gamma_j^I) \sim (0, 0; \sigma_{\mu I}^2, \sigma_{\gamma I}^2, \sigma_{\mu \gamma I}), \\ (\mu_j^R, \gamma_j^R) \sim (0, 0; \sigma_{\mu R}^2, \sigma_{\gamma R}^2, \sigma_{\mu \gamma R}). \quad (13)$$

As in the simple model, intergenerational covariances identify the intergenerational parameters of the model, while sibling covariances identify the sum of intergenerational and residual sibling parameters. The intergenerational covariance

¹⁰ There are additional empirical considerations supporting our specification. See note 13.

between periods t and $q \geq t$ for son i and father k of family j is

$$E(y_{ijt}y_{kjq}) = (\sigma_{\mu I}^2 + \sigma_{\gamma I}^2 A_{it} A_{kq} + \sigma_{\mu \gamma I} (A_{it} + A_{kq})) \pi_t \pi_q, \quad (14)$$

while the sibling covariance in the same years for brothers i and l of family j is

$$E(y_{ijt}y_{ljq}) = ((\sigma_{\mu I}^2 + \sigma_{\mu R}^2) + (\sigma_{\gamma I}^2 + \sigma_{\gamma R}^2) A_{it} A_{lq} + (\sigma_{\mu \gamma I} + \sigma_{\mu \gamma R}) (A_{it} + A_{lq})) \pi_t \pi_q. \quad (15)$$

The difference with the age-invariant model is that now the sibling correlation and its decomposition are age dependent,

$$r_S(A) = r_I(A) + r_R(A), \quad (16)$$

where the components of the sibling correlation derive from estimated life cycle parameters:

$$r_I(A) = \frac{\sigma_{\mu I}^2 + \sigma_{\gamma I}^2 A^2 + 2\sigma_{\mu \gamma I} A}{\sigma_{y(A)}^2},$$

$$r_R(A) = \frac{\sigma_{\mu R}^2 + \sigma_{\gamma R}^2 A^2 + 2\sigma_{\mu \gamma R} A}{\sigma_{y(A)}^2},$$

and

$$\sigma_{y(A)}^2 = ((\sigma_{\mu I}^2 + \sigma_{\mu R}^2) + (\sigma_{\gamma I}^2 + \sigma_{\gamma R}^2) A^2 + (\sigma_{\mu \gamma I} + \sigma_{\mu \gamma R}) 2A + \sigma_{a0S}^2 + \sigma_{\phi S}^2 A).$$

B. Transitory Earnings

Studies of individual earnings dynamics use low-order ARMA processes to model transitory shocks. In contrast, intergenerational or sibling studies take multiperiod averages to smooth out transitory shocks and reduce measurement error biases, choosing the number of periods on the basis of the assumed degree of serial correlation. In this paper, we model, rather than average out, the transitory part of the earnings process. When estimating the simple model with time-invariant permanent earnings, we assume that transitory earnings are white noise shocks, with member-specific variances of innovations. When permanent earnings vary over the life cycle, we specify transitory earnings as member-specific AR(1) processes. In this case, we allow for age-related heteroskedasticity in the innovations of the process by using an exponential spline. Baker and Solon (2003) find that the dispersion of transitory shocks is U-shaped in age. Age-related heteroskedasticity in our model might otherwise be spuriously attributed to permanent earnings. We also allow for time effects and for

contemporaneous correlation of transitory shocks between family members. Our AR(1) transitory earnings model is as follows:

$$v_{ijt} = \tau_t u_{ijt} = (\rho_h u_{ijt-1} + \varepsilon_{ijt}) \tau_t,$$

$$\varepsilon_{ijt} \sim (0, \sigma_{\varepsilon hA}^2), \quad \sigma_{\varepsilon hA}^2 = \sigma_{\varepsilon h}^2 \exp(x_h(A_{it}))$$

$$u_{ijs} \sim (0, \eta_c^{d(s=t_0)} \sigma_{u0h}^2), \quad s = \max(t_0, c + A_0),$$

$$E(\varepsilon_{ijt} \varepsilon_{kjt}) = \sigma_{hl}, \quad h, l = FS_1, S_2, \quad h \neq l, \quad (17)$$

where $c = c(i)$ denotes the birth cohort of person i and t_0 the first year of data, so that s is the first year in which individuals from a given cohort are observed. We allow for nonstationarity by modeling the initial condition of the transitory process (σ_{u0h}^2) and introduce cohort effects in initial conditions (η_c) for cohorts starting their working life prior to the initial observation year, $d()$ being a binary indicator function. τ_t is a period-specific loading factor and $x_h()$ a member-specific linear spline. Each family member draws transitory shocks from a member-specific distribution indexed by h , and shocks are (contemporaneously) correlated between members. Our model includes parameters for intergenerational and sibling correlations of transitory earnings, which have both been assumed away in previous studies.

C. Estimation

The model fully specifies the intertemporal distribution of permanent and transitory earnings for each family member and between members. The second moments of this distribution are a nonlinear function of a parameter vector θ that in the most general model contains RW-RIP, RG-HIP, and AR(1) coefficients, plus period factor loadings on permanent and transitory earnings. Details of moment restrictions for permanent and transitory earnings are provided in the online appendix. We estimate θ by minimum distance (Chamberlain, 1984; Haider, 2001).¹¹ In order to identify age effects separately from time effects, we derive empirical earnings moments specific to birth cohorts and stack them in a single-moment vector for estimation. The model is estimated using age in deviations from 25.

V. Results

For both models presented in section IV (constant and life cycle permanent earnings), parameters are estimated by imposing the moment restrictions implied by the model on empirical second moments of earnings. We base the analysis on 7,140 within-person moments (3,609 refer to fathers, 1,809 to

¹¹We use equally weighted minimum distance (EWMD) and a robust variance estimator $\text{Var}(\hat{\theta}) = (G'G)^{-1}G'VG(G'G)^{-1}$, where V is the fourth-moments matrix and G is the gradient matrix evaluated at the solution of the minimization problem.

TABLE 2.—ESTIMATES FOR THE MODEL WITH CONSTANT PERMANENT EARNINGS

	Coefficient	SE
A. Idiosyncratic Component		
Father (σ_{aF}^2)	0.1515	0.0023
Son 1 (σ_{aS1}^2)	0.1449	0.0034
Son 2 (σ_{aS2}^2)	0.1369	0.0035
B. Shared components		
Intergenerational ($\sigma_{\mu I}^2$)	0.0242	0.0008
Residual Sibling ($\sigma_{\mu R}^2$)	0.0128	0.0021
C. Sibling correlation and decomposition		
Sibling correlation (r_S)	0.2086	0.0106
Intergenerational component (r_I)	0.1363	0.0052
Residual sibling component (r_R)	0.0723	0.0115
Intergenerational share (r_I/r_S)	0.6531	0.0402

Number of observations: 5,488,445. Number of individuals: 303,231. Number of moments: 55,741. Number of parameters = 8, $\chi^2(55,733) = 1.132e + 08$.

first sons, and 1,344 to second sons), 20,419 father/first-son moments, 17,085 father/second-son moments, and 11,475 brother/brother moments. In total, 55,741 empirical moments are used in estimation. We discuss estimates of permanent earnings and the decomposition of the sibling correlation. We report estimates of transitory earnings and time effects in the online appendix.

A. Constant Permanent Earnings

In table 2 we report results on permanent earnings from estimation of the simple model of section IV, which assumes away any time or age effect in permanent and transitory earnings and also assumes that transitory earnings are white noise. The model has eight parameters: three member-specific variances of idiosyncratic permanent earnings (panel A), three member-specific variances of transitory earnings (not shown), and two variances for the shared components (panel B). Variances of idiosyncratic components are rather stable across family members. The estimate of the intergenerational parameter is roughly double in size compared with the residual sibling effect. This difference is reflected in the decomposition of the sibling correlation reported in panel C. Using equation (10), the sibling correlation is estimated to be 0.21, and 65% of it is attributed to the intergenerational component using equation (10'). This share is about ten times larger than previously thought for Denmark on the basis of calibrations.¹²

B. Life Cycle Permanent Earnings

Parameter estimates. Results for the RG-HIP/RW-RIP model are reported in table 3. Including life cycle effects in permanent and transitory earnings, with time effects on both and serial correlation of transitory earnings, yields 115

¹²Table 2 also reports Newey's (1985) χ^2 statistic for a test of the model against the alternative hypothesis of an unspecified covariance structure. As Baker and Solon (2003, note 25) noted, with many empirical moments and relatively few parameters, the test is bound to reject the maintained specification.

parameters. A Wald test of this model against the simpler model without dynamics overwhelmingly rejects the latter ($\chi^2(107) = 3.5e + 05$). There are differences in idiosyncratic parameters between fathers and sons, demonstrating the importance of allowing for member-specific idiosyncratic dynamics. Shocks are more dispersed for sons than for fathers, which might reflect life cycle variation in the variance of shocks, as fathers are observed on average later in their lives than sons.¹³

The next set of estimates refers to the parameters of shared components (see panel B). Heterogeneity in sibling effects—intergenerational and residual sibling—is substantial. Half of the total variance of initial earnings comes from sibling effects; intergenerational and residual sibling effects each account for about half of the variance within the sibling-specific distribution of initial earnings.¹⁴ Sibling effects are also evident in the distribution of earnings growth rates, but with most dispersion among the intergenerational component.

The covariances between RG-HIP intercepts and slopes for both the intergenerational and residual sibling components are negative and statistically significant. The negative signs indicate the presence of Mincerian cross-overs in the distribution of permanent earnings, with cross-over age A^* at 31 ($= -\sigma_{\mu I}^2 / \sigma_{\gamma I}^2 + 25$) and 39 ($= -\sigma_{\mu R}^2 / \sigma_{\gamma R}^2 + 25$) years for the intergenerational and residual sibling components, respectively. The faster compression of the intergenerational component reflects the fact that there is more heterogeneity of earnings profiles in the intergenerational component.

Insofar as Mincerian cross-overs emerge from heterogeneous investments in human capital, results suggest that the determinants of these investments are shared by siblings. In families that invest more in human capital, siblings will have lower earnings at age 25, but their earnings profiles will be steeper than those of siblings from families investing less. Mincerian cross-overs imply that the predicted variance of permanent earnings explained by earnings components shared by siblings will first decrease and then fan out over the life cycle. These patterns do not reflect shared instability while young because the model controls for age effects in transitory earnings.

Sibling correlation in permanent earnings and its components. Figure 2 shows the life cycle evolution of the brother correlation and its decomposition into intergenerational and

¹³In preliminary analyses, we experimented with an RW-RIP specification also for the shared components, obtaining negative estimated variances of the shocks for the residual sibling component, suggesting that this specification is not identified in the data. This result might be a consequence of the U-shaped pattern of empirical brother correlations illustrated in figure 1, which cannot be captured by an RW-RIP specification. Similarly, augmenting the RG-HIP model of the intergenerational component with an RW-RIP shock yielded an insignificant estimate of the variance for slope parameters, indicating insufficient variation in the data.

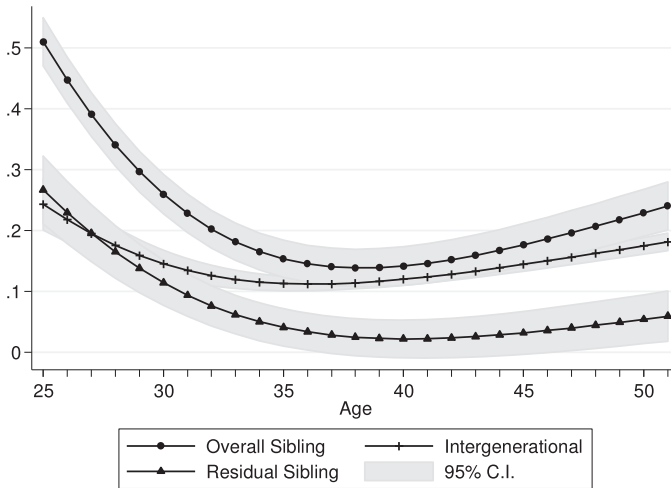
¹⁴Using the average of brothers' estimated variance of initial idiosyncratic earnings, the total variance of initial earnings is given by $0.5\sigma_{a0S1}^2 + 0.5\sigma_{a0S2}^2 + \sigma_{\mu I}^2 + \sigma_{\mu R}^2 = 0.16$ of which $(0.08 = \sigma_{\mu I}^2 + \sigma_{\mu R}^2)$ comes from the factors that brothers share.

TABLE 3.—ESTIMATES FOR THE MODEL WITH LIFE CYCLE PERMANENT EARNINGS

		Coefficient	SE
A. Idiosyncratic Component			
Variance of initial earnings	Father (σ_{a0F}^2)	0.0452	0.0040
	Son 1 (σ_{a0S1}^2)	0.0861	0.0061
	Son 2 (σ_{a0S2}^2)	0.0733	0.0059
Variance of shocks	Father ($\sigma_{\phi F}^2$)	0.0060	0.0004
	Son 1 ($\sigma_{\phi S1}^2$)	0.0123	0.0009
	Son 2 ($\sigma_{\phi S2}^2$)	0.0133	0.0011
B. Shared Components			
B.1 Intergenerational			
	Variance of initial earnings ($\sigma_{\mu I}^2$)	0.0395	0.0032
	Variance of growth rates ($\sigma_{\gamma I}^2$)	0.00021	0.00001
	Covariance ($\sigma_{\mu \gamma I}$)	−0.0017	0.0002
B.2 residual Sibling			
	Variance of initial earnings ($\sigma_{\mu R}^2$)	0.0433	0.0055
	Variance of growth rates ($\sigma_{\gamma R}^2$)	0.00018	0.00002
	Covariance ($\sigma_{\mu \gamma R}$)	−0.0026	0.0003
C. Average Sibling Correlation and Decomposition			
Sibling correlation (r_S)		0.2205	0.0150
Intergenerational component (r_I)		0.1474	0.0064
Residual sibling component (r_R)		0.0731	0.0151
Intergenerational share (r_I/r_S)		0.7154	0.0611

Reported correlations and intergenerational share are obtained as averages of their life cycle profiles. Number of observations: 5,488,445. Number of individuals = 303,231. Number of moments = 55,741. Number of parameters = 115, $\chi^2(55626) = 2.946e + 08$.

FIGURE 2.—PREDICTED DECOMPOSITION OF SIBLING CORRELATION OF PERMANENT EARNINGS



residual sibling effects. This decomposition is obtained by substituting estimated parameters into equation (16). The overall brother correlation is just above 0.5 at the start of the life cycle and depends on both intergenerational and residual sibling effects. The value of the brother correlation at age 25 is about twice that found previously for Denmark without allowing for life cycle variation. As individuals age, overall brother correlations diminish and become smaller than 0.3 for ages 30 and above. The reason for the rapid drop in brother correlations is the shrinking of the overall intragenerational earnings distribution (Mincerian cross-overs), which is driven by brother effects. After the cross-over point, the intragenerational earnings distribution starts opening up again as an effect of heterogeneous earnings growth, so that the overall brother correlation increases.

The U-shaped profile of brother correlation in figure 2 results from the combination of variance estimates of intercepts and slopes of RG-HIP processes and the estimated negative intercept-slope covariance. In estimation we do not constrain parameters and therefore do not impose a particular sign on the slope or curvature of the life cycle profile of brother correlations. The average brother correlation is 0.22 (see panel C of table 2), and is very close to that reported by Björklund et al. (2002) for Denmark.

Figure 2 confirms the importance of intergenerational factors in shaping the overall brother correlation. Intergenerational effects explain on average 72% of the total brother correlation (see panel C of table 3). While life cycle variation is evident in both the residual sibling and intergenerational components, it is more pronounced for the former. In contrast to the intergenerational correlations of raw earnings at the same age, which are rather flat (figure 1), the intergenerational correlation of permanent earnings in figure 2 displays a U-shaped profile consistent with Mincerian cross-overs and heterogeneity of human capital investments between families. The residual sibling component is sizable only at the start of the life cycle and falls to insignificance for ages 35 to 48 before rising slightly at age 51.

VI. Sensitivity Analysis

Unlike previous studies, we find that most of the brother correlation in long-term earnings is accounted for by correlation with fathers' earnings. This result is a consequence of heterogeneous intergenerational transmission and emerges from both the simpler model with constant permanent earnings and the more complex model with life cycle earnings, which suggests that specification choices underlying the earnings model do not influence our key finding of a predominant intergenerational share.

TABLE 4.—SENSITIVITY ANALYSIS

		Coefficient	SE
1. Individual earnings average	r_S	0.1724	0.0039
	r_I/r_S	0.6636	0.0224
2. Percentiles of individual earnings averages	r_S	0.2081	0.0034
	r_I/r_S	0.6347	0.0146
3. Individual earnings average ages 30–40	r_S	0.1497	0.0041
	r_I/r_S	0.7122	0.0297
4. Present discounted value of earnings	r_S	0.1849	0.0037
	r_I/r_S	0.7669	0.0223
5. Years of schooling	r_S	0.3377	0.0035
	r_I/r_S	0.7357	0.0116

The table reports estimates of the sibling correlation (r_S) and its intergenerational share (r_I/r_S) obtained from applying the simple model of section IV to time-invariant outcomes.

In this section, we further assess the robustness and generality of these findings. Identification of permanent earnings in our model is achieved by modeling transitory shocks rather than averaging them out, as in most studies of sibling correlations in earnings. We check the sensitivity of results to this specific aspect of our approach by applying the simpler permanent earnings model of section IV to individual averages of earnings profiles and other economic-relevant time-invariant outcomes.

We report the results of this sensitivity check in table 4. We consider five time-invariant outcomes: permanent earnings (the life cycle average of residualized log earnings residuals), percentiles of permanent earnings, permanent earnings between ages 30 and 40, the log of the present discounted value of life cycle earnings, and years of completed schooling.¹⁵ For permanent earnings, we estimate a brother correlation of 0.17 and an intergenerational share of 66%, which is close to the estimate from our simpler model of section IV. Similar results emerge when we consider percentiles of permanent incomes rather than permanent incomes per se. When we calculate permanent earnings over the age range of 30 to 40, our findings are in line with figure 2: the brother correlation is lower in that range compared to the full life cycle, and the intergenerational share is larger. Also for the present discounted value of earnings and years of completed schooling, we find that a similarly large percentage of the brother correlation is accounted for by the intergenerational component. Overall, the evidence supports the robustness of our findings to the particular modeling choice adopted or outcome considered.

VII. Heterogeneous Intergenerational Transmission

In this section, we further investigate the role of heterogeneous intergenerational transmission. We begin by performing the decompositions of equations (5) and (5') in our data. The calibration factors are the sibling correlation of permanent earnings and the IGE or the IGC. We define permanent earnings as the life cycle average of log earnings residuals,

¹⁵We discount earnings with a 3% interest rate and divide the present discounted value by the number of individual observations to account for the unbalanced design of the earnings panel. Results are very similar when using 1% or 5% interest rates.

and we take deviations from generational means. Following Mazumder (2008), we estimate the variance components (σ_a^2 and σ_f^2) using a mixed model and an REML estimator, while we estimate the IGE (from which we also derive the IGC) using the canonical intergenerational regression of log sons' earnings on log fathers' earnings. Results are reported in panel A of table 5. We estimate the brother correlation to be 0.17, the IGE to be 0.08, and the IGC to be 0.09.¹⁶ Using equation (5), these estimates imply that the share of the brother correlation that is associated with fathers' earnings is 4%; using equation (5') to relax the assumption of stationarity, the share becomes 5%.¹⁷ Using instead the sequential conditioning approach of Mazumder (2008), the share of the correlation due to fathers' earnings is 4%.

Applying the approaches of previous studies on our data yields a share of brother correlation explained by fathers' earnings that is low and in line with the findings of those studies, which rules out data differences as the driver for differences in results. It must therefore be the set of assumptions behind the approaches that makes the difference. As we have seen in section IV, the key assumption of previous studies that we relax is that the IGE is constant between families. To further understand the role of the assumption, we now allow for IGE heterogeneity in equation (4) by means of a random coefficient specification within the mixed model, which results in the following sibling effect:

$$f_j = (\bar{\beta} + \beta_j) y_j^F + \mu_j^R. \quad (18)$$

The term on the right-hand side introduces heterogeneity of intergenerational persistence between families, where $\bar{\beta}$ is the population average IGE and β_j is the family-specific deviation from it, assumed independent of y_j^F in order to apply the REML estimator of the mixed model. Combining equations (2) and (18) with the normality assumptions of the REML estimator, sons' permanent earnings can be written as

$$y_{ij} = a_{ij} + (\bar{\beta} + \beta_j) y_j^F + \mu_j^R, \\ a_{ij} \sim N(0, \sigma_a^2), \mu_j^R \sim N(0, \sigma_{\mu R}^2), \beta_j \sim N(0, \sigma_\beta^2), \quad (19)$$

¹⁶Using the same data source as we do, Hussain, Munk, and Bonke (2009) report a set of IGE estimates for Denmark showing sensitivity to sample selection and the age range when sons are observed. They report an IGE of 0.07 for sons taken in the same age range as in our sample: 25 to 51. The figure reported by Björklund and Jäntti (2009; IGE = 0.12) is cited from Hussain et al. (2009), who obtain it when using sons' data in the 30–40 age range. Using data in that same 30–40 range, we obtain an IGE of 0.12.

¹⁷Replacing the IGC with the corresponding intergenerational component derived from our model ($r_I = 0.11$) yields an intergenerational share of 7.5%. Applying the decomposition formula of previous studies, we obtain a similarly low share (4% using the IGE and 7% using the IGC) when we use the log present discounted value of earnings in place of permanent earnings. Using years of education instead yields a larger share of the brother correlation that is ascribed to intergenerational transmission (20% using the IGE and 22% using the IGC), which is still much lower than the intergenerational share for the brother correlation in education that we obtain in section VI (73%).

TABLE 5.—DECOMPOSITIONS OF THE SIBLING CORRELATION WITH AND WITHOUT IGE HETEROGENEITY

A. Decompositions with Homogeneous IGE			B. Decompositions with Heterogeneous IGE		
	Coefficient	SE		Coefficient	SE
IGE (β)	0.0782	0.0023	Average IGE ($\bar{\beta}$)	0.0967	0.0023
IGC (λ)	0.0946	0.0028	Variance of IGE (σ_{β}^2)	0.0229	0.0013
Sibling correlation (r_S)	0.1724	0.0030	Sibling correlation (r_S)	0.1785	0.0031
Sibling correlation after regression on fathers' earnings ($\bar{r}_S$)	0.1649	0.0031			
Intergenerational shares			Intergenerational shares		
Solon (1999) (equation 5, β^2/r_S)	0.0355	0.0022	Assuming normality, stationarity, and independence of β_j and y_j^F (equation 21, $(\sigma_{\beta}^2 + \bar{\beta}^2)/r_S$)	0.1810	0.0078
Björklund et al. (2010) (equation 5', λ^2/r_S)	0.0519	0.0032	Assuming normality and independence of β_j and y_j^F (equation 20, $(\sigma_{\beta}^2 + \bar{\beta}^2)var(y_j^F)/r_S var(y_{ij})$)	0.2626	0.0112
Mazumder (2008) ($\bar{r}_S/r_S$)	0.0433	0.0245	Assuming normality (r_I/r_S)	0.6037	0.0176

which yields the following decomposition of the sibling correlation:

$$r_S = \frac{(\sigma_{\beta}^2 + \bar{\beta}^2) \text{var}(y_j^F)}{\text{var}(y_{ij})} + r_R. \quad (20)$$

The first term on the right-hand side captures the component of the sibling correlation that is due to paternal earnings, and the second term is the residual sibling correlation. Assuming a stationary distribution of permanent earnings across generations, equation (20) becomes

$$r_S = \sigma_{\beta}^2 + \bar{\beta}^2 + r_R. \quad (21)$$

Equation (21) is the counterpart of the decomposition of equation (5) in the case of heterogeneous IGE. It is clear from the decomposition formula, equation (21), that allowing for heterogeneous IGE adds a positive component—the variance of the IGE—to the computation of intergenerational effects within the sibling correlation.

We report results obtained from the mixed model with heterogeneous IGE in panel B of table 5. The sibling correlation is virtually identical to the one estimated with the standard mixed model. If we assume stationarity of the earnings distribution across generations (decomposition equation [21]), we find fathers' earnings account for 18% of brother correlations. Using earnings variances of fathers and sons estimated from the data to relax the stationarity assumption (decomposition equation [20]; $\text{var}(y_j^F) = 0.40$ and $\text{var}(y_{ij}) = 0.28$) fathers' earnings account for 26% of brother correlations. Thus, extending the modeling approach of previous studies by allowing for heterogeneous rather than homogeneous IGEs increases the share of brother correlation in earnings due to fathers' earnings from 4% to 5% to 18% to 26%.

The estimated intergenerational share of 26% is still far from the 66% that we have estimated in table 4 by applying our model to a simple measure of permanent earnings. The remaining discrepancy can be explained by the two distributional assumptions made when moving from the model in equations (2) to (4) to the model of equation (19): normality and independence between the family-specific IGE and fathers' earnings. Both assumptions are needed by the REML

estimator of the model with IGE heterogeneity, but not by the minimum distance estimator of variance components, and both assumptions might be rejected by the data.

Regarding independence, Björklund et al. (2012) show that intergenerational transmission is stronger at the top of the earnings distribution, while Corak and Piraino (2011) report that the probability of a father and son working in the same firm is the highest at the top of the fathers' earnings distribution. Both findings are consistent with a positive covariance between fathers' earnings and intergenerational transmission. Because the independence assumption is instrumental for separating the two intergenerational factors in equations (20) and (21) (squared average IGE and variance of the IGE), empirically we can relax the independence assumption by estimating the overall variance of the intergenerational component $\sigma_{\mu}^2 = \text{var}[(\bar{\beta} + \beta_j)y_j^F]$ without factorizations. This amounts to estimating the simple version of our model for permanent earnings under normality. We retrieve the relevant parameters from the covariance matrix of the errors in a seemingly unrelated system of three normal linear equations for the permanent earnings of fathers, first sons, and second sons. Results from this exercise are in table 5, panel B, with an intergenerational share of 60%. Comparing this estimated intergenerational share with the analogous share estimated under the assumption of independence (26%), suggests a substantial degree of correlation between β_j and y_j^F .

To understand the importance of the independence assumption, apply the formula for the variance of a product of two random variables to equation (20) (Bohrnstedt & Goldberger, 1969). Under bivariate normality of β_j and y_j^F , relaxing the assumption that they are independent yields $\text{var}[(\bar{\beta} + \beta_j)y_j^F] = (\sigma_{\beta}^2 + \bar{\beta}^2)\text{var}(y_j^F) + \text{cov}(\beta_j y_j^F)^2$, and the decomposition of the sibling correlation becomes

$$r_S = \frac{(\sigma_{\beta}^2 + \bar{\beta}^2) \text{var}(y_j^F) + \text{cov}(\beta_j y_j^F)^2}{\text{var}(y_{ij})} + r_R. \quad (20')$$

Equation (20') shows that because $\text{cov}(\beta_j y_j^F)^2$ is nonnegative no matter the sign of the covariance between β_j and y_j^F , equations (20) or (21) still provide a lower bound for the overall effect of intergenerational persistence within the

brother correlation. The existence of a correlation between β_j and y_j^F has implications also for traditional OLS regressions producing estimates of the population average IGE. Those regressions ignore the presence of a family-specific IGE and effectively treat it as an unobservable. We suggest this unobservable is correlated with the regressor of interest (fathers' earnings) and induces an omitted variable bias in the estimates of the IGE.

The remaining discrepancy between table 5, panel B and the first row of table 4 can be attributed to the normality assumption. The null hypothesis of normality is overwhelmingly rejected; the $\chi^2(6)$ test statistic for the hypothesis of joint normality of permanent earnings of the three family members is 202,449. When we consider the null hypothesis of bivariate normality, the $\chi^2(4)$ test statistic is 100,513 for the brother-brother pair and 150,662 (147,069) for the father-first (second) son pair. These test statistics show that the normality assumption is more strongly rejected for intergenerational associations than for brother associations, and there are differential deviations from normality in the distribution of permanent earnings for fathers and sons, hence reducing the share of brother correlation accounted for by intergenerational persistence when normality is assumed.

VIII. Conclusion

Family background has important effects on child outcomes in later life through parental and community influences, but for the past thirty years, it has been thought that most of the explained variation in earnings that siblings share is due to factors uncorrelated with parent's earnings. We show that this finding originates in assuming intergenerational transmission is homogeneous between families. Allowing for intergenerational transmission to be heterogeneous between families, we show that fathers' lifetime earnings account for 72% of the correlation in brothers' lifetime earnings. We also find large life cycle effects in brother correlations with a U-shape between ages 25 and 51. This variation has been masked in previous studies, which estimate averages over age.

Our findings relate to the large part of brothers earnings' similarity, which is driven by father-to-son transmission of earnings. This transmission does not leave much of a role for school or neighborhood factors that are uncorrelated with fathers' earnings to affect sons' earnings. But many known determinants of child outcomes are correlated with fathers' earnings—for example, household income (Dahl & Lochner, 2012), school quality (Chetty et al., 2011), and neighborhoods (Chetty, Hendren, & Katz, 2016). Nevertheless, showing that factors unrelated to fathers' earnings explain only 28% of brothers' shared earnings leaves brothers' lifetime earnings much less affected than previously thought by common influences orthogonal to fathers' earnings.

We have established that paternal earnings are important in determining brother correlations, and the same approach could be extended to further decompose the two components

of sibling correlations identified in this paper. Within the family, the relative importance of endowments versus parenting, and in the community the relative importance of schools versus neighborhoods, could be established. Assessing the importance of these factors is not new to the literature, but applying multiperson models of earnings dynamics with heterogeneous intergenerational transmission similar to the ones of this paper may provide new insights into these long-standing issues.

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