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Family, Community and Long-Term Earnings Inequality

By

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Abstract

Correlations between the earnings of siblings reflect shared family and community background, but evidence is mixed on the relative magnitudes of these influences. Using administrative data on the Danish population we link brothers, schoolmates and teenage neighbors and estimate a model of multiple group earnings dynamics to measure jointly the relative importance of family, neighborhoods and schools for long-term earnings. We find that: (1) family is by far the most relevant factor; (2) the influence of neighborhoods and schools falls rapidly, becoming insignificant by age 30; and (3) community effects are persistent and upward biased by a factor of five if family effects are ignored.

JEL classification: D31, J62

Keywords: Sibling correlations; Neighborhoods; Schools; Life-cycle earnings; Inequality

Outline

1. *Introduction*
2. *Background and related Literature*
3. *Data*
4. *Descriptive statistics on earnings of sibling and peers*
5. *Econometric model*
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Non-Technical Summary

Family and community background are perceived as being important determinants of socioeconomic outcomes such as earnings. Families can determine earnings by transmitting abilities, preferences and resources, while communities can influence earnings through neighborhood quality, school quality and peers. Understanding the relative magnitude of the influences of family, neighborhoods and schools on earnings in the long-run is important for identifying the driving forces of existing inequalities and for interventions that aim to reduce them, especially because some early life influences may be longer-lasting than others.

In this paper, we exploit the links between brothers, schoolmates and neighbors by merging tax records from the registers of the Danish population to create earnings histories for family and teenage community reference groups. Our comprehensive register data ensures we can avoid measurement error biases and estimate the influence of the determinants of long run earnings up to age 51. By observing siblings as well as their teenage neighbors and schoolmates we are able to separately identify the influence of families, neighborhoods and schools on permanent earnings.

We find that family is by far the most relevant factor determining long-term earnings. The influence of neighborhoods and schools falls rapidly, becoming insignificant by age 30. This implies on average a zero influence of community background over the life-cycle, which means that any community effects early in life are relatively small and are not long-lasting. These findings highlight the importance of considering the long-term effects of community background on earnings beyond the first years of the working life. We also show that, if family effects are ignored, the influence of neighborhoods and schools are persistent and upward biased by a factor of five. This finding suggest that linking siblings and their peers and jointly estimating the family and community factors within our model captures correlated effects due to residential sorting that would otherwise lead to biased estimates of community influences. Finally, when we look at heterogeneity of community effects by family, neighborhood and school types, we find some variation but community effects are always very small compared to the effect of the family.

1. Introduction

Family and community background are perceived as being important determinants of socioeconomic outcomes such as earnings. Families can determine earnings by transmitting abilities, preferences and resources, while communities can influence earnings through neighborhood quality, school quality and peers. Existing research measuring the influence of community background on earnings through the neighborhood of residence provides mixed evidence of either substantial positive (e.g. Page and Solon, 2003; Raaum, Sörensen and Salvanes, 2006; Chetty, Hendren and Katz, 2015), or zero neighborhood effects (e.g. Oreopoulos, 2003; Ludwig et al., 2013). Besides this mixed evidence, because community background has been associated with the neighborhood, the influence of school quality on earnings – relative to neighborhood quality – has not received much attention. Also, mostly due to data limitations, little is known about the influence of community background on *long-term earnings*.

In this paper, using administrative data on the Danish population we link brothers, teenage neighbors and schoolmates and estimate a model of *multiple group* earnings dynamics to measure *jointly* the relative importance of family, neighborhoods and schools for long-term earnings. Using the parameter estimates of the model we decompose for the first time the sibling correlation of earnings into the three components of interest – family, neighborhood and school – allowing for sorting of families across neighborhoods and schools. Our comprehensive register data ensures we can avoid measurement error biases and estimate the influence of the determinants of long run earnings up to age 51. Understanding the relative magnitude of the influences of family, neighborhoods and schools on earnings in the long-run is important for identifying the driving forces of existing inequalities and for interventions that aim to reduce them, especially because some early life influences may be longer-lasting than others.

The correlation of sibling earnings, which measures the fraction of the variation in permanent earnings that can be attributed to both observed and unobserved factors shared by siblings during childhood, has been widely used as an omnibus measure of the influence of *both* family and community background (for reviews see Solon, 1999; Björklund and Jännti, 2009; Black and Devereux, 2011). By observing siblings as well as their teenage neighbors and schoolmates we are able to separately identify the influence of families, neighborhoods and schools on permanent earnings. While siblings share both the family and the community, neighbors and schoolmates share only their specific community factor (neighborhood or school, respectively) but do not share the family. We can also separate neighborhood from school effects because public school catchment areas do not correspond with parishes – our neighborhood measure. Individuals in the same parish might be enrolled in different schools and schools may enroll individuals from different parishes. [1]

We exploit the links between brothers, schoolmates and parish neighbors by merging tax records to create earnings histories for family and teenage community reference groups. We propose a model of individual earnings dynamics similar to Baker and Solon (2003) and extend this to account for the joint earnings dynamics of multiple groups of individuals.[2] This joint model allows us to decompose the sibling correlation of earnings into family, neighborhood and school effects allowing for sorting of families across neighborhoods and schools.[3]

We find that family is by far the most relevant factor determining long-term earnings. The influence of neighborhoods and schools falls rapidly, becoming insignificant by age 30. This implies on average a zero influence of community background over the life-cycle, which means that any community effects early in life are relatively small and are not long-lasting. These findings highlight the importance of considering the long-term effects of community background on earnings beyond the first years of the working life. We also show that, if family effects are ignored, the influence of neighborhoods and schools are persistent and upward biased by a factor of five. This finding suggest that linking siblings and their peers and jointly estimating the family and community factors within our model captures correlated effects due to residential sorting that would otherwise lead to biased estimates of community influences. Finally, when we look at heterogeneity of community effects by family, neighborhood and school types, we find some variation but community effects are always very small compared to the effect of the family.

The paper is structured as follows. In Section 2 we present the theoretical background and discuss the related literature. In Section 3 we describe the data and the definition of teenage neighbors and schoolmates, while in Section 4 we present descriptive statistics on earnings of siblings and peers over the life-cycle. In Section 5 we develop the econometric

[1] There is a good deal of overlap between public school catchment areas and parishes. However these community measures are by no means synonymous, with 60.1 percent of parish cohorts containing individuals attending two or more schools. See section 3 for details.

[2] Bingley and Cappellari (2013) extended Baker and Solon (2003) to account for dynamics within a three person family, i.e. three pairwise relationships. With respect to Bingley and Cappellari (2013) we account for dynamics within three *groups*, i.e. three types of relationships, but each type of relationship could have arbitrarily many pairwise relationships, depending on how many individuals belong to each group. We have a cross-classified model.

[3] We discuss identification of the model formally in section 5.3.

model for assessing the relative importance of families, neighborhoods and schools within the sibling correlation, based on the joint analysis of life-cycle earnings for brothers, neighbors and schoolmates. The main results are presented in Section 6 together with a sensitivity analysis and evidence of heterogeneity by family, neighborhood and school types. We conclude in the last section.

2. Background and Related Literature

The aim of this paper is to identify the determinants of long-term earnings and, in particular, the extent to which earnings inequality can be explained by differences in family and social background. Based on the analysis of Becker and Tomes (1979), parents can influence the human capital of their offspring by transmitting abilities, preferences and resources, and thereby affect offspring earnings. Community background can also influence individual outcomes through institutions such as the school and its quality (e.g. Hanushek, 2006), or through the quality of neighborhood, or peer influences, social norms and role models in the neighborhood (e.g. Wilson, 1987). Differences between families in the availability of these traits, resources and exposure to the community environment would lead to differences in human capital accumulation. According to human capital theory, differential investments of human capital would generate heterogeneity of both initial earnings and earnings growth (Mincer, 1958, Ben-Porath, 1967). These models predict that heterogeneous investments in human capital induce a negative correlation between initial earnings and earnings growth rates. This negative correlation arises because investors trade off lower initial earnings with higher earnings growth in later parts of their working life. The prediction is that inequality of earnings should follow a *U-shape pattern* by age because earnings trajectories would cross.

The correlation of sibling earnings (or other outcomes) has been used as a way of measuring the *joint* influence of family and community background shared by the siblings (see the reviews in Solon, 1999; Björklund and Jännti, 2009; and Black and Devereux, 2011). To disentangle family from community effects, where community is defined by the neighborhood of residence, a common approach followed in the literature is to compare the correlation of sibling earnings with the correlation of earnings among unrelated neighbors. The idea is that while siblings share both the family and the neighborhood, unrelated neighbors share only the neighborhood but not the family. Following this approach, Page and Solon (2003) using data from the PSID, and Raaum, Sörensen and Salvanes (2006) using administrative data from Norway, find a substantial or non-negligible effect of neighborhoods on earnings. However, the estimated neighborhood effect is recognized to be an upper bound because of non-random sorting of families into neighborhoods, which leads to a positive correlation between the two factors. The correlation of neighbors' earnings will correctly measure the proportion of earnings variance due to neighborhood effects only in the absence of sorting. Dealing with sorting by exploiting quasi-random assignment of families to public housing projects in Toronto, Oreopoulos (2003) finds a zero influence of neighborhood quality in the total variance of income and wages. Instead, the neighborhood effect is found to be positive and significant for the whole population of Toronto, where assignment to neighborhoods is not random.

Outside the sibling correlation literature, the evidence from social experiments such as the Moving to Opportunity program, in which families living in high poverty neighborhoods in five US cities were randomly assigned vouchers to move to less impoverished neighborhoods, suggests that changes in neighborhood quality had on average little impact on economic outcomes (e.g. Ludwig et al., 2013). However, Chetty, Hendren and Katz (2015) using administrative data from tax returns in an observational study find that moving to a higher income county is associated with increased earnings in the mid-twenties for children who were below age 13 when their families moved. Gould, Lavy and Paserman (2011) using the airlift of Yemenite immigrants as a natural experiment find long run effects of early childhood environment on education but not on other economic outcomes.[4]

Within the sibling correlation literature, because community background has been largely associated with the neighborhood, the influence of school quality on earnings – relative to neighborhoods – has not received much attention. Several papers look at the association between different measures of school quality and peers on earnings. Exploiting variation of school quality across cohorts within U.S. regions, Card and Krueger (1992) find that higher quality as measured by a lower pupil/teacher ratio increases the rate of return to schooling and earnings. For the UK, Dearden, Ferri and Meghir (2002) find zero effects. More recently the focus has shifted to long run earnings. Black, Devereux and Salvanes (2013) correlate characteristics of 9th grade Norwegian schoolmates with outcomes at age 33-44 and find the strongest relation between focal pupil earnings and peer fathers' earnings. For Norway, Leuven and Kokken (2015) consider 7-9th grade, and Falch, Strom and Sandsor (2015) consider 8-10th grade, and both find zero class size effects on earnings for ages 20-48.

[4] Studies focusing on educational achievement outside the sibling correlation framework but using quasi-experimental variation of neighborhood quality have also found no impact of neighborhoods (e.g. Jacob, 2004; Gibbons, Silva and Weinhardt, 2013).

Linking the data from the Tennessee STAR experiment, which randomly assigned students and their teachers to classrooms of different size with tax return data, Chetty et al. (2011) find no effect of class size on earnings at age 27, but they find a positive effect of teacher quality. Exploiting a maximum class size rule in Sweden, Fredriksson, Öckert and Oosterbeek (2013) find a significant (at the 10 percent level) effect of smaller classes on earnings at ages 27-42. In summary, long run school effects on earnings are often found to be zero or borderline significant.

We contribute to these different strands of the literature by developing a unified framework decomposing the influence of families, neighborhoods and schools on long-term earnings while allowing for sorting of families into communities. The two unique features of this study are the following: (1) we provide the first joint decomposition of sibling correlation between family and community effects distinguishing the influence of neighborhoods from schools, and (2) we exploit longitudinal earnings data to estimate long run relationships allowing for flexible and shared life-cycle dynamics.

3. Data

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. In outline, construction of our dataset proceeds as follows: First we create our sample of brothers by sampling fathers and finding their first and second born sons. Second we link sons to their teenage communities of neighbors and schoolmates.

In order to create our dataset of brothers we consider men who are their father's first born son in the years 1960-1982 and their immediately younger brothers. This selection is because of completeness of registered parentage and the small number of first sons observed born before 1960.[5] We consider brothers who share both legal parents from registration at birth and are not adopted before age 17. Following the tradition in the sibling literature we keep singletons (men without a younger brother) in the sample. The robustness analysis in Section 6.3 shows that excluding singletons does not affect results. Next we link our sampled brothers (and singletons) to all other males who are born in the same year and share their

[5] Subsequent sons beyond the first two are very few (4 percent) and are not considered in the analysis. The son birth order is determined irrespective of daughters present in the family. We also exclude from the sample sons who were adopted before age 17; sons who are themselves observed as fathers; brothers born less than 12 months apart; and brothers who are born more than 12 years apart.

teenage communities (schools or neighborhoods). School enrolment rules were such that pupils should start in first grade in the August of the calendar year they turn seven. The national pupil database was established to monitor compliance with the 1972 school reform which made 8th and 9th grade schooling compulsory in 1972/3 and 1973/4 respectively. Beginning in August 1973, the database links pupils to the schools they are enrolled from 8th grade and above.[6] School identifiers are consistent over time and schools are classified according to whether they are publicly run (77% of schools and 89% of pupils in our estimation sample) or privately run, and whether they are exclusively for pupils with special educational needs (10% of schools and 1% of pupils in our gross sample).[7]

We link pupils to schoolmates on 31 October of the calendar year they turn 15, which is in the academic year they would normally attend 9th grade.[8][9] During our sample period, pupils were assigned to public schools on a catchment area basis according to place of residence. Parents can alternatively choose to send their child to a private school. Private schools are smaller on average than public schools, are primarily in urban areas and are heavily subsidized, with municipalities covering 85 percent of expenditure.

Our sample contains 2657 schools with males attending 9th grade. They have on average 19.5 male schoolmates in the same grade. Primary and lower secondary education usually takes place in the same school and most pupils attend the same school for all grades. From 2007 we can see that 92% of pupils in grades 1-8 were enrolled in the same school the following year. Due to the organization of primary and secondary schools largely as a single unit, there is likely to be less pupil mobility between schools than in other countries. This institutional setting makes Denmark a good place to look for school effects, because of the coherence of the schoolmate group.

Address of residence is obtained from the central person register. Individuals are required to report changes of address to the municipality within five days. Precision of historical address registration has improved over time and we use parish of residence which is

[6] In anticipation of grade K enrolment being made compulsory from August 2009, the national pupil database was extended to cover grades K-7 from August 2007. Hence we are unable to match pupils to schoolmates in earlier grades to look at long run outcomes.

[7] We exclude from our estimation sample individuals enrolled at schools which are exclusively for pupils with special educational needs.

[8] In 1980, 95 percent of pupils began 9th grade during the year they turned 15. In recent years delays have been more common – in 2007, 13 percent of pupils delayed their school start by a year and 4 percent repeated the same grade the following year.

[9] In robustness checks we match pupils to schoolmates based on the school attended the year they turn 14, or the school attended at both ages 14 and 15.

recorded consistently throughout our sample period.[10] As with schools, our census point is 31 October of the calendar year a male turns 15. There are 1905 parishes in our sample containing on average 14.6 males turning 15 in the same year.

It is informative to contrast our neighborhood definition with that used in comparable studies such as Page and Solon (2003), Raaum, Sörensen and Salvanes (2006) and Oreopoulos (2003).[11] Table 1 characterizes ours alongside these three other studies according to characteristics of the different types of neighborhoods and exposures considered, and outcomes observed. Neighborhood geography and exposure group – an area and an age range – together define the cluster of individuals within which later outcomes are correlated. Neighbors in study (3) have the closest proximity because of the medium-to-high density of housing projects, followed by study (2) because of the clustered PSID sampling frame. Interestingly, study (1) finds neighborhood effects only for urban areas, where neighbors are in closest proximity. Our Danish parishes cover a much wider area than the neighborhoods used in studies (1) and (3), but are only about half the size of Norwegian census tracts used in study (2). For Denmark in the year 2000 we can calculate the distribution of distances between the different residences of 15 year olds within parish: 25 percent of distances are within 0.5 km, 50 percent within 1.1km, and 75 percent within 1.9km.

The other three studies pool neighbors together of quite different ages – with up to 9 and 11 years age differences – to form neighborhood clusters. We only consider neighbors of the same age (15) as belonging to the same cluster. All else equal, if neighbors of the same age are more likely to interact than neighbors of different ages, then we would expect stronger neighbor correlations with our definition than those used in the other studies.

The number of men in each of our neighborhood clusters is in the middle of the range for the other studies. The estimation sample in studies (1) - (3) comprises a similar percentage of the total population of individuals in each cluster with 4.6, 3.1, and 4.8 percent respectively. Due to our narrower age range for clustering neighbors for Denmark the estimation sample covers only 0.6 percent of the cluster population. Although our neighbors are more homogeneous in terms of age, they represent only between one eighth and one fifth of the within-cluster sampling density of the other studies. However, this sparser sampling would reduce precision rather than introduce any bias.

[10] Complete information on municipality of residence is available from 1971 and full addresses are complete from 1977 (see Pedersen, et.al. 2006 for details). We use an intermediate aggregation of locality as our neighborhood indicator - parish of residence, which is available from 1973.
[11] In what follows we refer to Page and Solon (2003) as study (1), Raaum, Sörensen and Salvanes (2006) as study (2) and Oreopoulos (2003) as study (3).

Neighborhood exposure at 15 years of age is at the upper end of the 5-16 age range together considered in the other studies. The duration of neighborhood exposure observed for an individual differs between studies, with only study (3) using more than a single point in time. Although studies (1) and (2) consider a range of ages of exposure, attachment to a neighborhood is only considered at a single point in time, just as in our study. The persistence of neighborhood affiliation is likely to differ between contexts, and this will affect saliency of the neighbor groupings used, but it is difficult to establish how important this might be for explaining differences in findings between studies. In sensitivity analyses for Denmark we consider neighbors at ages 14, 15 and those continuously exposed to each other between 14 and 18.

Our administrative dataset, in terms of coverage, dominates those that have been used in these other comparable studies. In terms of outcomes, we encompass the age range and calendar years of observations used in the three other studies. Our estimation sample contains three times as many men as in the largest previous study (2) and because we do not use means of earnings, we have over 10 million earnings observations – two orders of magnitude greater than in study (2). An important Danish institutional feature is that parishes and public school catchment areas do not completely overlap. As a consequence, neighbors may attend different schools, and schoolmates may come from different neighborhoods. Parents can also send their children to a private school outside their public school catchment area. Amongst school-birth-cohort clusters, 89.5 percent have individuals from more than one parish, and amongst parish-birth-cohort clusters 60.1 percent have individuals from more than one school.[12]

Finally, for both brothers and for peers we use pre-tax annual labor earnings measured in 2005 prices. Table 2 presents the cohorts we include in the sample, the years for which we observe earnings and sample sizes in various dimensions. Following Baker and Solon (2003) we group data in 2-years birth cohorts, as shown in column 1, and we compute age by imputing each cohort with its first year of birth. The selection of birth cohorts ensures that each cohort is observed for at least 6 years (cohort 1982) and for as long as 28 years (cohort 1960). Columns 5 and 6 present the number of earnings observations and number of men

[12] We can isolate the non-overlap due to public school catchment areas by dropping private schools and recalculating. Amongst school-birth-cohort clusters, 89.9 percent have individuals from more than one parish, and amongst parish-birth-cohort clusters 48.0 percent have individuals from more than one school. 12.1 percent of parish-birth-cohort clusters contain only one public and one private school. In sensitivity analyses we show that results are robust to private school exclusion.

used in estimation. The number of community cohorts into which men are grouped is shown in columns 7 and 8, totaling 33,907 school cohorts and 47,622 parish cohorts.

Half of earnings observations are from the first third of birth cohorts. Cohort size peaks in 1966-7 and falls by 44 percent by the last cohorts in 1982-3. Number of school cohorts and parish cohorts is quite stable, reflecting an absence of administrative unit reform. Population demographics dictate birth cohort sizes and the falling number of earnings observations by birth cohort is due to later cohorts having less time to accumulate earnings histories.

To summarize, in terms of coverage, our sample dominates those used in previous studies of neighborhood effects on long run earnings, and is comparable to samples used in Norwegian studies of long run class size effects. We are the first to exploit the longitudinal dimension of earnings data to estimate community effects in order to avoid well known biases – rather than taking means of earnings over a range of ages as in other studies, we estimate on almost complete earnings trajectories allowing for life-cycle dynamics.

4. Descriptive statistics on earnings of siblings and peers

In this section we provide a description of the interpersonal covariance structure of earnings. There are two types of cross-person relationships that are of interest to our analysis: 1) between members of the same family (brothers), and 2) between peers attending the same school at age 15 and/or residing in the same neighborhood at the same age.

The covariance of earnings among brothers is computed from families with at least two male children. We group non-sibling peers in clusters depending on whether they shared the school and the neighborhood, only the school, or only the neighborhood. We obtain the between-peers covariance of earnings (at each relevant age) by first computing the within-cluster covariance and then averaging covariances between clusters using the weighting scheme of Page and Solon (2003, pp. 841), which gives more importance to more populated clusters, and makes inference person-representative.

We begin by describing the sibling earnings correlation by age in Figure 1. The plot labeled "At same age" reports the computed correlation when the brothers are at the same point in their life-cycle, a comparison that is available in our data. The earnings correlation declines between age 24 and 30, and remains stable after age 30. The decline suggests that sources of initial earnings heterogeneity that are shared between brothers are negatively correlated with heterogeneity in earnings growth. As discussed in Section 2, human capital models predict investments in education or training to induce such a negative correlation. The second plot fixes the age of the older among the two brothers at 35 and reports the sibling correlation by age of the younger brother. In this case, the earnings correlation is relatively low at age 24 (actually close to zero) and increases sharply so that by the early-30s it matches the “same age” correlation. This pattern illustrates that the earnings correlation computed between siblings of different ages is an underestimate of the correlation one would obtain observing siblings at the same point in their life-cycle. This is a form of life-cycle bias as discussed in Jenkins (1987), Haider and Solon (2006), Bohlmark and Lindquist (2006) and Nybom and Stuhler (2016). The figure shows that we can observe this bias in the data, which suggests that we have the information required for controlling it in estimation.

Besides human capital investments, the large contemporaneous associations at the early stage of the life-cycle in Figure 1 may also reflect the correlation of transitory shocks. It is well known that earnings instability is large while young (see e.g. Baker and Solon, 2003). It is also plausible that siblings are subject to common shocks, for example, because of similar local economic conditions at labor market entry. As a way to assess if the relatively large sibling correlation at young ages is driven by permanent earnings differences or transitory fluctuations, we also computed sibling correlations for brothers born at least five, eight or ten years apart, which are shown in Figure 2. The larger the age difference, the less likely it is that brothers entered the same labor market and shared transitory shocks at entry, so that these samples are less likely to be influenced by transitory fluctuations compared with the samples underlying Figure 1. A declining pattern of the sibling correlation between the mid-20s and the early-30s persists even after excluding closely spaced brothers that most likely share transitory earnings fluctuations. This suggests that the source of the convex evolution of sibling correlations is in the permanent earnings component.

In Figure 3 we plot the earnings correlations for non-brother peers at the same point in their life-cycle distinguishing between those sharing both the school and the neighborhood, sharing only the school, or only the neighborhood. These empirical correlations pick-up all sources of peer similarities, both those correlated with family effects and those independent of them. A few points are worth highlighting from this graph. The first is the magnitude of the peer earnings correlation, which is roughly one tenth of the correlation of sibling earnings reported in Figures 1 and 2. Second, the earnings correlation is higher at the beginning of the life-cycle and up to age 30, which implies that after that age the influence of peers appears to be negligible. Third, schools seem to exhibit stronger influence compared to neighborhoods. Finally, the graph also reports the correlation of earnings for “Unrelated” peers, i.e. nonrelatives that share neither the school nor the neighborhood. This correlation is computed by randomly matching each individual in the sample with 1000 unrelated peers of the same age. We find this correlation to be equal to zero at each age, which suggests that the evolution of sibling and peer correlations over age is picking up some underlying forces due to families, schools and neighborhoods, and is not simply an artifact of age effects.

5. Econometric model

To estimate the independent contributions of family and community background on permanent earnings we exploit the linked earnings records of siblings, teenage neighbors and schoolmates within a model of multi-person earnings dynamics, distinguishing permanent from transitory earnings and allowing for heterogeneous earnings growth.

In particular, the logs of age- and time- adjusted gross annual earnings, denoted by *w*, are assumed to be the sum of two components, a permanent one denoted by *y* and a transitory one denoted by *v*, which are orthogonal by definition:

$$w_{ifsna} = y_{ifsna} + v_{ifsna}\ ;\ E(y_{ifsna}v_{ifsna}) = 0, \tag{1}$$

where the indices *i, f, s, n* and *a* stand for individual, family, school, neighborhood and age.[13] The model extends the joint earnings dynamics model of Bingley and Cappellari (2013) for three persons (father and sons) to several multi-person groups. The model also tackles the two measurement error biases in the estimation of correlations in permanent earnings between persons which are highlighted in the literature of earnings correlation between family members, particularly fathers and sons. The first source of bias addressed by the model is related to transitory income shocks, which make current earnings a poor measure of permanent earnings (Solon, 1992; Mazumder, 2005). Separate identification of permanent and transitory earnings is granted by the availability of individual level panel data. The second source of bias addressed by the model is related to life-cycle bias due to age differences between family members and the heterogeneous earnings variation over individual life-cycles (Jenkins, 1997; Haider and Solon, 2006; Bohlmark and Lindquist, 2006; Nybom and Stuhler, 2016).

5.1 Specification of permanent earnings

We allow permanent earnings (*y*) in equation (1) to depend on both *shared* and *idiosyncratic* components. Shared components capture those determinants of permanent earnings that are

[13] Age is measured in deviation from the life cycle starting point, which is set at 24.

common between brothers, schoolmates and neighbors. The idiosyncratic component represents individual-specific sources of variation in permanent earnings. We model life-cycle dynamics of shared components using a specification based on *heterogeneous income profiles* (HIP), which is also known as a *random growth* model. We augment this with a *restricted income profile* (RIP) process for individual-specific components, which is an idiosyncratic unit root (*random walk*) shock.

As discussed in Section 2, the heterogeneous income profiles specification is inspired by human capital models in which heterogeneity of initial earnings and heterogeneous earnings growth are generated by differential investments (Mincer, 1958; Ben-Porath, 1967). These models predict that heterogeneous investments in human capital induce a negative correlation between initial earnings and earnings growth rates, because investors trade off initial earnings against earnings growth throughout the life-cycle. The resulting negative covariance of intercepts and growth rates would generate a *U-shaped* evolution of earnings dispersion by age due to the 'Mincerian cross-overs' of earnings profiles. These observations, combined with insights from the model of Becker and Tomes (1979) on parental preferences for child human capital, motivate our specification choice for shared earnings determinants, which reflect the idea that resemblance of earnings across individuals stems from similarities in social background and human capital investments. As shown in Section 4, the life-cycle patterns of earnings correlations between siblings and peers are consistent with these mechanisms.

Besides the earnings profile shared by siblings, neighbors and schoolmates, we assume permanent earnings to follow a unit root in age (ω_{ia}) capturing long-term individual deviations from the shared profile. This represents idiosyncratic ability revealed over time, either to the labor market or to individuals themselves. Overall, our permanent earnings model is specified as follows:

$$y_{ifsna} = \pi_t\left[\left(\mu_f + \mu_s + \mu_n\right) + \left(\gamma_f + \gamma_s + \gamma_n\right)a + \omega_{ia}\right]; \tag{2}$$
$$\omega_{ia} = \omega_{i(a-1)} + \xi_{ia};\ t = c(i) + 24 + a,$$

where $c(i)$ is the birth cohort of person i and π_t is a calendar time shifter allowing for the possibility of aggregate changes of the permanent earnings process over time. The parameters of the individual-specific linear profile of earnings are factored into three zero-mean components, with their variances capturing family (f), school (s) and neighborhood (n) heterogeneity in *initial earnings* (denoted by μ_f, μ_s, μ_n) and life-cycle *earnings growth* (denoted by $\gamma_f, \gamma_s, \gamma_n$).

In particular, the assumptions on the variance-covariance structure of permanent earnings are as follows:

$$(\mu_f, \gamma_f) \sim (\sigma^2_{\mu\Phi}, \sigma^2_{\gamma\Phi}, \sigma_{\mu\gamma\Phi}) \tag{3.a}$$

$$(\mu_s, \gamma_s) \sim (\sigma^2_{\mu\Sigma}, \sigma^2_{\gamma\Sigma}, \sigma_{\mu\gamma\Sigma}) \tag{3.b}$$

$$(\mu_n, \gamma_n) \sim (\sigma^2_{\mu\mathrm{N}}, \sigma^2_{\gamma\mathrm{N}}, \sigma_{\mu\gamma\mathrm{N}}) \tag{3.c}$$

$$(\mu_f, \mu_s, \mu_n) \sim (\sigma_{\mu\Phi\Sigma}, \sigma_{\mu\Phi\mathrm{N}}, \sigma_{\mu\Sigma\mathrm{N}}) \tag{3.d}$$

$$(\omega_{i24}, \xi_{ia}) \sim (0{,}0; \sigma^2_{\omega_{24}b}, \sigma^2_{\xi b}), b = 1{,}2\ , \tag{3.e}$$

where the specific dimensions of heterogeneity of the variance-covariance parameters are denoted by Φ (for family), Σ (for school) and N (for neighborhood).

Assumptions (3.a-3.c) allow for arbitrary correlation of initial and growth rate heterogeneity within each of the shared components (denoted by $\sigma_{\mu\gamma\Phi}, \sigma_{\mu\gamma\Sigma}, \sigma_{\mu\gamma\mathrm{N}}$). By assumption (3.d) we also allow for arbitrary correlation across each of the shared components (denoted by $\sigma_{\mu\Phi\Sigma}, \sigma_{\mu\Phi\mathrm{N}}, \sigma_{\mu\Sigma\mathrm{N}}$), which is important for taking into account sorting of families across communities (schools and neighborhoods).[14] While previous studies comparing neighbor and sibling correlations have acknowledged the importance of sorting of family into communities (see Page and Solon, 2003; Oreopoulos, 2003; Raaum, Sörensen and Salvanes, 2006), the modeling approach followed in this study is arguably the first attempt of actually estimating these sorting correlations. Finally, assumption (3e) allows the idiosyncratic parameters to vary by birth order (denoted by b).

5.2 Specification of transitory earnings

We model transitory earnings (v) in equation (1) to capture any serial correlation of transitory shocks using an autoregressive AR(1) process. We allow brothers to draw shocks from birth-order-specific distributions and we account for age effects in the variance of these shocks through an exponential spline. Our model for transitory earnings can be summarized as follows:

$$\begin{gathered} v_{ifsna} = \eta_t u_{ifsna};\ u_{ifsna} = \rho_b u_{ifsn(a-1)} + \varepsilon_{ifsna}; \\ \varepsilon_{ifsna} \sim (0, \sigma^2_{\varepsilon b} \exp(g_b(a))),\ u_{ifsn24} \sim (0, \sigma^2_{u_{24}b})\ , \end{gathered} \tag{4}$$

where η_t is a time loading factor and u_{ifsna} is the birth-order-specific AR(1) process (note the index b). The autoregressive process begins at age 24 and we specify the variance of the

[14] Correlation across family and community effects is allowed through the intercepts of the individual-specific profiles. This choice is made because empirically most of the community effects vanish after two or three years (see Figure 4), and for not overcrowding the parameter space.

initial condition denoted by $\sigma^2_{u_{24}b}$. The process evolves through the arrival of white noise shocks (denoted by ε) whose variance is age-and-brother-specific ($\sigma^2_{\varepsilon b}\exp\left(g_b(a)\right)$, with $g_b(a)$ denoting a linear spline in age with knots at 28, 33, 38 and 43.

We allow transitory earnings to be correlated across individuals. The specific way in which we model such correlation depends on the type of relationship between individuals. For brothers, the use of birth order specific distributions of shocks enables identifying the contemporaneous correlation of AR(1) innovations. Let i and i' index two individuals; the brother correlation of AR(1) innovation is specified as follows:

$$E\left(\varepsilon_{ifsna}\varepsilon_{i'fs'n'a'}\right) = \sigma_f,\ \ \forall\ s, s', n, n', a = a' \pm |c(i) - c(i')|. \tag{5}$$

That is, when the two individuals belong to the same family and when their age difference is such that the two shocks belong to the same time period, then these shocks are allowed to be correlated with covariance denoted by σ_f. This correlation of shocks between siblings does not depend on whether the two brothers attended the same school, or lived in the same parish when they were aged 15 and is transmitted to non-contemporaneous time periods through the autoregressive structure of the model.

Due to the high dimensionality that would be required to parameterize the correlation of shocks between numerous community members belonging to different families (f and f'), we follow a different approach to that used for pairs of brothers. We allow for catch-all "mass-point" covariances (λ) collapsing all the parameters of the underlying stochastic processes, and allow such covariances to fade away over time. For any two non-necessarily different age levels a and a', correlations of transitory shock across non-sibling peers are specified as follows:

$$E\left(u_{ifsna}\, u_{i'f'sna'}\right) = \lambda_{sn}^{1+|t-t'|}, E\left(u_{ifsna}u_{i'f'sn'a'}\right) = \lambda_{s}^{1+|t-t'|}\ \ \forall\ n \neq n', \tag{6}$$

$$E\left(u_{ifsna}u_{i'f's'na'}\right) = \lambda_{n}^{1+|t-t'|}\ \forall\ s \neq s'.$$

5.3 Identification of permanent earnings components and decomposition of the sibling correlation

Assumptions (3.a) – (3.e) fully specify the intertemporal and interpersonal distribution of *permanent* earnings.[15] Identification of parameters is achieved by exploiting different types of moment restrictions generated by the model. For a given individual, moment restrictions for

[15] Parameter identification of transitory earnings is discussed in the Appendix.

two time periods are a function of all sources of earnings heterogeneity, which include the idiosyncratic component, as well as the components due to the influences from the family, the school and the neighborhood. The moment restrictions for a single individual for two non-necessarily different age levels a and a' can be written as follows:

$$E\left(y_{ifsna}, y_{ifsna'}\right) = \left\{\sigma_{\mu\Phi}^2 + \sigma_{\mu\Sigma}^2 + \sigma_{\mu\mathrm{N}}^2 + \left(\sigma_{\gamma\Phi}^2 + \sigma_{\gamma\Sigma}^2 + \sigma_{\gamma\mathrm{N}}^2\right)aa' + \left(\sigma_{\mu\gamma\Phi} + \sigma_{\mu\gamma\Sigma} + \sigma_{\mu\gamma\mathrm{N}}\right)(a + a') + 2\sigma_{\mu\Phi\Sigma} + 2\sigma_{\mu\Phi\mathrm{N}} + 2\sigma_{\mu\Sigma\mathrm{N}} + \sigma_{\omega_{24}b}^2 + \sigma_{\xi b}^2 min(a, a')\right\}\pi_t\pi_{t'} \tag{7}$$

Cross-person moments (between siblings, neighbors, or schoolmates) do not depend on idiosyncratic heterogeneity. Moment restrictions between siblings (different i but same f) depend on the family effects. Moreover, they are also functions of school effects, neighborhood effects, both, or none, depending on the extent to which siblings share schools and/or neighborhoods.[16] Moment restrictions for siblings can be written as follows:

$$E\left(y_{ifsna}, y_{i'fs'n'a'}\right) = \left\{\sigma_{\mu\Phi}^2 + \sigma_{\gamma\Phi}^2 aa' + \sigma_{\mu\gamma\Phi}(a + a') + I(s = s')\left[\sigma_{\mu\Sigma}^2 + \sigma_{\gamma\Sigma}^2 aa' + \sigma_{\mu\gamma\Sigma}(a + a')\right] + I(n = n')\left[\sigma_{\mu\mathrm{N}}^2 + \sigma_{\gamma\mathrm{N}}^2 aa' + \sigma_{\mu\gamma\mathrm{N}}(a + a')\right] + 2\sigma_{\mu\Phi\Sigma} + 2\sigma_{\mu\Phi\mathrm{N}} + 2\sigma_{\mu\Sigma\mathrm{N}}\right\}\pi_t\pi_{t'}, \tag{8}$$

where $I(\quad)$ is an indicator function. Equation (8) nests moments restrictions for four types of siblings, corresponding to the four elements of the set generated by intersecting $I(s = s')$ and $I(n = n')$. These types include siblings who: (1) share both the school and the neighborhood; (2) share only the school; (3) share only the neighborhood; and (4) share only the family but neither the school nor the neighborhood.

The above moment conditions are sufficient for identifying family, school, and neighborhood effects because school and neighborhood effects are identified by the presence of siblings that went to different schools or grew up in different neighborhoods due to family mobility. In other words, peers are not needed for identifying the model. However, the cross-effect covariances are not identified. This is evident from the fact that the term $2\sigma_{\mu\Phi\Sigma} + 2\sigma_{\mu\Phi\mathrm{N}} + 2\sigma_{\mu\Sigma\mathrm{N}}$ enters equation (8) irrespective of whether siblings went to the same school or lived in the same parish. Because families sort across schools and neighborhoods, school and neighborhood effects are always correlated between brothers, and such covariance is not separable from the variance of family effects $\sigma_{\mu\Phi}^2$. To identify the sorting parameters $\sigma_{\mu\Phi\Sigma}$, $\sigma_{\mu\Phi\mathrm{N}}$ and $\sigma_{\mu\Sigma\mathrm{N}}$, we exploit moment restrictions for non-sibling peers that *do not* share the

[16] This is one difference with PSID-based studies (e.g. Page and Solon, 2003) in which all siblings share the neighborhood by sampling design.

family effect and the fact that there is incomplete overlap between schoolmates and neighbors. Using these restrictions is also helpful for estimating community effects without relying exclusively on family mobility across communities. Moment restrictions for peers belonging to different families f and f' can be written as follows:

$$E\left(y_{ifsna}, y_{i'f's'n'a'}\right) = \{I(s = s')\left[\sigma^2_{\mu\Sigma} + \sigma^2_{\gamma\Sigma} aa' + \sigma_{\mu\gamma\Sigma}(a + a') + 2\sigma_{\mu\Phi\Sigma}\right] + I(n = n')\left[\sigma^2_{\mu\mathrm{N}} + \sigma^2_{\gamma\mathrm{N}} aa' + \sigma_{\mu\gamma\mathrm{N}}(a + a') + 2\sigma_{\mu\Phi\mathrm{N}}\right] + 2\sigma_{\mu\Sigma\mathrm{N}}\} \pi_t \pi_{t'} \tag{9}$$

Equation (9) nests moment restrictions for three types of peers depending on them sharing the school, the neighborhood or both. This identifies the three sorting parameters, where the covariance is zero for those who do not share any community effect. Note that the covariance between family and a given community effect (school or neighborhood) enters the moment restrictions in (9) only for peers sharing that specific effect.

Using parameter estimates from the model we can predict the contributions of each factor to the sibling correlation of permanent earnings over the life-cycle as follows:

$$r^F(a) = \frac{E\left(y_{ifsna}, y_{i'fs'n'a}\right)}{E\left(y_{ifsna}, y_{ifsna}\right)},\ r^S(a) = \frac{E\left(y_{ifsna}, y_{i'f'sn'a}\right)}{E\left(y_{ifsna}, y_{ifsna}\right)},\ r^N(a) = \frac{E\left(y_{ifsna}, y_{i'f's'na}\right)}{E\left(y_{ifsna}, y_{ifsna}\right)}\ , \tag{10}$$

where r denotes correlation coefficients of permanent earnings, F, S and N denote the three relevant dimensions of heterogeneity (family, school, neighborhood). It should be emphasized that correlations vary with age because they are estimated from a model of life cycle earnings. Given the model assumptions, the sibling correlation of permanent earnings is the sum of the three components:

$$r^B(a) = r^F(a) + r^S(a) + r^N(a) \tag{11}$$

5.4 Estimation

The model is estimated by Minimum Distance matching moment restrictions implied by the model to the empirical moments derived from the data.[17] Empirical moments are based on the residuals after regressing log real gross annual earnings on year dummies and a quadratic age trend by birth cohort. There are three types of empirical moments entering into the estimation. First, there are *individual moments* which include the variances and inter-temporal covariances of individual earnings. Second there are *sibling moments* which are

[17] Moment restrictions for transitory earnings are given in the Appendix. The orthogonality assumption between permanent and transitory earnings in equation (1) implies that moment restrictions of the full model are the sum of moment restrictions for permanent and transitory earnings. We use Equally Weighted Minimum Distance which does not weight the minimization problem but adjusts parameter variance post estimation using the empirical fourth moments matrix (see, for example, Haider, 2001).

defined only in families where there are at least two brothers. This implies that each family contributes at most once in the estimation of sibling empirical moments, where families with only one son do not contribute to such estimation.[18] We estimate separate empirical moments for siblings depending on whether they shared the school, the neighborhood, both or none, so as to match the four different moment restrictions that are nested in equation (8). Finally, there are empirical moments for *non-sibling peers* who shared the community. In contrast to families, the number of peers varies within community clusters. We account for such varying importance of community clusters using the weighting scheme proposed by Page and Solon (2003, pp. 841). In particular, we first estimate the within-cluster covariances and then we take the between-clusters weighted average of within-cluster covariances using weights that are proportional to the number of individuals in that cluster. Similar to the case for siblings, we estimate empirical moments distinguishing whether peers shared the school, the neighborhood, or both.

6. Results

We concentrate the discussion on estimates for the 'core' parameters of the permanent and transitory components.[19] We present the results for the parameter estimates of the permanent component in Section 6.1 and those for the transitory component in Section 6.2. Sensitivity analysis and heterogeneous effects are discussed in Sections 6.3 and 6.4, respectively.

6.1 Permanent earnings correlation between siblings, schoolmates and neighbors

According to equation (2), permanent earnings depend on *shared* and *idiosyncratic* components. The parameter estimates for the shared components reported in Table 3 (Panel A) show that family is by far the most relevant factor for long-term earnings. This is true both for initial earnings (intercepts) and for earnings growth rates (slopes). The other relevant source of permanent inequality in earnings is the individual idiosyncratic component reported in Panel B of Table 3.

The covariances between the three components of shared earnings determinants ($\sigma_{\mu\Phi\Sigma}$, $\sigma_{\mu\Phi\mathrm{N}}$ and $\sigma_{\mu\Sigma\mathrm{N}}$) capture the sorting of families into schools and neighborhoods. The

[18] As explained in the data section, we focus on the first two brothers because subsequent brothers are a tiny proportion (4 percent) of the population.

[19] Parameter estimates of the time effects on both components are reported in Table A1 of the Appendix.

estimates in Panel A suggest that these sorting effects are relevant, as the covariances of family effects with both school and neighborhood effects ($\sigma_{\mu\Phi\Sigma}$, $\sigma_{\mu\Phi\mathrm{N}}$) are positive, sizeable and statistically significant. These effects imply that a high draw from the distribution of family effects in permanent earnings is associated with similarly high draws in the distributions of school and neighborhood effects. We also find a positive covariance among community effects ($\sigma_{\mu\Sigma\mathrm{N}}$), which suggests that school and neighborhood effects are positively correlated. Once these sorting effects are accounted for there is no remaining statistically significant heterogeneity in initial earnings related to school and neighborhood effects (i.e. $\sigma^2_{\mu\Sigma}$ and $\sigma^2_{\mu\mathrm{N}}$ are insignificant).

All shared components of long-term earnings in Table 3 display the Mincerian cross-over property, as indicated by all covariances between intercepts and slopes of earnings profiles ($\sigma_{\mu\gamma\Phi}, \sigma_{\mu\gamma\Sigma}, \sigma_{\mu\gamma\mathrm{N}}$) being negative. This negative covariance indicates that families associated with low earnings at age 24 are also associated with faster growth in life-cycle earnings. A corollary of the negative covariance is that the variance of permanent earnings across families is *U-shaped in age* because it falls in the years of catch up and increases after the cross over point. The point of cross over can be computed as the year in which the earnings variance is minimized, and it is located at age 34 for the between-family earnings distribution. A similar U-shape pattern of the variance of earnings over age is also observed across schools and across neighborhoods. The cross over point is age 36 for the between-neighbors earnings distribution, and age 38 for the between-schoolmates earnings distribution.

We use these parameter estimates to generate predictions, based on the formulae provided in Section 5.3 (equations 10 and 11), of the sibling correlation and its decomposition into the three factors of interest: family, school and neighborhood. In particular, we consider the case of two brothers who attended the same school and lived in the same neighborhood when they were 15, so that the resulting sibling correlation is the sum of family, school and neighborhood effects. As shown in Figure 4, the life-cycle pattern of the sibling correlation is U-shaped in age. More specifically, the estimated sibling correlation is equal to 0.59 (s.e. 0.11) at age 25, drops to 0.15 (s.e. 0.12) at age 35, and rises back to 0.34 (s.e. 0.018) by age 49, which is the last age we observe younger brothers. The average sibling correlation over the life-cycle is 0.28 (s.e. 0.012), which is in line with previous estimates for

Denmark.[20] As mentioned earlier, the U-shaped pattern is a symptom of the "Mincerian cross-overs" of earnings profiles. That is, the negative estimates of the covariance between intercepts and slopes for all the shared factors of earnings profiles imply that the distribution of shared components, and therefore the sibling and peer correlations, first shrink and then fan out over the life-cycle. The same U-shaped pattern was also a feature of the raw cross-person covariances in Figures 1 to 3, and in particular Figure 2, which depicted siblings' earnings covariances for brothers born only a few years apart.

Considering the decomposition of the sibling correlation, it is evident from Figure 4 that family accounts for most of the dispersion of permanent earnings over the life-cycle. The community effects are small and are only significant at the beginning of the working life, while by age 30 they become negligible and not significantly different from zero. In particular, the estimated community correlation of earnings (the sum of neighbors and schoolmates correlations) is equal to 0.12 (s.e. 0.022) at age 24, drops to 0.055 (s.e. 0.016) at age 27 and becomes zero at age 30. On average, over the life-cycle, we estimate the correlation in permanent earnings across schoolmates to be 0.004 (s.e. 0.010), and across neighbors to be 0.009 (s.e. 0.010), which are both close to zero and not statistically significant. These results indicate that the only factor that generates a substantial correlation in permanent earnings between brothers is the family – there is not much room for community effects in shaping the sibling correlation.

Our findings are in line with those of Oreopoulos (2003) who used quasi-random assignment of neighbors to deal with sorting of families into neighborhoods and showed that the correlation between neighbors in adult earnings was virtually zero. While random assignment eliminates the effects of sorting by design, our model takes sorting into account when estimating community effects. Instead, without taking sorting into account Page and Solon (2003) estimated in the PSID the neighbors' correlation to be equal to 0.16, which was half of the estimated sibling correlation of 0.32. With our model we can replicate the approach of Page and Solon (2003) on a restricted sample that excludes sibling moments by constraining family-related model parameters to be zero. The idea of this exercise is that, by ignoring family effects and the sorting of families into communities, community effects should capture not only the effects of communities but will also pick up the influence of families. When family effects are ignored, we find a sizeable correlation among members of

[20] Using a model without community effects, Bingley and Cappellari (2013) report an average sibling correlation of 0.23 between ages 25 and 48. Using our sample to estimate a model without community effect in the 25-48 age range we obtain an average sibling correlation of 0.25. Differences between the two estimates are due to the different age range investigated, different specifications and different sample selections.

the youth community, which is significant throughout the life-cycle. The average community correlation in the restricted model is 0.071 (s.e. 0.001), which amounts at 25 percent of the sibling correlation. As we have seen in Figure 4, the baseline model that controls for family effects tells a radically different story about the relevance of community effects, with a correlation of permanent earnings between members of the same youth community of just 0.013 (s.e. 0.009), which is insignificant. This suggests that when sorting is ignored the community effects are upward biased by a factor of five. The results of the baseline model are close to those from studies using the quasi-randomized allocation of families across communities in order to control for selection into neighborhoods.

One potential concern with our findings is the extent to which they are driven by the proposed model. To address this we also estimate a simpler version of the model which abstracts from life-cycle effects and we find similar evidence of upward biased community effects if sorting is not taken into account. In particular, the average community correlation in this simple model is 0.053 (s.e. 0.001), which is comparable to the estimate of 0.071 in the model which includes life-cycle effects. In both cases, the community effects are upward biased compared to the model which jointly estimates family and community effects.

6.2 Transitory earnings

Parameter estimates of transitory earnings in Table 4 show a clear age pattern of transitory shocks whose variance decreases between the mid-20s and the mid-30s, while the decrease slows down after age 35. The sharp decline followed by a leveling-off is consistent with the patterns reported by Baker and Solon (2003) who find the variance of transitory shocks to be declining at decreasing rates between the ages of 25 and 45. These patterns look similar between brothers. Also, the autoregressive coefficient (roughly 0.5) is very similar between brothers and of a moderate size. Table 4 shows that transitory shocks are contemporaneously correlated between brothers. However, compared to the variance of the shocks, the size of the covariance is negligible. The model also yields estimates of the covariance in transitory earnings between non-relative peers, which turns out to be negligible and imprecisely estimated.

6.3 Sensitivity analysis

We subject our results to several sensitivity checks by estimating the model for different family sizes (up to 2 or up to 3 children), excluding singletons, and by varying the degree of exposure to communities. We report in Table 5 the average sibling correlation and its decomposition by family, school and neighborhood factors. Overall, the findings from these additional estimations do not change the main conclusion from the baseline model that family accounts for most of the variation in permanent earnings, while the influence of community factors is overall negligible and only significant early in the working life and before age 30.

More specifically about the definition of youth communities, the concern with the baseline model might be that it is based on membership only at age 15, which might miss part of the effects of communities due to potentially limited exposure (see also Gibbons, Silva, Weinhardt, 2013 and Chetty, Hendren and Katz, 2015 for similar discussions). To address this concern, we re-estimated the model using two alternative criteria to define community membership, which are characterized by greater exposure to communities relative to the one-year definition used in the baseline model. First, we define schoolmates and neighbors as those sharing schools and neighborhoods, respectively, for two years during both ages 14 and 15. Second, we define the neighborhood as the prevalent parish of residence between ages 14 and 18.[21] As reported in Table 5, none of these alternative definitions alters our finding that community effects account for only a limited share of the sibling correlation in earnings. Defining peers as those sharing schools and neighborhoods both at age 14 and 15 yields an average correlation of permanent earnings between schoolmates equal to 0.002 (s.e. 0.009), and an average correlation between neighbors equal to 0.010 (s.e. 0.010). Similarly, using the parish in which individuals lived most frequently between the ages of 14 and 18 as identifier of youth neighborhoods, we find the average earnings correlation among neighbors to be 0.008 (s.e. 0.010), and the correlation among schoolmates to be 0.006 (s.e. 0.009). Based on this evidence it seems plausible to conclude that our finding of negligible community effect is not driven by the specific community definition that we adopt. However, due to data limitations we are not able to consider school and neighborhood effects at ages earlier than 14, so we cannot test for differential exposure effects at a younger age. However, we argue that at least for the school effects this is less likely to be the case because of the coherence of the schoolmate groups in Denmark since primary and secondary education usually takes place in the same school and most pupils attend the same school for all grades.

6.4 Heterogeneous effects

[21] More than three quarters of individuals in our sample (76.5%) do not change parish of residence between ages 14 and 18. We cannot apply a similar definition to schools because of compulsory schooling ending typically when individuals are aged 15.

Our results so far show that community effects are negligible and that family effects are the driving force that determines the overall sibling correlation. While these results hold on average in the population, it may still be that the relevance of community effects varies with the characteristics of the families or the communities considered. For example, Page and Solon (2003) found that most of neighborhood effects were stemming from urban communities. To address these possibilities, we now turn to the potential heterogeneity of family and community effects by the type of family, school or neighborhood. For families, we split the sample by father's education, for neighborhoods by population density (or urbanicity), and for schools by the expected class size implied by whether the size of the school grade is below or above the threshold of 24 pupils used in Denmark for splitting classes (Browning and Heinensen, 2007). Note that groupings by community characteristics imply that some siblings pairs are dropped from the analysis, namely pairs for whom the parish urbanicity or expected class size are different between siblings.

We summarize the results of the heterogeneous effects analysis in Table 6, which reports the life-cycle averages of the sibling correlation by sub-samples together with their components. Starting with family heterogeneity, we group families depending on whether the father has more than 13 years of education, which corresponds to at least one year of post-secondary or tertiary education. The sibling correlation is larger (0.38) for families with highly educated fathers compared to the baseline estimate for the overall population (0.28). Interestingly, also the community effect, which is the sum of neighborhood and school effect, increases to 0.038 (s.e. 0.003) and is significant. The share of the sibling correlation that originates from community effects in the sample of families with highly educated fathers is 10 percent compared to 5 percent in the baseline estimates. On the other hand, when fathers have a low educational attainment, community effects are insignificant.[22] Heterogeneity by father's education shows the importance of family sorting across communities. Only the sons of highly educated fathers are exposed to youth communities that have some long-term impacts on top of family effects, although these effects are still of limited size. Instead, for the sons of less educated fathers all what matters is the family effect.

We next take into account urbanicity by exploiting information on population density (measured in 1976) in the parishes individuals lived in when they were age 15. Specifically,

[22] A negative point estimate of the correlation means that, on average, long term earnings are less similar among peers than among unrelated individuals. We already know from Figure 4, where the age profile of the community correlations becomes sometimes insignificantly negative, that this may happen after the initial phase of the life cycle, during the years when income profiles cross over. Evidence from Table 6 indicate that in the subsample with low education fathers these negative community effects dominate over the life cycle, but they are still not significantly different from zero.

we cut the density distribution across parishes at the upper third and define as urban (rural) individuals living in parishes that are above (below) this threshold. It is likely that youths residing in more densely populated communities end up interacting more with each other, which may in turn result in larger community correlations. Indeed, Page and Solon (2003) identified urbanicity as one of the main determinants of neighboring boys' correlations in their PSID sample. Consistently with those results, we find that the overall community effect is stronger in urban than in rural communities (0.043 vs. 0.015) and it is significant. This difference originates both from the neighborhood and from the school dimension of the community effects. While more pronounced than in the baseline sample, the incidence of the community effect is still only 14 percent of the overall sibling correlation.

Finally, we consider school heterogeneity by grouping individuals into small and large classes depending on school enrollment in the grade attended at age 15. Pupils who attended schools with total grade enrollment below 24, between 37 and 48, between 61 and 72, and so on, were grouped in the "large class size" sub-sample. On the other hand, pupils who attended schools with enrollment between 25 and 36, between 49 and 60 and so on, were grouped in the "small class size" sub-sample. This classification is based on the fact that in Denmark larger cohorts exceeding the class size threshold of 24 are split into smaller classes. We find that the school effect is higher for small classes (0.024) compared to large classes (0.005), which speaks to the mixed findings from the long run class and school effects literature. It is also interesting to note that the neighborhood effect is stronger for students in large classes, possibly reflecting the location of these students in more densely populated urban areas. In general, while the variation by class size goes in the direction we would expect in the light of recent studies, its quantitative relevance is negligible compared to the family effect.

The previous analysis of heterogeneous effects shows some variation in the importance of community effects, which is consistent with previous research in various strands of the literature. However, the share of the sibling correlation that can be explained by community effects never exceeds 14 percent (found for urban neighbors), which is well below the share of 25 percent estimated when family effects are ignored.

7. Conclusion

This paper develops a unified framework which enables disentangling the contribution of families, schools and neighborhoods in labor earnings over the life-cycle. This is achieved within a model of multiple group earnings dynamics distinguishing permanent from transitory earnings and allowing for heterogeneous earnings growth. The analysis is based on administrative registers from the Danish population which we use to link brothers, schoolmates and teenage neighbors and follow them over their life-cycle and up to age 51.

Our analysis indicates that family is by far the most relevant factor that shapes long-term earnings. The contribution coming from schools and neighborhoods on long-term earnings is overestimated if the family component is ignored, which suggests that not accounting for sorting leads to an upward bias in the estimated influence of community background. Despite the negligible average community effects, we find that both schools and neighborhoods exhibit a positive and significant effect at the beginning of working life. However, these effects do not persist beyond age 30. These results contribute to our understanding about the effects of family and community background on labor market outcomes showing that while family influences are long-term, community influences do not have very long-term earnings consequences.

Table 1

Neighborhood and long run earnings – key study characteristics.

	(1) Page and Solon	(2) Raaum, et.al.	(3) Oreopoulos	(4) Our study
Location	United States	Norway	Toronto, Canada	Denmark
Neighborhood	PSID cluster	Census tract	Housing project	Parish
Proximity	20-30 dwellings	44 km^2	20 buildings	20 km^2
#Clusters	120	7,996 and 8,818	81	47,622
#Men observed	443	228,700	4,060	695,960
Men/cluster	4	14	50	15
Others/cluster	86	450	1,036	2,443
Exposures				
Birth cohorts	1952-62	1946-65	1963-70	1960-84
Years	1968	1960 and 1970	1978-86	1975-99
Ages	6-16	5-15	8-16	15
Duration	snapshot	snapshot	1-9 years	snapshot
Outcomes				
Measure	Earnings	Residual earnings	Income	Residual earnings
Duration (years)	5	6	3	6-28 (mean 16)
Transformation	total mean	total mean	total mean	untransformed
Years observed	1987-91	1990-95	1997-99	1984-2011
Ages observed	25-39	25-50	27-36	24-51
#Observations	443	228,700	4,060	10,930,859

Table 2

Cohorts included in the sample

(1) Birth cohorts	(2) First year observed	(3) # years observed	(4) Last age observed	(5) Earnings Observations	(6) Persons	(7) School cohorts	(8) Parish cohorts
1960-61	1984	28	51	1,468,021	61,366	2,402	3,762
1962-63	1986	26	49	1,438,443	64,167	2,514	3,950
1964-65	1988	24	47	1,432,075	68,440	2,724	4,081
1966-67	1990	22	45	1,326,020	69,213	2,873	4,078
1968-69	1992	20	43	1,077,084	61,503	2,896	4,052
1970-71	1994	18	41	981,639	61,724	2,933	4,033
1972-73	1996	16	39	879,885	61,720	2,964	4,005
1974-75	1998	14	37	749,119	59,731	2,958	3,991
1976-77	2000	12	35	579,591	53,530	2,909	3,958
1978-79	2002	10	33	452,792	49,850	2,903	3,954
1980-81	2004	8	31	327,221	44,426	2,913	3,900
1982-83	2006	6	29	227,969	40,320	2,918	3,858
1960-83	1984-2006	6-28	29-51	10,930,895	695,960	33,907	47,622

Table 3

Parameter estimates of permanent earnings

Panel A - Shared components (heterogeneous income profile –random growth)

	Coef.	s.e.
Variance of intercepts		
Family ($\sigma^2_{\mu\Phi}$)	0.0633	0.0109
School ($\sigma^2_{\mu\Sigma}$)	0.0022	0.0031
Neighborhood ($\sigma^2_{\mu\mathrm{N}}$)	0.0034	0.0035
Variance of slopes		
Family ($\sigma^2_{\gamma\Phi}$)	0.0003	0.00006
School ($\sigma^2_{\gamma\Sigma}$)	0.00003	0.00002
Neighborhood ($\sigma^2_{\gamma\mathrm{N}}$)	0.0001	0.00002
Covariance between components		
Family-School ($\sigma_{\mu\Phi\Sigma}$)	0.0037	0.0012
Family-Neighborhood ($\sigma_{\mu\Phi\mathrm{N}}$)	0.0037	0.0013
School- Neighborhood ($\sigma_{\mu\Sigma\mathrm{N}}$)	0.0011	0.0002
Covariance intercepts-slopes		
Family ($\sigma_{\mu\gamma\Phi}$)	-0.0039	0.0006
School ($\sigma_{\mu\gamma\Sigma}$)	-0.0005	0.0002
Neighborhood ($\sigma_{\mu\gamma\mathrm{N}}$)	-0.0010	0.0003

Panel B - Idiosyncratic components (restricted income profile-random walk)

	Coef.	s.e.
Initial condition (age 24)		
Brother 1 ($\sigma^2_{\omega 24,1}$)	0.0542	0.0091
Brother2 ($\sigma^2_{\omega 24,2}$)	0.0374	0.0067
Variance of innovations		
Brother 1 ($\sigma^2_{\xi 1}$)	0.0066	0.0011
Brother 2 ($\sigma^2_{\xi 2}$)	0.0071	0.0012

Table 4

Parameter estimates of transitory earnings

	Coef.	s.e.
Initial condition (age 24)		
Brother 1 ($\sigma^2_{24,1}$)	0.6613	0.0447
Brother 2 ($\sigma^2_{24,2}$)	0.6477	0.0459
Variance of innovations at 25		
Brother 1 ($\sigma^2_{\varepsilon 1}$)	0.4935	0.0357
Brother 2 ($\sigma^2_{\varepsilon 2}$)	0.4731	0.0341
Age splines in variance of innovations		
Brother 1		
26-28	-0.1370	0.0083
29-33	-0.1016	0.0058
34-38	-0.0244	0.0076
39-43	-0.0358	0.0100
44-51	-0.0153	0.0110
Brother 2		
26-28	-0.1515	0.0089
29-33	-0.1122	0.0066
34-38	-0.0364	0.0092
39-43	-0.0184	0.0125
44-51	0.0080	0.0175
Autoregressive coefficient		
Brother 1 (ρ_1)	0.4979	0.0049
Brother 2 (ρ_2)	0.5164	0.0053
Cross-person associations in transitory earnings		
Sibling covariance of innovations (σ_f)	0.0072	0.0006
Peers covariance of transitory earnings (catch-all components)		
Sharing both school and neighborhood (λ_{sn})	-0.0003	0.0006
Sharing only school (λ_s)	0.0027	0.0007
Sharing only neighborhood (λ_n)	-0.0006	0.0007

Table 5

Sensitivity analysis – Decomposition of sibling correlation

	Sibling	Family	Neighborhood	School	Community (N+S)
Baseline	0.282	0.269	0.009	0.004	0.013
	(0.012)	(0.012)	(0.010)	(0.010)	(0.009)
Families with up to 2 Children	0.329	0.311	0.021	-0.004	0.018
	(0.016)	(0.022)	(0.014)	(0.013)	(0.013)
Families with up to 3 Children	0.293	0.292	0.020	-0.019	0.001
	(0.014)	(0.018)	(0.015)	(0.013)	(0.012)
Excluding singletons	0.286	0.275	0.008	0.003	0.011
	(0.012)	(0.012)	(0.009)	(0.009)	(0.009)
Peers at age 14 and age 15	0.282	0.270	0.010	0.002	0.012
	(0.012)	(0.012)	(0.010)	(0.009)	(0.009)
Main parish of residence (age 14 -18)	0.280	0.267	0.008	0.006	0.014
	(0.012)	(0.012)	(0.010)	(0.009)	(0.009)
Excluding private schools	0.304	0.302	-0.002	0.004	0.002
	(0.011)	(0.015)	(0.012)	(0.011)	(0.010)

Table 6

Heterogeneous effects – Decomposition of sibling correlation

	Sibling	Family	Neighborhood	School	Community (N+S)
Baseline	0.282	0.269	0.009	0.004	0.013
	(0.012)	(0.012)	(0.010)	(0.010)	(0.009)
Father education > 13 years	0.378	0.340	0.018	0.020	0.038
	(0.113)	(0.111)	(0.001)	(0.004)	(0.003)
Father education <= 13 years	0.270	0.282	-0.002	-0.010	-0.012
	(0.013)	(0.016)	(0.013)	(0.012)	(0.011)
Urban parish	0.313	0.270	0.024	0.019	0.043
	(0.015)	(0.015)	(0.005)	(0.010)	(0.005)
Rural parish	0.300	0.285	0.018	-0.003	0.015
	(0.015)	(0.022)	(0.016)	(0.013)	(0.013)
Small class size	0.308	0.270	0.014	0.024	0.038
	(0.021)	(0.025)	(0.010)	(0.016)	(0.009)
Large class size	0.318	0.290	0.023	0.005	0.028
	(0.018)	(0.019)	(0.007)	(0.012)	(0.007)

Figure 1

Sibling correlation of annual earnings

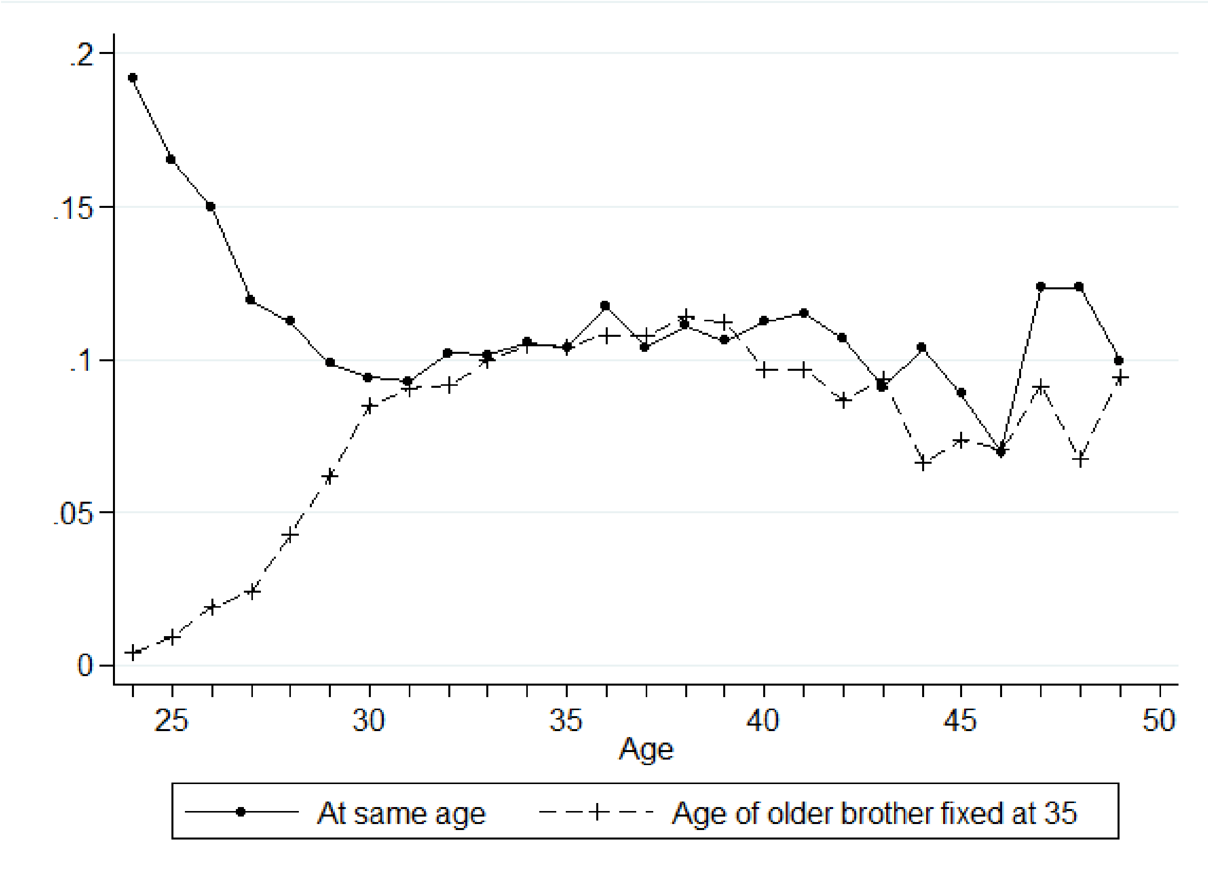


Figure 2

Sibling correlation of annual earnings by siblings' age gap

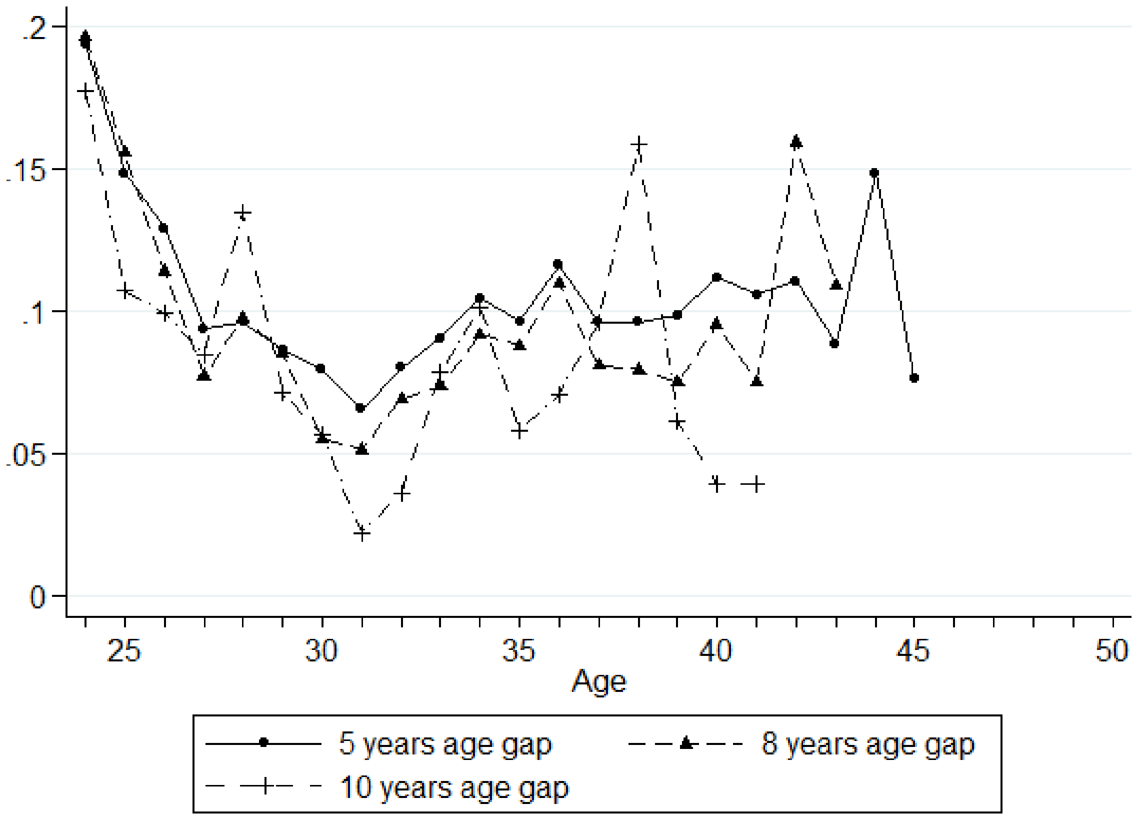


Figure 3

Correlation of annual earnings for members of youth communities

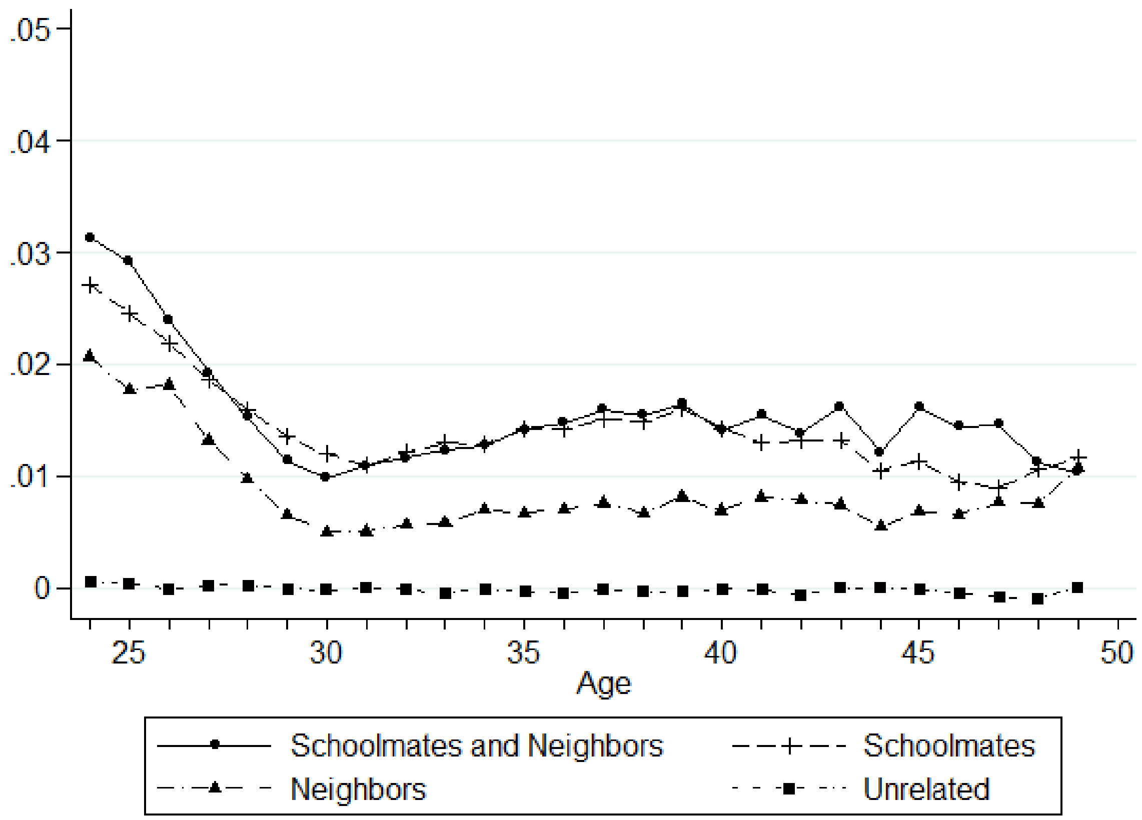
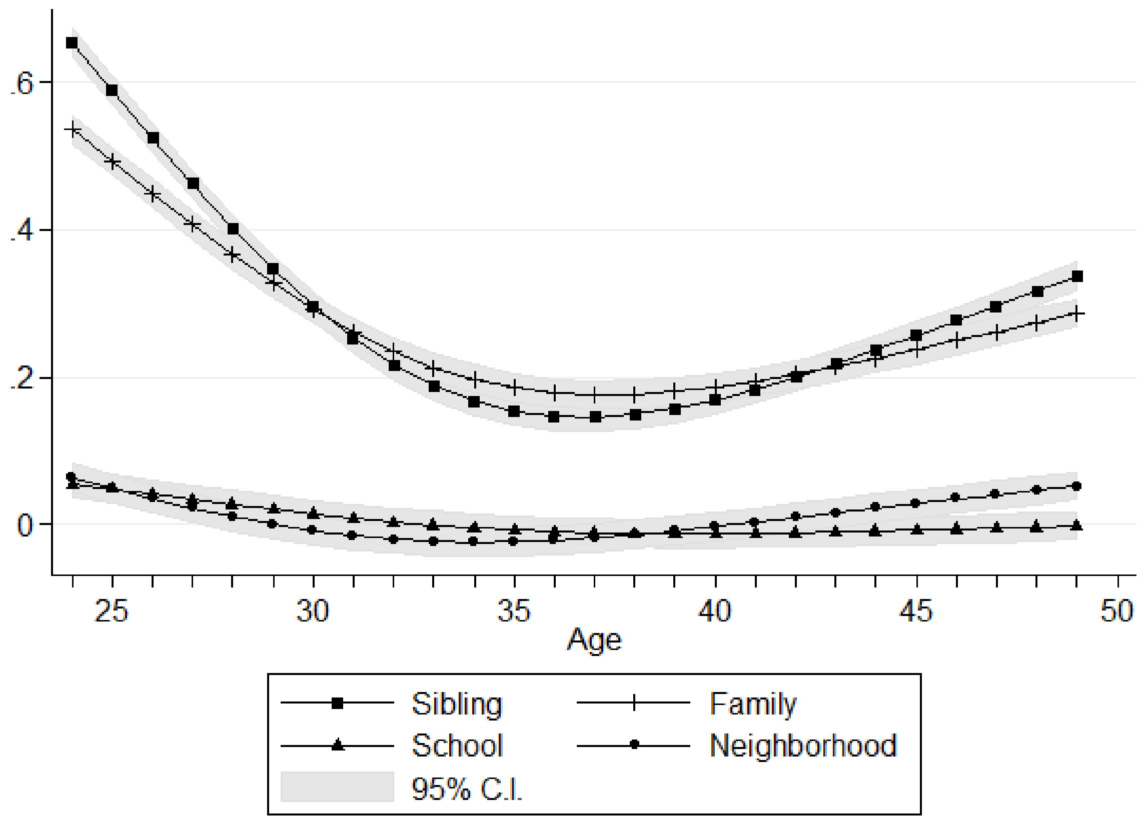


Figure 4

Predicted sibling correlation of permanent earnings and factor decomposition



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Appendix A

Moment restrictions for transitory earnings

Considering two non-necessarily different age levels a and a', the intertemporal covariance structure of the transitory component of *individual* earnings from the birth order specific AR(1) process is as follows:

$$\begin{aligned} E\left(v_{ifsna}v_{ifsna'}\right) &= [I(a = a' = 24)\sigma_{24b}^2 \\ &+ I(a = a' > 24)\left(\exp\left(g_b(a)\right) + var\left(u_{ifsn(a-1)}\right)\rho_b^2\right) \\ &+ I(a \neq a')\left(E\left(u_{ifsn(a-1)}u_{ifsna'}\right)\rho_b\right)]\eta_t\eta_{t'}. \end{aligned} \tag{A.1}$$

Allowing for correlation of AR(1) innovations across brothers, the model yields restrictions on transitory earnings also for cross-brothers moments:

$$E\left(v_{ifsna}v_{i'fs'n'a'}\right) = \sigma_f\left(\frac{\left(1-\left(\rho_1\rho_2^{|t-t'|}\right)^P\right)}{1-\rho_1\rho_2^{|t-t'|}}\right)^{I(t\leq t')}\left(\frac{\left(1-\left(\rho_2\rho_1^{|t-t'|}\right)^P\right)}{1-\rho_2\rho_1^{|t-t'|}}\right)^{I(t>t')}\eta_t\eta_{t'};\ \ \forall\, s,s',n,n', \tag{A.2}$$

where P is the number of overlapping years the two brothers are observed in the data.

We also model the correlation of transitory earnings across *non-sibling peers*. Differently from the case of brothers, we do not model the correlation of AR(1) innovations among peers because it would require distinguishing idiosyncratic components of transitory earnings for each member of school or neighborhood clusters, generating dimensionality issues. We, therefore, collapse all the cross-peers covariance structure of the transitory component into catch-all "mass point" factors absorbing all the parameters of the underlying stochastic process. For any two non-necessarily different age levels a and a', correlations of transitory earnings across non-sibling peers are as follows:

$$E\left(v_{ifsna}, v_{i'f'sna'}\right) = \lambda_{sn}^{1+|t-t'|}\eta_t\eta_{t'} \tag{A.3}$$

$$E\left(v_{ifsna}, v_{i'f'sn'a'}\right) = \lambda_{s}^{1+|t-t'|}\eta_t\eta_{t'} \quad \forall\, n \neq n'$$

$$E\left(v_{ifsna}, v_{i'f's'na'}\right) = \lambda_{n}^{1+|t-t'|}\eta_t\eta_{t'} \quad \forall\, s \neq s'$$

The moment restrictions above characterize the inter-temporal distribution of transitory earnings for each individual and between siblings and peers. The orthogonality assumption between permanent and transitory earnings in equation (1) implies that moment restrictions of the full model are the sum of moment restrictions for permanent and transitory earnings, the former being discussed in Section 5.3 of the paper. In general, these restrictions are a non-linear function of a parameter vector θ. We estimate θ by Minimum Distance (see Chamberlain, 1984; Haider, 2001). We use Equally Weighted Minimum Distance (EWMD) and a robust variance estimator $Var(\theta) = (G'G)^{-1}G'VG(G'G)^{-1}$, where V is the fourth moments matrix and G is the gradient matrix evaluated at the solution of the minimization problem.

Table A1: Parameter estimates of time effects (1984=1)

	Permanent Component (π_t)		Transitory Component (η_t)	
	Coeff	se	Coeff	se
t=				
1985	0.9212	0.0807	0.9492	0.0209
1986	0.9129	0.0830	0.9755	0.0231
1987	0.9653	0.0890	0.9591	0.0245
1988	1.0513	0.0960	0.9972	0.0248
1989	1.0356	0.0963	1.0511	0.0264
1990	1.1306	0.1027	1.0688	0.0265
1991	1.2037	0.1083	1.0692	0.0271
1992	1.1435	0.1016	1.1319	0.0271
1993	1.1594	0.1044	1.1397	0.0280
1994	1.2067	0.1070	1.1285	0.0274
1995	1.1561	0.1031	1.0581	0.0263
1996	1.2260	0.1078	1.0605	0.0261
1997	1.1714	0.1024	1.0543	0.0257
1998	1.2097	0.1053	1.0442	0.0254
1999	1.1890	0.1043	1.0723	0.0261
2000	1.2250	0.1073	1.0935	0.0265
2001	1.1845	0.1036	1.1162	0.0269
2002	1.2459	0.1092	1.1406	0.0276
2003	1.2526	0.1100	1.2066	0.0291
2004	1.2350	0.1085	1.1690	0.0281
2005	1.1710	0.1029	1.1628	0.0280
2006	1.1024	0.0971	1.1335	0.0270
2007	1.0175	0.0898	1.1243	0.0268
2008	0.9650	0.0856	1.1467	0.0276
2009	0.9457	0.0840	1.3173	0.0312
2010	0.9263	0.0826	1.3721	0.0325
2011	0.9135	0.0810	1.3731	0.0324