Correlations of Brothers' Earnings and Intergenerational Transmission*

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January 2015

Abstract

Correlations between parent and child earnings reflect intergenerational mobility, and more broadly, correlations between siblings' earnings reflect shared community and family background. We estimate intergenerational correlations and sibling correlations of earnings jointly 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 on average 80 percent of sibling correlations. This is higher than all previous studies because we allow for life-cycle effects and heterogeneous intergenerational transmission between families. Allowing for differential intergenerational transmission within families, we find mild evidence of stronger transmission to second sons.

Keywords: Sibling correlations; Intergenerational transmission; Life-cycle earnings
JEL codes: D31, J62

*We thank Anders Björklund, Mette Ejrnæs, Bo Honorè, Markus Jäntti, Matthew Lindquist, Bash Mazumder, Costas Meghir, Claudia Olivetti, Luigi Pistaferri, Gary Solon and audiences at Copenhagen Business School, University of Copenhagen, the University of Milan, La Sapienza University in Rome, ZEW-Mannheim, the 3rd LEED Workshop, ICEEE 5th, EEA 2013, ESPE 2013 and EALE 2013 for their comments. Cappellari gratefully acknowledges the hospitality of SFI in Copenhagen. Financial support was provided by the Danish Strategic Research Council (DSF-09-065167). The usual disclaimers apply. Addresses for correspondence: Bingley, SFI, The Danish National Centre for Social Research, Herluf Trolles Gade 11, DK-1052, Copenhagen, pbingley@sfi.dk; Cappellari, Department of Economics and Finance, Università Cattolica Milano, Largo Gemelli 1 I-20123 Milano, lorenzo.cappellari@unicatt.it.

I. Introduction

Explaining inequality of individual outcomes on the basis of family background is the subject of a vast literature in economics, sociology, and other disciplines. The theoretical background in economics 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 their children and maximize utility by choosing between their own consumption and investment in child earnings capacity. Offspring outcomes also depend on other productive endowments which are transmitted through the generations. As a result, lifetime earnings are transmitted between generations, through parental incomes and productive endowments. Solon (1999), Björklund and Jännti (2009) and Black and Devereux (2011) document the progress of economists in this field over the past 30 years, illustrating various angles from which one can study the importance of family background. Among these, intergenerational and sibling studies represent two prominent research approaches: the first explicitly considers the parent-child transmission, while the second provides an omnibus measure of family and community influences on offspring outcomes.

How much of the correlation in sibling outcomes is due to intergenerational transmission? Answering this question is key for understanding the channels through which outcomes are transmitted within the family and informing scope for policy interventions. Yet a direct empirical answer to this question is still missing in the literature. This paper provides such an answer by developing an econometric model of intergenerational and sibling correlations in life-cycle earnings.

We provide two main contributions to the literature. This paper is the first to study intergenerational and sibling correlations of earnings jointly within a unified framework. We draw data from administrative registers of the Danish population and model earnings dynamics within father/first-son/second-son triads. Using these triads identifies intergenerational effects separately from residual sibling effects within the overall sibling correlation. Our model nests those of previous research focussing on either intergenerational or sibling correlations, approaches that have complemented each other over the past twenty years, albeit indirectly. With a focus on permanent incomes, Corcoran et al. (1990) and Solon (1999) show analytically how the sibling correlation can be decomposed into a part due to intergenerational transmission and a residual sibling effect, the latter being interpreted as "[T]he combined effect of family background characteristics uncorrelated with parental income" (Solon, 1999, p. 1776). Subsequent research has been using this decomposition in calibration, by combining statistics of intergenerational and sibling associations estimated for different families and from separate studies. Other researchers have provided answers to this question by estimating the sibling correlation before and after conditioning sons' permanent earnings on parental permanent earnings (Mazumder, 2008; Björklund et al., 2010). In both cases, intergenerational transmission is assumed to be homogeneous in the population. In this paper we provide a direct decomposition of sibling correlations allowing for intergenerational links to differ across families. In this way, we estimate the importance of parental earnings to be much larger than has been found in previous research, by a factor of thirteen.

Our second contribution is to combine insights from the sibling and intergenerational literatures with the literature on individual earnings dynamics. The seminal works 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) have pioneered the use of these models for analyzing trends in 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.[1] For the first time we apply this approach to the analysis of the joint earnings dynamics of fathers, sons, and siblings.[2] Our model allows for individual heterogeneity in earnings growth and serially correlated transitory shocks. In this way we are able to tackle life-cycle biases and transitory shocks, which are the estimation issues plaguing the study of intra-family earnings correlations.

Previous studies have dealt with estimation issues either by taking averages of individual earnings over time to smooth out transitory shocks, or by limiting the analysis to a specific age range to mitigate life cycle biases. Both approaches entail a loss of information. Furthermore, tension exists between the two approaches because the time interval required for integrating out shocks of even moderate persistence is longer than the one in which the life-cycle bias is considered minimized.[3] We take an entirely different route by modelling both sources of bias, enabling us to avoid informational losses and to show how siblings and intergenerational correlations evolve from ages 25 to 48-60.

Using data on individual earnings averaged between age 25 and 42, previous research for Denmark has estimated the sibling correlation of permanent earnings to be around 0.23

[1] This complements other approaches to earnings mobility, namely transition matrices and comparisons of inequality in current and lifetime earnings (see Buchinsky and Hunt, 1999, and Bönke et al., 2015).
[2] The one study of multi-person earnings dynamics is Ostrowsky (2012), who analyzes spouses' earnings in Canada. He builds on the earlier work of Hyslop (2001) who modeled the covariance structure of spouses' earnings in the U.S., but without allowing for life-cycle effects.
[3] Observing earnings for the full working life of two generations would obviously mitigate life-cycle biases. In our data we are able to observe at most 32 years of earnings for fathers and 27 years of earnings for sons.

(Björklund et al., 2002). While confirming this finding on average, our results show that such correlation varies 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 0.23 by age 48. The u-shaped life cycle pattern of the sibling correlation reflects the existence of Mincerian cross-overs of earnings profiles within birth cohorts: there is a negative association between starting earnings and earnings growth across individuals, so that the intra-generational distribution of permanent earnings first shrinks and then fans out over the life cycle. We find that the compression/decompression occurs through the earnings component shared by siblings, generating a u-shaped pattern of sibling correlations.

We also find that intergenerational associations play a major role in determining the sibling correlation of permanent earnings; moreover, they display less life-cycle variation than the overall correlation. Our results indicate that intergenerational factors account for about 60 percent of the overall sibling correlation at age 25; this rises to 90 percent towards the mid-30s, and decreases to two thirds by the late 40s. On average, the intergenerational component accounts for 80 percent of the overall correlation. These results differ from those of previous studies that have implemented indirect decompositions. The finding in those studies was that in the Nordic countries the share of sibling earnings correlation accounted for by intergenerational factors is about 10 percent (6 percent for Denmark), and in the U.S. it is about 40 percent.

Our model nests the models of previous studies, and we exploit this property to provide further insights on our main results. The decomposition formula used by existing research does not allow for life-cycle variation of permanents earnings. Our first nested model imposes this restriction and we find that the intergenerational component accounts for 60 percent of the sibling correlation, which is somewhat closer to previous estimates for Denmark than our estimates from the main model. This suggests that the inclusion of life-cycle effects partly explains the differences between our results and those of others. In a second nested model, we only account for intergenerational effects and ignore any residual sibling components. Comparing the predicted intergenerational effect between this model and the full one is informative on the existence of a correlation between intergenerational and residual sibling effects, a correlation that we exclude when estimating the main model. We show that there are only minor differences in predictions between the full and the nested models, and that these are concentrated at young ages. Finally, our model nests a sibling-only model and we estimate this model using data only on brothers, finding that the predicted overall sibling correlation from this model matches that from the main model.

To further benchmark our findings with non-nested models, we use our data to replicate the approaches followed by previous studies, calibrations and sequential conditioning, on fathers' earnings. For both approaches we find that fathers' permanent earnings account for only 3 percent of the sibling correlation. The share explained by fathers' permanent earnings increases 6-9 fold when we use these same approaches but allow the intergenerational elasticity to be heterogeneous across families. Our multi-person model of earnings dynamics accounts for heterogeneity of intergenerational transmission and this largely explains why our findings differ from previous studies.

In the last part of the paper we consider how the results vary with sisters in the family, and finally we develop a variant of the model that allows intergenerational transmission to differ between brothers. We find that intergenerational transmission is stronger in the absence of sisters and to second sons, although in both cases the differences become statistically insignificant after age 35.

II. Related Literatures

A. *Sibling Studies*

Research on sibling correlations in outcomes has a long tradition in the economic and sociological literatures (see the reviews in Griliches, 1979; Solon, 1999; Björklund and Jännti, 2009; and Black and Devereux, 2011). Siblings are "[M]ore 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 et al., 1982). In addition, sibling effects capture those influences that are shared by siblings but that do not come from the parents, such as orthogonal school or community effects. Yet there may be family-transmitted factors that are not shared by siblings, (e.g., because of differential treatment from parents) and which are not captured by sibling correlations.

The prototypical earnings model used by previous research on sibling correlations specifies individual log earnings (w) as the sum of three orthogonal components:

$$w_{ijt} = a_{ij} + f_j + v_{ijt}, \qquad a_{ij} \sim \big(0, var(a)\big), f_j \sim \big(0, var(f)\big), v_{ijt} \sim \big(0, var(v)\big) \tag{1}$$

where i indexes individuals, j indexes families and t indexes time (see e.g. Solon, 1999, and Björklund et al., 2009).[4] The a and f components are assumed time invariant and measure permanent earnings, whereas v is a transitory shock typically assumed white noise.[5] Permanent earnings depend on an individual-specific factor a_{ij} capturing idiosyncratic components, and on a family-specific one f_j absorbing all determinants of permanent earnings that are shared by siblings, including both intergenerational transmission and all other sources of sibling similarities in earnings; we label the latter "residual sibling effects". Intergenerational earnings transmission may depend on endowments passed on at birth or on the extent with which parents are able to transmit their skills and preferences to their sons after birth. Conversely, residual sibling effects include parental influences not captured by earnings transmission, or other community effects shared by siblings, all independent of the parents' earnings. Schools, friendship networks, or other influences operating at the community level are examples of residual sibling effects. We label the effects captured by f_j (intergenerational plus residual sibling) "overall sibling effects".

The sibling correlation of permanent earnings (r^S) is the ratio between the variance of the overall sibling effect and the total variance of permanent earnings:

$$r^S = \frac{var(f)}{var(a) + var(f)} \tag{2}$$

it 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. Identification of the sibling correlation is achieved when data are available on earnings for sibling pairs over multiple years, as the multi-year requirement enables separation of permanent from transitory earnings. Existing studies report estimates of the correlation in brothers' permanent earnings ranging from 0.4 – 0.5 in the US (Solon et al., 1991; Altonji and Dunn, 1991; Solon, 1999; Mazumder, 2008) to a little higher than 0.3 in Sweden (Björklund et al., 2009) and about 0.2 for Norway and Denmark (Björklund and Jännti, 2009). Thus between one fifth and one half of the dispersion of permanent earnings is due to between-

[4] Residualizing earnings on an age or time trend or other observables is common, so that equation (1) is better understood as a model of individual deviations from the mean.
[5] One exception is Björklund et al., 2009, who adopt a stationary AR(1) process.

sibling differences in income-generating factors and the remainder is due to differences within sibling pairs.

Understanding how much of the sibling correlation indeed mirrors intergenerational transmission is important both for understanding the mechanisms behind between-family differences in the distribution of outcomes and for gauging the scope for inequality-reducing policies implemented at the community level. A formal characterization of the link between sibling income correlation and the intergenerational income 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 (1) and write the family component as the sum of father's permanent income and a residual sibling effect orthogonal to father's income, capturing remaining shared factors independent of father's income. The IGE is specified as constant in the population. Assuming stationarity in the distribution of permanent incomes of both fathers and sons, the resulting decomposition of the sibling correlation is:

$$r^S = IGE^2 + residual\ sibling\ correlation\ . \tag{3}$$

Solon (1999) reports an IGE of 0.4, which when matched to a sibling correlation of about the same size implies that 40 percent (=0.40^2/0.40) of the sibling correlation can be ascribed to intergenerational transmission. 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 Jännti (2009) report an IGE of about 0.12 and a brother correlation of about 0.23, implying in Denmark the role of parental income is negligible, explaining 6 percent of the overall sibling correlation. One of our contributions is to provide a counterpart to this decomposition, allowing intergenerational transmission to be heterogeneous in the population.

Björklund and Jännti (2012) use Swedish register data and apply the sibling correlation model to a range of traits and outcomes such as IQ, non-cognitive skills, height, schooling, and long-term earnings. They find that sibling correlations in earnings are the lowest, and that the strongest associations characterize height and IQ. They also estimate intergenerational correlations and apply the decomposition formula of equation (3), finding 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 equivalent to the decomposition of equation (3), the difference being that Mazumder's approach does not assume stationarity of the distribution of permanent incomes between generations. Using this method on U.S. data, he reports that approximately one third of the sibling correlation in long-run incomes is accounted for by parental incomes. Applying this approach to Swedish data, Bjorklund et al. (2010) report a reduction of the sibling correlations of 0.032 (or 13 percent) after controlling for fathers' income.

Understanding which factors determine the sibling correlation is also the aim in Page and Solon (2003a, b) where the focus is neighborhood effects rather than parental incomes. They contrast sibling correlations in earnings with correlations in earnings between neighboring boys and girls, finding that family effects matter more than neighborhood effects. Thus, similar to the studies that consider the effects of parental incomes, they find that a large portion of the sibling correlation remains unexplained.

B. *Estimation Issues and Models of Earnings Dynamics*

Estimating intra-family 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) and Zimmerman (1992) show that when estimating the IGE the bias can be substantial and that averaging parental incomes over a limited number of years is sufficient for mitigating it. Mazumder (2005) shows that when transitory shocks are characterized by serial correlation, measurement error becomes more severe and harder to integrate out, requiring sequences of individual income data as long as 30 years

The second issue stems from the so-called 'life-cycle bias', whereby 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 over- estimate (respectively) long-term ones (see Jenkins, 1987, and Grawe, 2006). 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 30-40 age range.[6] In the context of intergenerational analyses, Nybom and Stuhler (2011) show how life-cycle bias gives rise to non-classical measurement error and call for an explicit allowance for heterogeneous life-cycle growth across individuals in studies of intergenerational income associations.

The strategies that previous studies have suggested for coping with transitory shocks and life-cycle biases conflict with each other. While transitory shocks are better dealt with using long strings of individual earnings, life-cycle bias is minimized over a limited range, the ten years between ages 30 and 40.[7] 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 averaging out) the two sources of bias. Our approach avoids informational losses and allows for life-cycle effects in intra-family correlations of permanent earnings.

There exists a well-established literature on modelling individual earnings dynamics. In this tradition, studies typically start from a permanent-transitory characterisation of the log earnings process (in deviation from some central tendency) and pay considerable attention to the dynamic properties of the permanent and transitory components.[8] The latter are usually specified as low order ARMA processes, thus allowing for serial correlation of transitory shocks. Long-term 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.

In the RG-HIP model individual earnings are assumed to evolve according to an individual-specific linear age (or experience) profile (see e.g. Lillard and Weiss, 1979, Hause, 1980, Baker, 1997, Haider, 2001, Guvenen , 2007, and Gladden and Taber, 2009). There are two sources of persistent individual earnings differences, time-invariant heterogeneity and growth rate heterogeneity, that can represent heterogeneous returns to schooling and to experience. The presence of growth 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 summarised as follows:

[6] For Sweden, Böhlmark and Lindquist (2006) obtain results remarkably close to the ones of Haider and Solon (2006).
[7] See e.g. Björklund et al. (2009) for an application of this approach to sibling studies.
[8] See the survey articles by Meghir and Pistaferri (2011) and Browning and Ejrnæs (2013). Most of these studies focus on the earnings process in isolation from other outcomes; exceptions are Abowd and Card (1989) and Altonji et al. (2013).

$$y_{it} = a_i + b_i A_{it};\, (a_i\ b_i) \sim \big(0{,}0; var(a), var(b), cov(a,b)\big) \tag{4}$$

where y_{it} is log permanent earnings and A_{it} is age. Many studies have found a negative covariance between intercepts and slopes, implying that individuals starting-off with low pay will see their earnings grow faster than initially higher paid individuals (see e.g. Gladden and Taber, 2009). These different trajectories may either reflect Mincerian cross-overs due to on-the-job training (Hause, 1980), or the willingness of those on fast tracks to accept low paid jobs at labor market entry. In these circumstances, different 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: $A^* = -cov(a,b)/var(b)$. Hence, within a birth cohort permanent inequality displays a u-shaped profile minimised at A^*.

RW-RIP models assume earnings evolve through the arrival of infinitely lived shocks (z):[9]

$$y_{it} = y_{it-1} + z_{it};\, y_{it(A_0)} \sim \Big(0, var\big(y_{it(A_0)}\big)\Big);\ z_{it} \sim \big(0, var(z)\big) \tag{5}$$

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. RW-RIP produces a linear evolution of earnings variance over the life cycle. One virtue of the RW-RIP model is that it fits well within models of life-cycle optimization with rational expectations. Guvenen (2007) shows that a process of individual learning on the heterogeneous profile needs to be specified in order for the RG-HIP model to be used in a dynamic optimization framework.

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. A Model of Earnings Dynamics for Fathers and Sons

We study earnings dynamics within the family and set up a multi-person model which contributes to each of the three strands of literature reviewed in the previous section. We contribute to the earnings dynamics literature because ours is a model of the joint earnings process of three family members. We contribute to the literature on estimation biases because

[9] See, among others, MaCurdy (1982), Dickens (2000), Meghir and Pistaferri (2004) and Hyrisko (2012).

we resolve the tension faced by previous studies when choosing the length of the income strings to analyze, by modelling both heterogeneous earnings growth and serially correlated transitory shocks. Finally, we contribute to the sibling literature by decomposing the sibling correlation into intergenerational and residual sibling components accounting for heterogeneity of intergenerational transmission in the population.

We focus on men and distinguish three types of family members, fathers (*F*), first-born sons (*S1*) and second-born sons (*S2*), indexed by h.[10] For each family member, we consider individual log-earnings in deviation (w) from the mean, where the mean varies by year, birth cohort and type of family member.[11] 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:

$$w_{ijt}^{h} = y_{ijt}^{h} + v_{ijt}^{h}; E\left(y_{ijt}^{h}, v_{ijt}^{h}\right) = 0 \tag{6}$$

where the indices i, j, and t stand for individual, family and year of observation.

A. *Permanent Earnings*

We model permanent earnings by combining insights from literatures on sibling correlations and earnings dynamics and extend the model of equation (1) in two ways. First, we distinguish between an intergenerational component and a residual sibling component within the overall sibling correlation. This allows us, for the first time, to attribute part of the omnibus sibling earnings correlation to intergenerational earnings transmission while allowing for heterogeneous transmission in the population. We identify the transmission of earnings from fathers to sons, and we are silent about other channels of intergenerational transmission working independently of father's earnings. In this sense our decomposition provides a lower bound to the intergenerational component of sibling earnings correlations.

Second, we introduce life-cycle effects. We specify earnings components shared across family members using the RG-HIP parameterisation. This is motivated by the need to allow

[10] Only 4 percent of families are observed with more than two sons, see Section IV.

[11] Considering 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 and Solon (2003). Here we apply the "de-meaning" procedure distinguishing the different types of family members and adjusting for within-cohort age differences (we work with three-year birth cohorts) through quadratic trends, which we achieve by taking residuals from cohort/member-specific regressions of log earnings on calendar year dummies and quadratic age trends.

for heterogeneous earnings profiles in order to avoid life-cycle biases. Also, in the next section we provide evidence that empirical sibling correlations are u-shaped in age, a pattern that can be captured by a RG-HIP model and not by a RW-RIP. Note that in this multi-person context the RG-HIP model can be more easily justified from the informational viewpoint than in models of single-person earnings dynamics, for example, sons may already know the parameters of their earnings process at labor market entry by observing the earnings profiles of their fathers or of other members of their communities. We maintain the RW-RIP specification for the idiosyncratic component of permanent earnings.[12] Sons' earnings are written as:

$$y_{ijt}^{h} = \left(\left(\mu_j^I + \mu_j^R\right) + \left(\gamma_j^I + \gamma_j^R\right)A_{it} + \omega_{ijt}^{h}\right)\pi_t, \qquad h = S1, S2 \tag{7}$$
$$\omega_{ijt}^{h} = \omega_{ijt-1}^{h} + \phi_{ijt}^{h}.$$

The earnings profile is linear in age, and intercepts and slopes of the RG-HIP model depend upon family-specific effects. Family effects have an intergenerational component indexed by superscript I, and a residual sibling component indexed by R. They split permanent earnings shared by brothers into that due to father's permanent earnings and other factors independent of father's earnings. The idiosyncratic component (ω_{ijt}^{h}) is a RW-RIP process capturing persistent individual-specific deviations from the family effect. We also introduce time effects through period-specific loading factors π_t, following Moffitt and Gottschalk (1995), in order to avoid life-cycle variation being confounded by secular trends of earnings inequality.

Father's earnings need to be modelled jointly with sons' earnings in order to identify an intergenerational component within the overall sibling correlation. We specify a model for father's earnings similar to that of sons, with the exception of residual sibling effects that are shared by siblings only and do not feature in father's earnings. The model for father's earnings is:

$$y_{ijt}^{F} = \left(\mu_j^I + \gamma_j^I A_{it} + \omega_{ijt}^{F}\right)\pi_t. \tag{8}$$

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

[12] There are additional empirical considerations supporting our choice of specification, see footnote 19.

of family-specific heterogeneity (intergenerational and residual siblings) and are assumed to be independent between dimensions.[13] RW-RIP parameters are drawn from member-specific distributions. In sum, the distribution of permanent earnings is specified as follows:

$$\begin{gathered}(\omega_{ijt(A_0)}^{h}, \phi_{ijt}^{h}) \sim \left(0,0; \sigma_{\omega 0h}^{2}, \sigma_{\phi h}^{2}\right)\\ \left(\mu_j^I, \gamma_j^I\right) \sim \left(0,0;\ \sigma_{\mu I}^2, \sigma_{\gamma I}^2, \sigma_{\mu\gamma I}\right)\\ \left(\mu_j^R, \gamma_j^R\right) \sim \left(0,0;\ \sigma_{\mu R}^2, \sigma_{\gamma R}^2, \sigma_{\mu\gamma R}\right).\end{gathered} \tag{9}$$

Having specified a model with age related growth and idiosyncratic, intergenerational and residual sibling sources of heterogeneity in permanent earnings, we show in the Appendix how we can use parameter estimates to derive an additive decomposition of the overall sibling correlation (ρ^S) into intergenerational (ρ^I) and residual sibling (ρ^R) components:

$$\rho^S(A) = \rho^I(A) + \rho^R(A). \tag{10}$$

This decomposition nests previous ones because we allow for age effects in sibling correlations and heterogeneity of intergenerational transmission.

B. *Transitory Earnings*

Studies of individual earnings dynamics use low order ARMA processes to model transitory shocks. In contrast, intergenerational or sibling studies, take multi-period averages to smooth out earnings shocks and reduce measurement error biases, choosing the number of periods on the basis of the assumed degree of serial correlation. One exception is Björklund et al. (2009) who explicitly model correlated shocks as stationary AR(1) processes concentrating on the 30 – 40 age range, assuming shocks are uncorrelated across siblings.

In this paper we specify transitory earnings as member-specific AR(1) processes. 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. Allowing for this in our model avoids it being spuriously attributed to permanent earnings. We also allow for contemporaneous correlation of transitory shocks across family members. Our transitory earnings model is as follows:

[13] We assess this last assumption in Section VI when we consider estimates from nested models.

$$v_{ijt}^{h} = \tau_t u_{ijt} = \left(\rho_h u_{ijt-1} + \varepsilon_{ijt}\right)\tau_t, \quad \varepsilon_{ijt} \sim (0, \sigma_{\varepsilon hA}^2), \sigma_{\varepsilon hA}^2 = \sigma_{\varepsilon h}^2 \exp\left(g_h(A_{it})\right)$$
$$u_{ijs} \sim \left(0, \lambda_c^{d(s=t_0)} \sigma_{sh}^2\right), \qquad s = \max(t_0, c + A_0), \qquad (11)$$
$$E\left(\varepsilon_{ijt}\varepsilon_{kjt}\right) = \sigma_{hl}, \; h, l = F, S1, S2, \quad h \neq l$$

where c=c(i) denotes the birth cohort of person i and t_0 the first year of data, so that s=s(c) is the first year in which individuals from a given cohort are observed. We allow for non-stationarity by modelling the initial condition of the transitory process and introduce cohort effects in initial conditions (λ_c) for cohorts starting their life cycle prior to the initial observation year, d( ) is a binary indicator function. τ_t is a period specific loading factor and g_h( ) a member-specific linear spline. Each family member draws transitory shocks from a member-specific distribution, and shocks are (contemporaneously) correlated across members. Our model includes parameters capturing intergenerational and sibling correlations of transitory earnings shocks which have both been assumed away in previous studies. If, for example, transitory shocks are positively correlated across persons, then the between-member correlations of current earnings yield an upward biased estimate of correlations in permanent earnings.

C. *Estimation*

The model fully specifies the inter-temporal distribution of permanent and transitory earnings for each family member and between members. The second moments of this distribution are a non-linear function of a parameter vector θ that contains RW-RIP, RG-HIP and AR(1) coefficients, plus period factor loadings on permanent and transitory earnings. Details of moment restrictions are provided in the Appendix. We estimate θ by Minimum Distance (see Chamberlain, 1984; Haider, 2001).[14] In order to identify age effects separately from time effects, we derive birth-cohort specific empirical earnings moments and stack them in a single moment vector for estimation.

IV. 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

[14] We use Equally Weighted Minimum Distance (EWMD) and a robust variance estimator Var(θ)=$(G'G)^{-1}G'VG(G'G)^{-1}$, where V is the fourth moments matrix and G is the gradient matrix evaluated at the solution of the minimisation problem.

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 onwards (Pedersen, et al. 2006). We have complete legal parentage for men and women born from 1935 onwards. Children changing legal parentage through adoption before age 17 are dropped from the sample. We sample fathers born from 1935 and consider only sons born to first father-mother pair, conditional on father's age at first birth being 18 or older. We drop grandsons, i.e. fathers who were themselves observed as sons. First sons and second sons are included, and subsequent sons (4 percent) are ignored. If the first son or second son has a twin brother, the twin pair is dropped. Non-twin brothers born less than 12 months apart are also dropped. Second sons are dropped if they are born more than 12 years after the first. Finally we derive a sample of father/first-son/second-son triads and father/first-son couples.[15] Women play no role in the main analysis after determining full brotherhood.[16] We select fathers born 1935-1964, first sons born 1959-1982 and second sons born 1962-1982. This is because of completeness of registered parentage and the small number of first sons observed born before 1959.

We model annual pre-tax labor earnings which are obtained from income tax returns. Each January employers report earnings for the previous year for each employee to the tax authorities and to the employees themselves for verification. We use the sum of earnings from all employments during the year for the period 1980-2011 over which it is available in the Statistics Denmark Income Statistics Register (Baadsgaard and Quitzau, 2011). In order to model life-cycle dynamics we require observation of 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 25-60, first sons 25-51 and second sons 25-48. Most observations are for fathers' earnings 7,103,657, with 4,557,218 for first sons and 1,157,438 for second sons. Mean observed ages are 45.8, 33.2 and 32.5 respectively.

We group individuals into 3-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 (see for example Baker and Solon, 2003).

[15] By analogy with the sibling correlations literature that uses samples including singletons, we also consider families consisting of father/first-son couples only.

[16] 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 in-between the two sons, before or after. We study men and do not consider mother/son, father/daughter or brother/sister associations. We assess results robustness to the presence of sisters in Section VIII.

The combination of sample selection criteria generates a data-set which is described in the left panel of Table 1 for selected years in terms of first and second moments of the annual earnings distribution and average age. For this sample we apply two additional selections which are typical in the earnings dynamics literature. First, we exclude outliers by trimming half 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.[17] Secondly, in order to measure earnings profiles precisely we require at least five consecutive positive earnings observations. This is a selection rule that is intermediate between the one used by Baker and Solon (2003), who use continuous positive earnings strings, and the approach of Haider (2001), who allows individuals to move in and out of the sample only requiring two positive but not necessarily consecutive observations of earnings.

In common with most of the earnings dynamics literature, we exclude zero earnings observations and assume that earnings are missing at random. It is also common to drop zeros in the sibling correlation literature, for example Björklund et al. (2009). The right panel of Table 1 describes the estimation sample after making these restrictions. Trimming outliers and imposing partially continuous income 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 741,038 persons belonging to 326,341 families of which 88,356 are triads. Individuals are observed for 17.3 years on average (fathers 21.7, first sons 14.0 and second sons 13.1), giving 12,818,313 earnings observations in total.

We begin describing patterns of earnings associations within the family in Figure 1, which plots intergenerational and sibling correlations of log real annual earnings, adjusted for time and age effects. Earnings moments in this and the following sections are based on residuals of regressions for each birth cohort on calendar year dummies and a quadratic function of age. We discard empirical second moments that are based on fewer than 100 cases throughout the analysis. In order to calculate intergenerational correlations we average father-son correlations for both sons by sons' ages. The left panel shows two plots; the plot labelled "Same age" is calculated from the average of correlations when fathers and sons reach the same given age, while the plot labelled "Fixed age" is calculated when fathers are 40.

Raw intergenerational correlations are low and correspond with other studies that find Denmark has the lowest intergenerational correlation of all countries, see for example

[17] Using Danish registers Bingley et al (2013) show that estimates of earnings dynamics models are robust to alternative trimming rules.

Björklund and Jännti (2009). The main contrast between same-age and fixed-age figures is that while same-age correlations fluctuate between 0.05 and 0.10 with no clear pattern, correlations with father at 40 are very low at young ages and converge to the level of same-age correlations at 30. This pattern is consistent with life-cycle bias: estimating intergenerational correlations between fathers and sons 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 administrative data provides an adequate basis for controlling the bias.

We repeat the exercise with sibling earnings raw correlations in the right panel of Figure 1. The "Fixed age" plot refers to an older brother aged 30 and again shows upward trends at early ages, followed by a stabilisation around "Same age" level of correlation. The "Same age" plot displays a u-shaped age profile, which is consistent with a RG-HIP model of earnings dynamics with Mincerian cross-overs, in which siblings share both fixed and time varying components of earnings and the two are negatively correlated. Large same-age correlations while young may also reflect shared transitory shocks. It is well known that earnings are unstable for young cohorts (see e.g. Baker and Solon, 2003) and it is plausible that siblings are subject to common shocks, for example because of similar local economic conditions at labour market entry.

To assess if the relatively large sibling same-age correlation while young is driven by permanent earnings differences or transitory fluctuations, we compute sibling correlations for brothers born at least five or eight years apart (not shown). Brothers from more distant cohorts are less likely to share transitory shocks at labor market entry. The same-age profile of correlations persists even after excluding closely spaced brothers. This suggests that the source of the u-shaped age profile of sibling correlations is in the permanent earnings component, and is supportive of a RG-HIP specification. It is worth emphasising that our model also features age-dependent transitory shocks and is thus capable of distinguishing age effects within each earnings component.[18]

V. Results

[18] An additional reason for the declining sibling correlation between age 25 and 30 could be selection into the labour market: at age 25 school-to-work transitions might still be incomplete for a non-random sample of the population and the sources of non-randomness might be correlated between siblings. In our estimating sample 8 percent of brothers enter the labour market after the age of 25. To assess whether life-cycle patterns of sibling correlations are an artefact of selection into the labour market, we re-estimated raw correlations limiting the sample to siblings whose earnings profiles are observed since the age of 25, and found that the level and life-cycle evolution of the sibling correlation are virtually identical to the ones depicted in Figure 1.

We begin the discussion of results by focusing on estimates of parameters for the permanent and transitory components, which are reported in Tables 2 and 3; estimates of period factor loadings for both components (the πs and τs) are not reported for brevity and are available upon request. Parameters are estimated by imposing the moment restrictions implied by the model on empirical second moments of earnings, after excluding moments based on fewer than 100 individuals. We base the analysis on 5394 within-person moments (of which 3624 refer to fathers, 1344 to first sons and 966 to second sons), 17,620 father/first-son moments, 12,702 father/second-son moments and 8046 brother/brother moments. There are 44,302 empirical moments in total.

A. *Permanent Earnings*

Results for the RG-HIP/RW-RIP model are reported in Table 2. The table distinguishes parameters of the distribution of shared components (intergenerational and residual sibling) from those of the (member-specific) idiosyncratic components.

There are differences in idiosyncratic parameters between fathers and sons, demonstrating the importance of allowing for type-specific distribution of idiosyncratic effects. These differences are especially evident in the variance of RW-RIP innovations, which is the parameter driving the evolution over time of idiosyncratic earnings dispersion. Shocks are more dispersed for sons than fathers, which might reflect life-cycle variation in the variance of shocks, as fathers in our sample are observed on average at later stages of the careers than sons. Substituting the member-specific RW-RIP with a member-specific RG-HIP process confirmed that sons earnings profiles are more dispersed than fathers, while leaving our substantive results on the sibling correlation (presented later in this section) unaffected. We therefore maintain the RW-RIP specification of the idiosyncratic component because it increases the generality of the model in that the resulting specification of permanent earnings brings together elements of both the RW-RIP and RG-HIP models.[19]

Heterogeneity in sibling effects –intergenerational and residual sibling– is substantial. Considering initial earnings, for sons almost half of the variance comes from sibling effects. Heterogeneity of intergenerational effects is predominant within the sibling-specific distribution of initial earnings. Sibling effects are also evident in the distribution of earnings

[19] In preliminary analyses we experimented with a RW-RIP specification also for the shared components, obtaining negative estimated variances of the shocks. This result might be a consequence of the u-shaped pattern of empirical sibling correlations illustrated in Figure 1, which cannot be captured by a RW-RIP specification.

growth rates, but with different patterns. The residual sibling and the intergenerational components contribute equally to heterogeneity in earnings growth.

The covariance 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 32 and 34 years for the intergenerational and residual sibling components, respectively. The faster compression of the residual sibling component reflects the larger (in absolute value) estimate of the intercept-slope covariance. Insofar as Mincerian cross-overs emerge from heterogeneous investments in human capital, results suggest that the determinants of these investments are shared by siblings. Mincerian cross-overs imply that the predicted variance of permanent earnings explained by shared components will first decrease and then fan out over the life cycle. It is worth stressing that we obtain this result in a model that controls for age effects in transitory earnings, ruling out "omitted variable bias" induced by greater instability while young.

B. *Sibling Correlation in Permanent Earnings and its Components*

Figure 2 shows the life-cycle evolution of the overall sibling correlation and its decomposition into intergenerational and residual sibling effects. This decomposition is obtained by substituting estimated parameters in equation (10).[20] It represents the counterpart of decompositions from previous studies on the basis of equation (3).

The overall sibling correlation is about 0.5 at the start of the life cycle and depends mainly on intergenerational effects. This value is about twice that found previously for Denmark without allowing for life-cycle variation. As individuals age, overall sibling correlations diminish, and become smaller than 0.3 for ages 30-40. The reason for the rapid drop in sibling correlations is the shrinking of the overall intra-generational earnings distribution (Mincerian cross-overs) which is driven by sibling effects. After the cross-over point, the intra-generational earnings distribution starts opening up again as an effect of heterogeneous earnings growth, so that the overall sibling correlation increases. Note also that the cross-over age of earnings profiles is the mid-30s, and that the 30-40 age range will contain many sibling pairs with one brother either side of the cross-over. Hence, while the earnings distribution of the older brother is opening up, the distribution for the younger brother will still be compressing, which further contributes to the reduction of sibling

[20] See the Appendix for details. The graph is generated using idiosyncratic parameters of younger brothers, but we obtained almost identical patterns using the average of brothers' parameters.

correlations over this age range. After the younger brother also passes the cross-over age sibling correlations start increasing. The average sibling correlation is 0.23 and is very close to Björklund et al. (2002).

The most striking result from Figure 2 is the importance of intergenerational correlations which explain on average 80 percent of the overall sibling correlation. This is a larger share than previously thought, but is in line with sibling studies concluding that community factors external to the family explain little of the income correlation between brothers (see e.g. Page and Solon, 2003a,b). While life-cycle variation is evident in both the residual sibling and intergenerational components, it is more pronounced for the former. The residual sibling component is sizeable only at the start of the life cycle and falls to insignificance for ages 35-44 before rising slightly to age 48.

C. *Transitory Earnings*

Results for the member-specific AR(1) model for the transitory part of the earnings process are reported in Table 3.[21] The characteristics of the process governing transitory shocks are similar for the three family members. The estimate of the parameter $\sigma_{\varepsilon h}^2$ (baseline shock volatility at age 26) is larger for fathers than sons, but the difference is not statistically significant. The volatility of shocks decreases while young and increases when older. Baker and Solon (2003) find similar age-related heteroskedasticity. Increasing shock volatility is only evident for fathers, and fathers are the only family members observed ages 52-60.

Autoregressive coefficient estimates are of moderate size and tend to be rather stable across family members. However, the estimated variance of the AR(1) initial conditions (σ_{sh}^2) is larger for sons because we do not allow for cohort-specific shifters of the initial conditions on uncensored cohorts, and all birth cohorts of sons are first observed at age 25. Therefore, for sons the variance of initial conditions also reflects heterogeneity between cohorts.

Transitory shocks are positively correlated across family members, especially between brothers. For brothers, the correlation coefficient at age 26 implied by the estimates is 0.028, which is 5 percent of the overall sibling correlation of permanent earnings at 26. While quantitatively small, the existence of a significant correlation questions the ubiquitous assumption in sibling studies that transitory shocks are uncorrelated between siblings. There

[21] As illustrated in Section IV, this model allows for age-related heteroskedasticity in transitory shocks through an exponential spline. We also experimented with the quartic specification of Baker and Solon (2003) finding results very similar to those discussed here.

is a stronger correlation between fathers and second sons than between fathers and first sons, but the difference is insignificant.

VI. Nested Models

Our model nests those of previous studies: intergenerational-only models, siblings-only models, and models without life-cycle effects. By imposing restrictions on our model we can reconcile our findings with those of studies that only consider one dimension of family earnings associations or ignore earnings growth.

We present results for permanent earnings from nested models in Table 4. We start in column (1) with a model that excludes life-cycle variation in permanent and transitory earnings. This is essentially the model of equation (1), but with the overall sibling effect f_j split into intergenerational and residual sibling components.[22] This is the workhorse model of many previous sibling studies and underlies the decomposition of sibling correlations of equation (3). We estimate the sibling correlation to be 0.26, which is slightly larger than the average of 0.23 for the age-specific sibling correlations in Figure 2. The model attributes 60 percent of sibling correlation to the intergenerational component, which compares to an average of 80 percent in the more comprehensive model with life-cycle variation. Thus, ignoring age effects leads to underestimating the intergenerational effect which is the less age-sensitive component. The decomposition formula used in previous studies was derived under the assumption of life cycle constancy of earnings and those studies all concluded that residual sibling effects are larger than intergenerational effects. However, comparing the 60 percent intergenerational share of overall sibling effects implied by our restricted model estimates with the 6 percent reported by Björklund and Jännti (2009), suggests that imposing constancy alone is not enough to replicate the finding from previous studies that intergenerational effects are negligible. Different assumptions underlying other approaches may play a role, and we examine this in the next section.

We estimate the full model assuming no correlation between intergenerational and residual sibling effects. This assumption is assessed in column (2) of Table 4 showing estimates of permanent earnings parameters from a nested model constraining residual sibling parameters to zero and only allowing for intergenerational effects. If, for example, residual sibling and intergenerational effects are positively correlated, then omission of the former should inflate the latter in the nested model. Estimates from the full and nested models are

[22] The other difference with equation (1) is the inclusion of time shifters π_t and τ_t in our model.

very close. Predictions are presented in the left panel of Figure 3 and show that omitting residual sibling effects leads to overestimating intergenerational correlations by 20 percent (0.1) at the start of the life cycle but there is no bias beyond age 30.

Our final nested model considers only siblings and constrains intergenerational parameters to zero. Hence residual sibling effects now correspond to the overall sibling effects considered in other studies. Estimates of permanent earnings parameters are presented in column (3) of Table 4 and predictions from this model are contrasted with the full model in the right panel of Figure 3. There is no substantive difference between the two models, apart from lower precision for the sibling-only model which is estimated only on the 27 percent of families with two sons.

VII. Heterogeneous Intergenerational Transmission

Our results point towards a predominant role of fathers' earnings in explaining the sibling correlation, which contrasts with the findings of previous studies that fathers' incomes account for only a limited fraction of the sibling correlation. In the previous section we saw that excluding life-cycle effects from our model explains some of the discrepancy. The aim of this section is to understand whether the difference in results are specific to our data or are due to the different assumptions underlying our model, especially that we allow intergenerational transmission to be heterogeneous across families. In order to do this we replicate the approaches of previous studies on our data and then we introduce IGE heterogeneity into those approaches.

We start with the decomposition of equation (3). The ingredients for the calibration are the sibling correlation of permanent earnings and the IGE. We define permanent earnings as the individual average of (residualized) annual log earnings, in deviations from generational means. Following Mazumder (2008), we estimate the variance components using a mixed model and a Restricted Maximum Likelihood (REML) estimator, while we estimate the IGE using the canonical intergenerational regression of log sons' earnings on log fathers' earnings. Results are reported in the first panel of Table 5. We estimate the sibling correlation to be about 0.19 and the IGE to be 0.075.[23] Using equation (3), these estimates imply that the share of the sibling correlation that is associated with fathers' earnings is 3 percent. The second

[23] Using the same data source as us, Bonke et al. (2009) report a set of IGE estimates for Denmark showing their sensitivity to sample selections, in particular the age range when siblings are observed. They report an IGE of 0.07 for siblings taken in the same age range as in our sample, 25-51. The figure reported by Björklund and Jännti (2009; IGE=0.12) is cited from Bonke et al. (2009), who obtain it using siblings data in the 30-40 age range. Using data in that same range we obtain an IGE of 0.119.

panel of Table 5 reports results from the sequential conditioning approach of Mazumder (2008) and Björklund et al. (2010). Again, the share of the correlation that can be ascribed to fathers' earnings is 3 percent.

Applying the approaches of previous studies on our data yields a share of sibling correlation explained by fathers' earnings that is even lower than the ones of previous studies, which rules out data differences as the driver for differences in results. It must therefore be the set of assumption behind the approaches that makes the difference. One key assumption that we relax is that the IGE is constant across families. Specifically, while previous studies assume that intergenerational transmission occurs through a parameter (the IGE) which is common to all families, our model allows earnings components to be shared by fathers and sons in an unrestricted way (see the terms μ_j^I and γ_j^I in equations 7 and 8). To assess the role played by the assumption of IGE homogeneity, we specify a family component of the error as a function of fathers' earnings by means of a random coefficient specification, which is natural in a mixed model. Using the same model underlying the decomposition of equation (3) we can therefore allow for heterogeneous IGE of permanent earnings. This strategy is close in spirit to our multi-person model of earnings because it considers the heterogeneous impact of fathers' earnings within the variance components of sons' earnings. Using the notation of equation (1), the mixed model with random coefficient specification is:

$$y_{ij} = a_{ij} + f_j;\ \ f_j = \eta_j y_j^F + \bar{\eta} y_j^F + \xi_j;\ \eta_j \sim (0, var(\eta)),\ \ \xi_j \sim (0, var(\xi)). \tag{11}$$

The model for the family-specific component f_j has three terms. The second and third terms on the right hand side are the ones yielding (under the assumption of stationary earnings distributions across generations) the decomposition formula of equation (3), $\bar{\eta}$ being the (population average) IGE, y_j^F being father's permanent earnings and ξ_j being the residual sibling effect. The first term introduces heterogeneity of intergenerational transmission across families, where η_j is the family-specific deviation from $\bar{\eta}$, assumed independent of y_j^F. Abstracting from life-cycle effects, this specification is similar to our main model, with the difference that in equations (7) and (8) we make a distinction between components of father's permanent earnings that are passed between generations and those that are purely idiosyncratic, whereas in equation (11) both are subsumed in the term y_j^F. Because permanent earnings are in deviations from generational means, all the random variables in (11) have expectation equal to zero, so that the sibling correlation decomposes as follows:

$$r^S = \frac{(var(\eta) + \bar{\eta}^2) * var(y^F)}{var(a) + var(f)} + \frac{var(\xi)}{var(a) + var(f)} \tag{12}$$

with the first term on the right hand side capturing the component of the sibling correlation that is due to paternal earnings, and the second term capturing the residual sibling correlation. By following Corcoran et al. (1990) and Solon (1999) in assuming a stationary distribution of permanent earnings across generations ($var(y_j^F) = var(a) + var(f)$), equation (12) becomes:

$$r^S = var(IGE) + IGE^2 + residual\ sibling\ correlation. \tag{13}$$

This is the counterpart of the decomposition of equation (3) in the case of heterogeneous IGE. It is clear from the decomposition formula (13) that allowing for heterogeneous IGE adds a positive component to the computation of intergenerational effects within the sibling correlation.[24]

We report results obtained from the mixed model with heterogeneous IGE in the third panel of Table 5. If we assume stationarity of the earnings distribution across generations (decomposition formula (13)) we find fathers' earnings accounts for 20 percent of sibling correlations. Fathers' earnings account for 26 percent if we do not assume stationarity (decomposition formula (12)). Thus, even within the same modelling approach of previous studies, allowing for heterogeneous rather than homogenous IGEs increases the share of sibling correlation in earnings due to fathers' earnings 6-9 fold.

VIII. Family Structure and Differential Intergenerational Transmission

In this section we provide answers to two questions. First, how sensitive are our results to the presence of other siblings in the family? And, second, does intergenerational transmission differ between brothers?

We investigate the impact of family structure by focussing on daughters and splitting the sample into families with and without daughters. Columns (1) and (2) of Table 6 show parameter estimates are stable across sub-samples. Figure 4 presents the decomposition of

[24] Note also that we have derived equation (13) assuming that the family-specific IGE is independent of the level of father's earnings. Björklund et al. (2012) show that intergenerational transmission is stronger at the top of the earnings distribution, i.e. $cov(\eta y^F) > 0$, implying that equation (13) still provides a lower bound for the overall effect of intergenerational transmission within the sibling correlation.

sibling correlations for families with at least one daughter (right panel) and without daughters (left panel). Families without daughters have larger intergenerational correlations and smaller residual sibling (brothers) effects, which fall to zero by age 35. The decomposition for families with daughters is similar to that for the pooled population in Figure 2.

Differential treatment of offspring by parents is a concern for sibling studies which aim to estimate shared family effects (see e.g. Björklund and Jännti, 2009). First born children have on average better outcomes than later born siblings and this is often interpreted as parents investing more in first born children (Black et al., 2005). Björklund and Jännti (2012) show that residualization of earnings on birth order via mixed models has little impact on estimated sibling correlations. Whether the intergenerational transmission of outcomes (rather than outcome levels *per se*) varies with birth order is a different and related question which has received only little attention (Behrman and Taubman, 1986, Behrman, et.al, 1994, Hotz and Pantano, 2013), and we address this now for earnings.

We observe intergenerational earnings moments for both sons and can relax the assumption that their intergenerational parameters are the same by allowing intergenerational components to enter into younger sons' process through specific factor loadings δ_μ and δ_γ:

$$y_{ijt}^{S2} = \left(\left(\delta_\mu \mu_j^I + \mu_j^R\right) + \left(\delta_\gamma \gamma_j^I + \gamma_j^R\right) A_{it} + \omega_{ijt}^{S2}\right)\pi_t. \quad (14)$$

We only consider the sub-sample of three-member families because otherwise between-sibling differentials may pick up single-son effects. The hypothesis of equal treatment corresponds to factor loadings of unity. Estimates of factor loadings which are larger (smaller) than unity mean that intergenerational transmission matters more (less) for second sons compared with first sons.

Results are presented in column (3) of Table 5. There is some variation in parameter estimates relative to Table 2 because now we are considering a smaller sample of only triads. The two intergenerational loading factors for the second son are precisely estimated. Initial earnings transmission is 32 percent higher from father to second sons than to the first, whereas earnings growth transmission is 4 percent lower to second sons than to first. To assess the joint (intercepts and slopes) significance of between-son differences, Figure 5 plots predicted intergenerational correlations for the two sons. At age 25 for second sons' intergenerational correlations are twice that of first sons, but the difference shrinks to insignificance by age 35. These modest differences in intergenerational transmission between brothers, concentrated at young ages to the benefit of second sons, may reflect parents' greater economic stability or longer experience of parenting.

At first glance, stronger transmission to second sons may appear to be at odds with findings from birth order studies that first born children do better. However, ours is not a model for which son does better, but a model for which son more closely resembles the father in an earnings correlation sense. Our result may actually emerge from a situation in which poor families concentrate investments on first sons (consistent with findings from birth order studies) which exhaust the resources available to second sons. This will make it more likely that second sons begin working for low earnings, thus resembling their fathers' earnings position more closely than their brothers' do.[25]

IX. Conclusion

Family background has important effects on child outcomes in later life through parental and community influences. We show that fathers' lifetime earnings account for 80 percent of the correlation in brothers' lifetime earnings. This is a much greater share than has been found in previous research that uses indirect decomposition methods and does not allow for heterogeneous intergenerational transmission between families. We also find large life-cycle effects in sibling correlations with a u-shape between ages 25 and 48. 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 does not leave much scope for school or neighbourhood factors that are *uncorrelated with fathers' earnings* to effect sons' earnings. But many known determinants of child outcomes are correlated with fathers' earnings, for example household income (Dahl and Lochner, 2012), school quality (Chetty et. al., 2011) and neighbourhoods (Ludwig et.al., 2008). Nevertheless, showing that factors unrelated to fathers earnings only explain 20 percent of brothers shared earnings, leaves brothers with much less scope than previously thought for common influences orthogonal to the father affecting their lifetime earnings.

We have established that paternal earnings are important in determining sibling 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

[25] We thank Gary Solon for suggesting this interpretation to us.

schools versus neighbourhoods could be established. Assessing the importance of these factors is not new to the literature, but applying multi-person models of earnings dynamics similar to the ones of this paper may provide new insights on these long-standing issues.

Appendix

Minimum Distance estimation of the model is based on imposing the moment restrictions implied by the model on empirical second moments estimated from the data.

Moment restrictions for the model of permanent earnings are provided below.

Father's covariance structure

$$E\left(y_{ijt}^{F}y_{ijq}^{F}\right) = \left(\sigma_{\mu I}^{2} + \sigma_{\gamma I}^{2}A_{it}A_{iq} + \sigma_{\mu\gamma I}(A_{it}+A_{iq}) + \sigma_{\omega 0F}^{2} + \sigma_{\phi F}^{2}A_{it}\right)\pi_t\pi_q, \qquad t \leq q. \quad \text{(A.1)}$$

Son's covariance structure

$$E\left(y_{ijt}^{Sb}y_{ijq}^{Sb}\right) = \Big(\left(\sigma_{\mu I}^{2} + \sigma_{\mu R}^{2}\right) + \left(\sigma_{\gamma I}^{2} + \sigma_{\gamma R}^{2}\right)A_{it}A_{iq} + \left(\sigma_{\mu\gamma I} + \sigma_{\mu\gamma R}\right)(A_{it}+A_{iq}) + \sigma_{\omega 0Sb}^{2} + \sigma_{\phi Sb}^{2}A_{it}\Big)\pi_t\pi_q,\ t \leq q,\ b = 1,2. \quad \text{(A.2)}$$

Father-Son covariance structure

$$E\left(y_{ijt}^{F}y_{kjq}^{Sb}\right) = \left(\sigma_{\mu I}^{2} + \sigma_{\gamma I}^{2}A_{it}A_{iq} + \sigma_{\mu\gamma I}(A_{it}+A_{iq})\right)\pi_t\pi_q,\ b = 1,2. \quad \text{(A.3)}$$

Son-Son covariance structure

$$E\left(y_{ijt}^{S1}y_{kjq}^{S2}\right) = \Big(\left(\sigma_{\mu I}^{2} + \sigma_{\mu R}^{2}\right) + \left(\sigma_{\gamma I}^{2} + \sigma_{\gamma R}^{2}\right)A_{it}A_{iq} + \left(\sigma_{\mu\gamma I} + \sigma_{\mu\gamma R}\right)(A_{it}+A_{iq})\Big)\pi_t\pi_q. \quad \text{(A.4)}$$

RG-HIP and RW-RIP parameters are identified by variation in age (in deviation from age 25). RW-HIP parameters are identified by individual earnings moments. Intergenerational RG-HIP parameters are identified by Father-Son earnings moments. RG-HIP sibling parameters are identified by Son-Son earnings moments, so that the difference between sibling moments and intergenerational moments identifies residual sibling parameters. Using parameter estimates we can decompose the total sibling correlation of permanent earnings into its intergenerational and residual sibling components over the life cycle, obtaining equation (10) of the main text:

$$\rho^{S}(A) = \rho^{I}(A) + \rho^{R}(A). \quad \text{(A.5)}$$

where

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

$$\rho^R(A) = \frac{\sigma_{\mu R}^2 + \sigma_{\gamma R}^2 A^2 + 2\sigma_{\mu\gamma R} A}{var\big(y(A)\big)}$$

and

$$var\big(Y(A)\big) = \Big(\big(\sigma_{\mu I}^2 + \sigma_{\mu R}^2\big) + \big(\sigma_{\gamma I}^2 + \sigma_{\gamma R}^2\big)A^2 + \big(\sigma_{\mu\gamma I}^2 + \sigma_{\mu\gamma R}^2\big)2A \ + \sigma_{\omega 0 Sb}^2 + \sigma_{\phi Sb}^2 A\Big),$$
$$b = 1{,}2.$$

Within person moment restrictions for the member-specific AR(1) model are as follows:

$$E\big(v_{ijt}^h v_{ijq}^h\big) = \Big(d(t = q = s)\eta_c^{d(s=t_0)}\sigma_{sh}^2 + d(t = q > s)\big(\sigma_{\varepsilon hA}^2 + var\big(u_{ijt-1}\big)\rho_h^2\big) + d(t \neq q)\big(E\big(u_{ijt-1}u_{ijq}\big)\rho_h\big)\Big)\tau_t\tau_q. \quad \text{(A.6)}$$

Allowing for contemporaneous correlation of transitory shocks across different persons, the model yields restrictions on transitory earnings also for cross-member moments:

$$E\big(v_{ijt}^h v_{kjq}^l\big) = \sigma_{hl}\left(\frac{\Big(1 - \big(\rho_h\rho_l^{|t-q|}\big)^P\Big)}{1 - \rho_h\rho_l^{|t-q|}}\right)^{d(t\leq q)}\left(\frac{\Big(1 - \big(\rho_l\rho_h^{|t-q|}\big)^P\Big)}{1 - \rho_l\rho_h^{|t-q|}}\right)^{d(t>q)}, \quad \text{(A.7)}$$
$$h = F, S1, S2;\ \ l = S1, S2;\ h \neq l.$$

where P is the number of years the two family members are simultaneously observed in the data.

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Figures and Tables

Figure 1: Intergenerational and sibling correlations of raw earnings

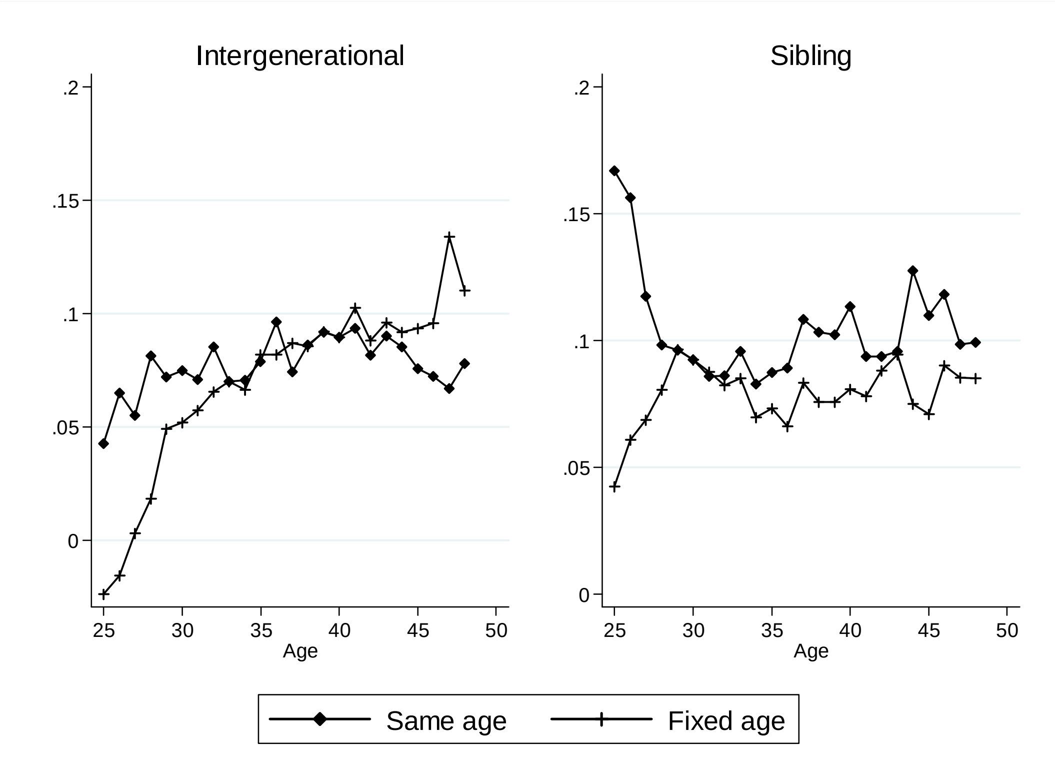

Figure 2: Decomposition of sibling correlation of permanent earnings

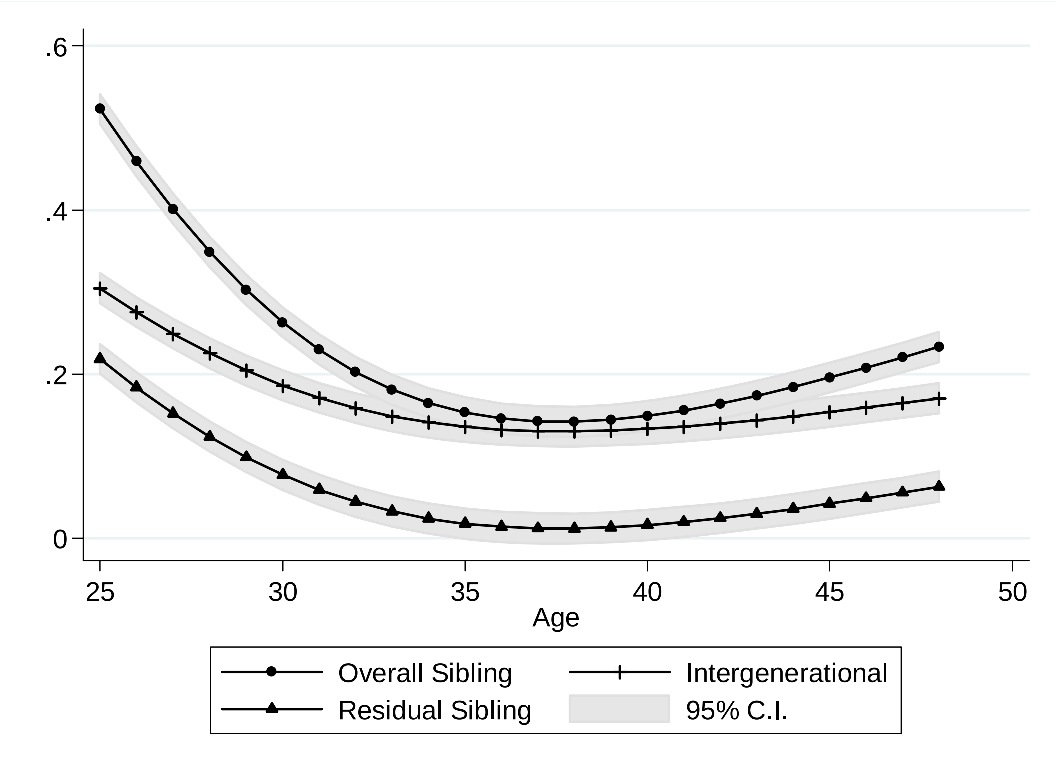

Figure 3: Comparison of intergenerational and overall sibling correlations of permanent earnings between full and nested models

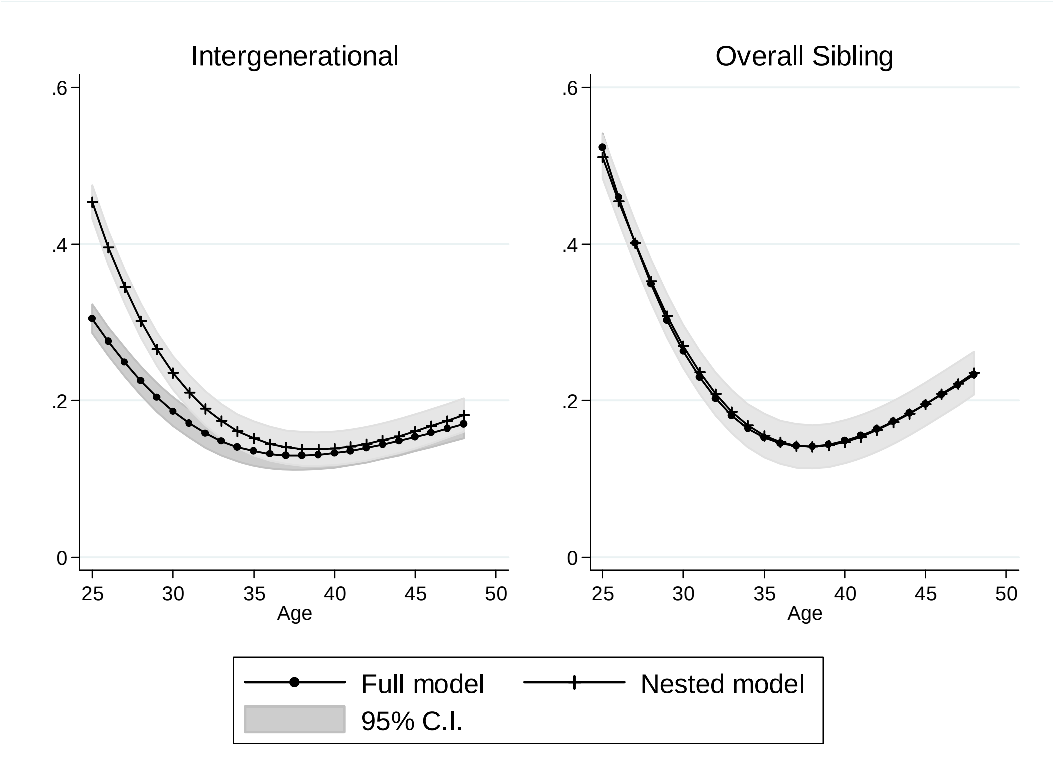

Figure 4: Decomposition of sibling correlations of permanent earnings by presence of sisters

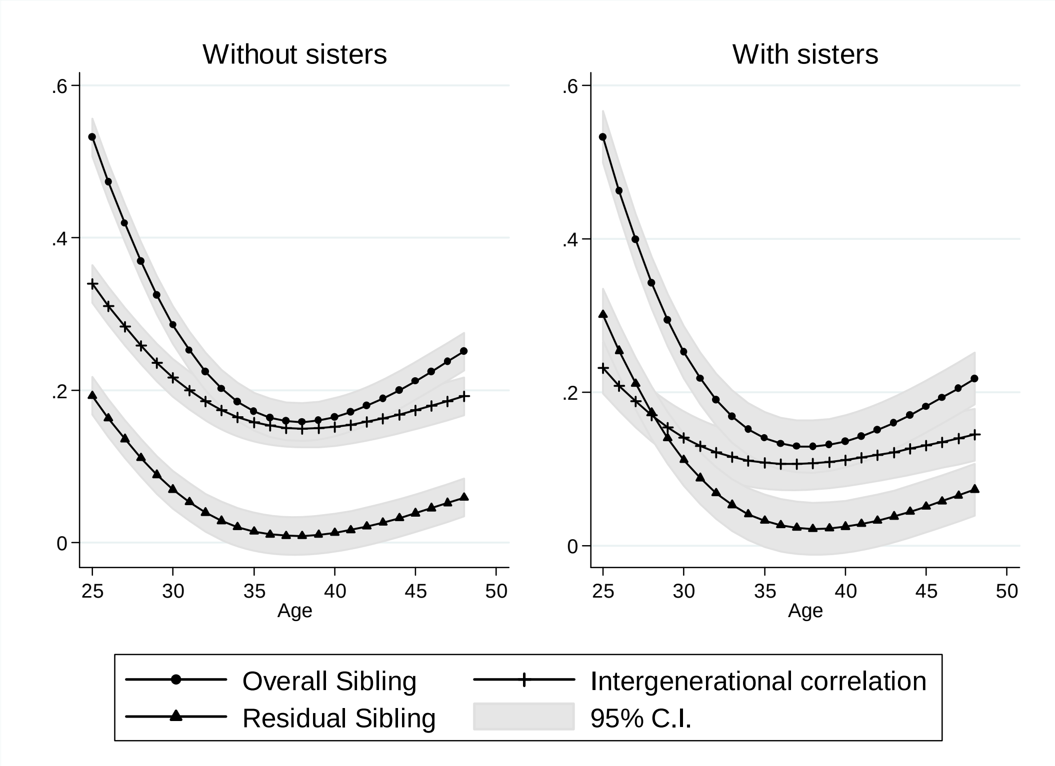

Figure 5: Intergenerational correlations of permanent earnings from model with differential transmission – Triads only sample

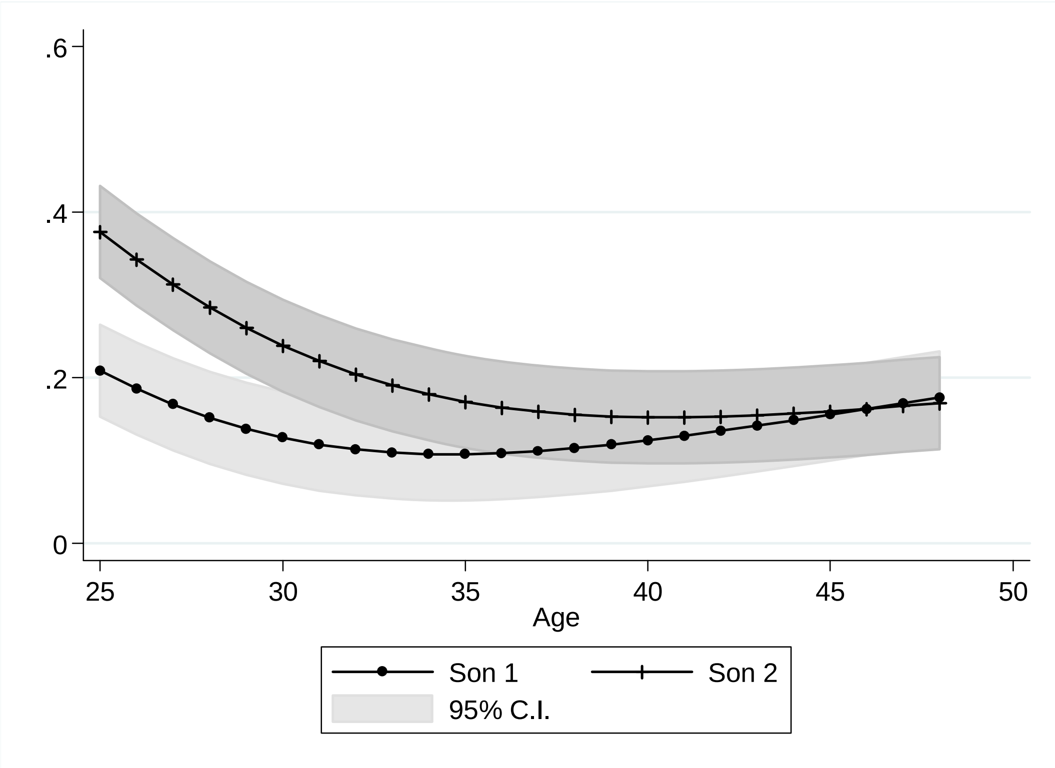

Table 1: Descriptive statistics

		(1) Sample without earnings selection			(2) Estimation sample		
		Father	Son 1	Son2	Father	Son 1	Son2
# Individuals		396736	396736	115509	326341	326341	88356
# Observations		8112986	5193082	1409792	7103657	4557218	1157438
1990	Earnings	367494	286872	269512	366484	290238	273853
	SD Earnings	200849	137865	126391	167141	125580	118398
	Age	44.7	27.9	27.0	44.8	27.9	27.0
1995	Earnings	376226	296507	283422	373952	298807	286928
	SD Earnings	220566	147595	137790	180687	134807	125366
	Age	49.4	29.2	28.2	49.6	29.2	28.1
2000	Earnings	394004	327994	312039	389313	329459	315138
	SD Earnings	250858	188471	167531	188667	161141	146507
	Age	52.1	30.8	29.6	52.2	30.8	29.6
2005	Earnings	392516	370406	355919	386897	370352	357991
	SD Earnings	246300	222133	195490	189057	178559	162501
	Age	55.5	34.3	33.1	55.6	34.3	33.2
2010	Earnings	402068	416365	401634	394428	414657	401868
	SD Earnings	293636	303068	268377	205427	211435	194422
	Age	56.7	37.9	36.8	56.8	37.9	36.9

Notes: Annual earnings are reflated to 2012 Danish Krone (1USD is worth about 5DKK)

Table 2: Estimates of parameters of permanent earnings

	Coeff.	S.E.
Shared components		
Variance of initial earnings		
$\sigma^2_{\mu I}$(Intergenerational)	0.0339	0.0015
$\sigma^2_{\mu R}$(Residual Sibling)	0.0243	0.0029
Variance of earnings growth rates		
$\sigma^2_{\gamma I}$(Intergenerational)	0.0002	0.00001
$\sigma^2_{\gamma R}$(Residual Sibling)	0.0002	0.00001
Covariance		
$\sigma_{\mu\gamma I}$(Intergenerational)	-0.0014	0.0001
$\sigma_{\mu\gamma R}$(Residual Sibling)	-0.0018	0.0002
Idiosyncratic component		
Variance of initial earnings		
$\sigma^2_{\omega 0F}$ (Father)	0.0697	0.0043
$\sigma^2_{\omega 0S1}$ (Son 1)	0.0711	0.0051
$\sigma^2_{\omega 0S2}$ (Son 2)	0.0531	0.0048
Variance of shocks		
$\sigma^2_{\phi F}$ (Father)	0.0021	0.0006
$\sigma^2_{\phi S1}$ (Son 1)	0.0071	0.0007
$\sigma^2_{\phi S2}$ (Son 2)	0.0082	0.0009

Table 3: Estimates of member-specific AR(1) parameters of transitory earnings

	Father		Son 1		Son 2	
	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
$\sigma^2_{\varepsilon h}$(Baseline variance)	0.2847	0.0355	0.2474	0.0254	0.2309	0.0246
Age splines						
26-30	-0.1024	0.0476	-0.1357	0.0037	-0.1392	0.0065
31-35	-0.0286	0.0176	-0.0501	0.0034	-0.0644	0.0066
36-40	-0.0263	0.0111	-0.0031	0.0040	-0.0002	0.0082
41-45	0.0010	0.0127	-0.0348	0.0093	-0.0134	0.0197
46-51	-0.0199	0.0055	-0.0301	0.0133	-0.1052	0.0483
52-60	0.0591	0.0029				
ρ_h(Autocorrelation coefficient)	0.5136	0.0102	0.5141	0.0034	0.5213	0.0055
σ^2_{sh}(Baseline initial condition)	0.2558	0.0255	0.4115	0.0419	0.4126	0.0428
λ_c(Initial condition shifter for left-censored cohorts, 1953-55=1)						
1935-37	1.3514	0.1982				
1938-40	1.4657	0.1895				
1941-43	1.3005	0.1585				
1944-46	1.0929	0.1257				
1947-49	0.8896	0.0972				
1950-52	0.9384	0.0961				
σ_{hl}(Between-person covariance)						
Father			0.0027	0.0003	0.0030	0.0003
Son1					0.0066	0.0007

Table 4: Estimates of parameters of permanent earnings from nested models

	(1) No life cycle effects		(2) Intergenerational only		(3) Sibling only	
	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
Shared components						
Variance of initial earnings						
$\sigma^2_{\mu I}$(Intergenerational)	0.0127	0.0008	0.0390	0.0021		
$\sigma^2_{\mu R}$(Residual Sibling)	0.0070	0.0007			0.0542	0.0040
Variance of earnings growth rates						
$\sigma^2_{\gamma I}$(Intergenerational)			0.0002	0.00001		
$\sigma^2_{\gamma R}$(Residual Sibling)					0.0003	0.00002
Covariance						
$\sigma_{\mu\gamma I}$(Intergenerational)			-0.0017	0.0001		
$\sigma_{\mu\gamma R}$(Residual Sibling)					-0.0030	0.0002
Idiosyncratic component						
Variance of initial earnings						
$\sigma^2_{\omega 0F}$ (Father)	0.0781	0.0022	0.0666	0.0046		
$\sigma^2_{\omega 0S1}$ (Son 1)	0.0616	0.0048	0.0627	0.0046	0.0708	0.0054
$\sigma^2_{\omega 0S2}$ (Son 2)	0.0477	0.0044	0.0469	0.0045	0.0518	0.0045
Variance of shocks						
$\sigma^2_{\phi F}$ (Father)			0.0020	0.0006		
$\sigma^2_{\phi S1}$ (Son 1)			0.0071	0.0007	0.0053	0.0006
$\sigma^2_{\phi S2}$ (Son 2)			0.0079	0.0008	0.0063	0.0007

Table 5: Decompositions of the sibling correlation using the approaches of previous research with and without IGE heterogeneity

	Coeff.	S.E.	%
Decompositions with homogeneous IGE			
Solon (1999) decomposition			
$var(a)$	0.2358	0.0010	
$var(f)$	0.0550	0.0010	
IGE	0.0757	0.0015	
r^S	0.1892	0.0034	
Share of r^S explained by y_j^F			3.02
Sequential conditioning			
$var(a)$ after conditioning on y_j^F	0.2359	0.0010	
$var(f)$ after conditioning on y_j^F	0.0527	0.0010	
r^S after conditioning on y_j^F	0.1828	0.0034	
Share of r^S explained by y_j^F			3.36
Decompositions with heterogeneous IGE			
$var(a)$	0.2354	0.0010	
IGE	0.0912	0.0016	
$var(IGE)$	0.0307	0.0011	
$var(\xi)$	0.0422	0.0010	
r^S	0.1953	0.0034	
Share of r^S explained by y_j^F			
Assuming stationarity			20.00
Without assuming stationarity ($var(y_j^F)$=0.3824)			26.15

Table 6: Estimates of parameters of permanent earnings by presence of sisters and with differential intergenerational transmission between brothers

	(1) Without sisters		(2) With sisters		(3) Differential IG	
	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
Shared components						
Variance of initial earnings						
$\sigma^2_{\mu I}$(Intergenerational)	0.0333	0.0021	0.0322	0.0009	0.0319	0.0015
δ_μ (Intergenerational loading Son 2)					1.3212	0.0188
$\sigma^2_{\mu R}$(Residual Sibling)	0.0188	0.0034	0.0418	0.0026	0.0353	0.0026
Variance of earnings growth rates						
$\sigma^2_{\gamma I}$(Intergenerational)	0.0001	0.00001	0.0002	0.00001	0.0002	0.00001
δ_γ (Intergenerational loading Son 2)					0.9689	0.0046
$\sigma^2_{\gamma R}$(Residual Sibling)	0.0001	0.00002	0.0002	0.00001	0.0002	0.00001
Covariance						
$\sigma_{\mu\gamma I}$(Intergenerational)	-0.0014	0.0001	-0.0013	0.00004	-0.0015	0.0001
$\sigma_{\mu\gamma R}$(Residual Sibling)	-0.0014	0.0002	-0.0029	0.0002	-0.0022	0.0001
Idiosyncratic component						
Variance of initial earnings						
$\sigma^2_{\omega 0F}$ (Father)	0.0740	0.0048	0.0581	0.0035	0.0532	0.0051
$\sigma^2_{\omega 0S1}$ (Son 1)	0.0726	0.0073	0.0777	0.0039	0.0859	0.0054
$\sigma^2_{\omega 0S2}$ (Son 2)	0.0459	0.0057	0.0650	0.0060	0.0570	0.0049
Variance of shocks						
$\sigma^2_{\phi F}$ (Father)	0.0013	0.0007	0.0039	0.0005	0.0045	0.0006
$\sigma^2_{\phi S1}$ (Son 1)	0.0063	0.0009	0.0089	0.0006	0.0102	0.0011
$\sigma^2_{\phi S2}$ (Son 2)	0.0061	0.0009	0.0118	0.0012	0.0118	0.0012