CESifo WORKING PAPERS

6743
2017

November 2017

Family, Community and Life-Cycle Earnings: Evidence from Siblings and Youth Peers

Paul Bingley, Lorenzo Cappellari, Konstantinos Tatsiramos

CESifo

Impressum:

CESifo Working Papers
ISSN 2364-1428 (electronic version)
Publisher and distributor: Munich Society for the Promotion of Economic Research - CESifo GmbH
The international platform of Ludwigs-Maximilians University's Center for Economic Studies and the ifo Institute
Poschingerstr. 5, 81679 Munich, Germany
Telephone +49 (0)89 2180-2740, Telefax +49 (0)89 2180-17845, email office@cesifo.de
Editors: Clemens Fuest, Oliver Falck, Jasmin Gröschl
www.cesifo-group.org/wp

An electronic version of the paper may be downloaded
· from the SSRN website: www.SSRN.com
· from the RePEc website: www.RePEc.org
· from the CESifo website: www.CESifo-group.org/wp

CESifo *Working Paper No. 6743*
Category 4: Labour Markets

Family, Community and Life-Cycle Earnings: Evidence from Siblings and Youth Peers

Abstract

Using longitudinal data based on administrative registers for the population of Danish men we develop a model which accounts for the joint earnings dynamics of siblings and youth community peers. We are the first to decompose the sibling correlation of permanent earnings into family and community effects allowing for life-cycle dynamics; finding that family is the most important factor influencing earnings inequality over the life cycle. Community background explains a substantial share of the sibling correlation of earnings early in the working life, but its importance diminishes over time and becomes negligible after age 30.

JEL-Codes: D310, J620.

Keywords: sibling correlation, neighborhoods, schools, long-term inequality.

Paul Bingley
VIVE – Danish Centre of Applied Social Science, Herluf Trolles Gade 11
Denmark – 1052 Copenhagen
pab@vive.dk

Lorenzo Cappellari
Department of Economics and Finance
Università Cattolica Milano
Italy – 20123 Milan
lorenzo.cappellari@unicatt.it

Konstantinos Tatsiramos
University of Nottingham
School of Economics
United Kingdom – Nottingham, NG7 2RD
tatsiramos@gmail.com

October 2017
We thank Anders Björklund, Stephen Gibbons, Markus Jännti, Bash Mazumder, Andreas Peichl, Josef Zweimüller, seminar audiences at IZA in Bonn, SOFI in Stockholm, Lund University, Paris School of Economics, JRC in Ispra, University of Padua, University of Venice, ZEW in Mannheim, European University Institute in Florence, IAB in Nuremberg, and conferences audiences at Royal Economic Society in Manchester, European Society of Population Economics in Braga, 16th IZA/CEPR European Symposium in Labour Economics (ESSLE), Fourth SOLE/EALE World Conference in Montreal, DynIPer in Marseille and the Intergenerational Mobility workshop in Madrid for their comments. The usual disclaimer applies. The research for this paper was supported by a British Academy Research Grant (award no. SG113192) and by an Independent Research Fund Denmark – Social Sciences Grant (code DFF-6109-00226).

1. Introduction

That the environment in which persons grow up and live in the early stages of their life is an important determinant of lifetime socioeconomic outcomes is well-established in the recent economic literature. Francesconi and Heckman (2016) report that at least 50 percent of the variability of lifetime earnings across persons is due to differences in attributes determined by age 18. While part of these attributes is purely idiosyncratic, they also depend on factors that are shared among individuals. Family and community background are two of the most important early-life shared factors determining later outcomes (Black and Devereux, 2011). Families influence earnings by transmitting abilities, preferences and resources, whereas communities may influence earnings through neighborhood quality, school quality and peers. While there is a large and growing body of evidence on the impact of family or community on adult outcomes, very little is known about their relative importance in explaining earnings inequality, and especially, whether and how these influences vary over the life cycle. Understanding the long-term importance of family and community background on earnings variability is relevant for identifying the driving forces of existing inequalities, and for interventions that aim to reduce them, especially since some early influences may be longer lasting than others.

In this paper, we study the relative influence of family and community background on earnings inequality over the life cycle using longitudinal data based on tax records from administrative registers for the population of Danish men. We develop an earnings dynamics model, in the spirit of Baker and Solon (2003), which accounts for the joint earnings dynamics of siblings and youth community peers (neighbors and/or schoolmates). To account for heterogeneous human capital investments and returns in the model, inequality of long-term earnings depends on inequality in both initial earnings and earnings growth rates. These two sources of inequality in long-term earnings depend on heterogeneity among families and youth communities, which reflects the idea that circumstances early in life may have long lasting effects. We also allow for purely idiosyncratic unit root shocks, which permanently shift individual earning trajectories. Using the parameter estimates of the model we are the first to decompose the sibling correlation of permanent earnings into family and community effects while allowing for life-cycle dynamics.[1]

The correlation of sibling earnings measures the fraction of permanent earnings variation that is attributed to both observed and unobserved factors shared by siblings during childhood, and is widely used as an omnibus measure of the combined influence of family and community background (for reviews, see Solon, 1999; Björklund and Jännti, 2009; Black and Devereux, 2011). To disentangle family from community effects, the common approach in the literature is to compare the correlation of sibling earnings with the correlation of earnings among unrelated neighbors (for instance, Page and Solon, 2003 and Raaum et al., 2006). The idea is that while siblings share both the family and the neighborhood, unrelated neighbors share only the neighborhood but not the family. Findings from these studies suggest that community background – through the neighborhood of residence – explains a substantial share of earnings inequality. However, this estimated neighborhood effect is recognized to be an upper bound because of non-random sorting of families into communities, which leads to positive correlation between the two factors. Exploiting quasi-random assignment of families to public housing projects in Toronto, which eliminates sorting, Oreopoulos (2003) finds instead a zero influence of neighborhood quality in the total variance of income and wages.

We contribute to the sibling correlation literature in the following ways. First, by modeling *jointly* the earnings of siblings and peers we identify family effects *net of any* community

[1] Bingley and Cappellari (2017) extend the model by Baker and Solon (2003) to account for dynamics within a three-person family, that is, three pairwise relationships. With respect to Bingley and Cappellari (2017) we account for dynamics not only within sibling pairs but also for community *groups* of arbitrary size.

influences. Second, by exploiting within-family community variation we show that it is possible to identify community influences separately from sorting of families into communities. Third, we define communities using both neighborhoods and schools so we can investigate any differential influences on earnings inequality between the two factors. Fourth, by observing earnings trajectories up to age 45 we trace the relative influence of these attributes on earnings for a relevant part of the life cycle. With long earnings histories, we can assess the importance of families and communities in shaping permanent earnings inequality while avoiding measurement error and life-cycle biases. Permanent earnings are generally considered to be the most relevant for individual welfare because transitory earnings shocks are more insurable (Blundell et al., 2008).

We find that the sibling correlation of earnings is U-shaped, which is consistent with the prediction from human capital models that heterogeneous investments in human capital induce an inverse relationship between initial earnings and earnings growth rates. That is, individuals trade off initial earnings against earnings growth, which implies a U-shaped pattern of earnings inequality over the life cycle. The decomposition of sibling correlations shows that family is the most important factor influencing earnings inequality throughout the life cycle. Community background explains a substantial share of the sibling correlation of earnings early in the working life, but its importance diminishes over time and becomes negligible after age 30. On average, community does not account for more than 12 percent of the sibling correlation of earnings. This finding holds for both community definitions, although neighborhood effects are slightly larger than school effects; and this finding is robust to the age we measure youth communities and to various sample selection choices. The diminishing community influence over the life cycle highlights the importance of observing long earnings histories beyond the first years of the working life; measuring earnings only at relatively young ages overstates the long-term relevance of community effects in explaining earnings variation.

Outside the sibling correlation literature, this paper relates to the large and growing literatures on the impact of schools and youth neighborhoods on adult outcomes. Some recent examples include Chetty and Hendren (2015) and Chetty et al. (2016) on the impact of age of moving to a higher income neighborhood during childhood, in observational and experimental frameworks respectively; Fredriksson et al. (2012) and Chetty, et al. (2011) on impact of class size and school peers, also in observational and experimental frameworks. Evidence emerging from these studies supports the view that environmental circumstances during youth may have impacts when adult. Our communities encompass schools and neighborhoods, enabling us to speak to both literatures.

The paper is structured as follows. In Section 2 we describe the data and contrast our community definition with that used in comparable studies. In Section 3 we present descriptive statistics on earnings of siblings and community peers over the life cycle. In Section 4 we develop the econometric model based on the joint analysis of life-cycle earnings for siblings and youth peers. In Section 5 we present the main results, discuss a series of robustness checks and compare our findings to the previous sibling correlation literature. We conclude in the last section.

2. Data

2.1 Sample Selection

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 our analysis, we consider men and we construct our dataset as follows. First, we create a sample of brothers by sampling fathers and finding their first and second sons born in the years 1965-1985 who share both legal parents from registration at birth and are not adopted. The year of birth selection starts in 1965 because of prior incompleteness of residential information and stops in 1985 to allow observation of individual earnings up to the late 20s for younger cohorts (earnings data described later in the Section are available until 2014).[2] We exclude from the sample sons who are also observed as fathers (of sons born 1965-85), brothers born less than 12 months apart and brothers born more than 12 years apart. Overall, we obtain 89,738 sibling pairs. We keep singletons (sons without a younger brother) in the sample; there are 320,094 singletons giving a total of 499,570 men who meet the selection criteria above and are either a first or second brother, or a singleton. In robustness analysis we find that excluding singletons does not affect our findings.

Next, we match men from the selected birth cohorts depending on whether they are born in the same year and share their youth communities by either being neighbors, schoolmates, or both. To match every person in the sample to their community peers we choose either a specific level of age or an age interval within which the persons share their community. In contrast to our treatment of siblings, peers are included in the analysis irrespective of birth order and age spacing from their own brothers. This adds 79,903 male individuals, giving a total sample of 579,473 men.

Using information on individual addresses from the central person register we define neighborhoods as the parish of residence.[3] Given data constraints, we can measure neighbors at any age level or age interval starting at age 11. For the descriptive analysis presented in Section 3, and for the baseline estimates reported in Section 5, we link persons to neighbors on 31 October of the calendar year they turn 15. There are 2,123 parishes in our sample containing on average 13.9

[2] 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.

[3] Complete information on municipality of residence is available from 1970 and full addresses are complete from 1976 (see Pedersen, et al. 2006 for details). We use an intermediate aggregation of locality as our neighborhood indicator – parish of residence – from 1973. Individuals are required to report changes of address to the municipality within five days.

male neighbors turning 15 in the same year. The robustness analysis in Section 5 shows also that measuring neighbors at any other age or age interval (from 11 to 15) does not affect our findings.

To characterize the degree of heterogeneity in socio-economic background between neighbors, Figure 1 presents a map of Danish parishes shaded according to mean level of fathers' gross annual labor earnings (in 2012 prices) when the son is age 15 in our sample. Highest earnings are concentrated in the biggest towns, but otherwise there is substantial paternal earnings dispersion around the country.

Using information from the educational register 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; the last year of compulsory education.[4] School enrolment rules were such that pupils should start in first grade in the August of the calendar year they turn 7. 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.[5] 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).[6] Our sample contains 1,821 schools with males aged 15, who have on average 18.9 male schoolmates born in the same calendar year.

---

[4] In 1990, 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.

[5] The national pupil database was first 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.

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

During our sample period, pupils were assigned to public schools on a catchment area basis according to place of residence. 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.

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. Amongst school-birth-cohort clusters, 53.1 percent have individuals from more than one parish, and amongst parish-birth-cohort clusters 34.1 percent have individuals from more than one school.

Because communities are defined on the basis of individual year of birth, not all brothers will share the community at a given age, mainly because of family mobility. That is, neighbors of brother 1 at a given age will be drawn from a different neighborhood than neighbors of brother 2 at that same age if there is family mobility. Similarly, schoolmates of brother 1 will be drawn from a different school than schoolmates of brother 2 if they attend different schools. For example, among our 89,738 brother pairs, 72 percent share both school and neighborhood at age 15, 4 percent share only the school, 15 percent share only the neighborhood, while the remaining 9 percent do not share any of the two community affiliations.

We use pre-tax annual labor earnings between 1990 and 2014, measured in 2012 prices. We select all valid observations on earnings and exclude zero-earnings observations. Assuming that earnings are missing at random, the exclusion of zero-earnings observations is common with most of the earnings dynamics literature, and is also applied in the sibling correlation literature (for instance, see Björklund et al., 2009). We 'trim' a quarter of a percentile from each tail of the annual earnings distribution and require at least three consecutive earnings observations for an individual to be included in the sample. This selection rule is intermediate between the one used by Baker and Solon (2003), that is, continuous earnings strings for each individual within a cohort, 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 valid observations on earnings.

Table 1 presents the cohorts we include in the sample, the years for which we observe earnings and sample sizes in various dimensions. We group data in three-year birth cohorts, as shown in Column 1, and we compute age by imputing each cohort with its central year of birth.[7] The selection of birth cohorts and time window ensures that we observe each cohort starting at age 24 (23-25) for at least 7 years (last cohort 1983-85) and for as long as 25 years (first cohort 1965-67) up to age 48 (47-49). Columns 5 and 6 show the number of earnings observations and number of men used in estimation. The number of community cohorts into which we group men is shown in Columns 7 and 8, totaling 10,654 school cohorts and 14,711 parish cohorts. The number of parish and school cohorts is quite stable, which reflects an absence of administrative unit reform during the exposure period.[8] The falling number of earnings observations by birth cohort is due to later cohorts having less time to accumulate earnings histories.

2.2 Sample comparison to other studies

[7] We could form only few sibling matches within the first birth cohort (1965-68), therefore we exclude families in which both siblings belong to this cohort. As a consequence, the first birth cohort contains only elder brothers or singletons.

[8] A 2007 reform changed the number of municipalities from 273 to 95. Responsibility for primary and lower secondary schools changed accordingly. This reform comes after the last year of community affiliation in our data – 2002.

It is informative to contrast our community definition with that used in comparable studies such as Page and Solon (2003), Raaum et al., (2006) and Oreopoulos (2003).[9] We focus the comparison on neighborhoods because this is the community definition used in these studies. Table 2 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 (1) 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 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 neighbors 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 different ages – with up to 9 and 11 years age differences – to form neighborhood clusters. In the main part of the analysis we consider neighbors at 15 years of age as belonging to the same cluster. Neighborhood affiliation at age 15 is at the upper end of the 5-16 age range together considered in the other studies. All else equal, if neighbors of the same age are more likely to interact than neighbors of different ages, then we would expect to find stronger neighbor correlations with our definition. In sensitivity checks we show robustness of results to neighborhood definitions based on affiliation down to age 11 or using age ranges between 11 and 15 rather than a single age.

---

[9] In what follows we refer to Page and Solon (2003) as study (1), Raaum et al. (2006) as study (2) and Oreopoulos (2003) as study (3).

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 0.5 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 should reduce precision rather than introduce any bias.

3. Descriptive statistics on earnings of siblings and community peers

To motivate the model, which we present in the next Section, we first provide a description of the interpersonal covariance structure of earnings in our sample. There are two types of cross-person relationships that are of interest for the analysis: i) between siblings and ii) between community peers.

Figure 2 (solid line) shows that the sibling correlation of earnings – when brothers are at the same point in their life cycle – is high at the beginning of the working life at age 24, declines to about age 30 and remains relatively stable thereafter with a slight increase up to about age 40. This *U-shaped pattern* of earnings correlation suggests that the sources of initial earnings heterogeneity that brothers share are negatively correlated with heterogeneity in earnings growth. As we discuss in the next Section, human capital models predict that investments in education or training induce such a negative correlation.

In Figure 2 (dashed line) we also report the sibling correlation of earnings by age of the younger brother, after we fix the age of the elder brother at 35. We find that the earnings correlation starts close to zero at age 24 and it increases sharply, so that by the early-30s it matches the "same age" correlation. This pattern illustrates that the earnings correlation between siblings at different ages is an underestimate of the actual correlation when they are at the same point in their life cycle. Haider and Solon (2006) discuss this as a form of life-cycle bias, which we can detect in the data and control for in estimation.

Besides human capital investments, the large contemporaneous associations at the early stage of the life cycle depicted in Figure 2 may also reflect the correlation of transitory shocks. It is well known that earnings instability is large in the beginning of the working life (for instance, see Baker and Solon, 2003). It is also plausible that siblings may be subject to common shocks, for example, due to similar local economic conditions at labor market entry. To assess if the relatively large sibling correlation at labor market entry is driven by differences in permanent earnings or transitory fluctuations, we compute the earnings correlation for not-closely-spaced brothers. The larger the age-spacing between siblings, the less likely that they enter the labor market at the same time and be influenced by common transitory fluctuations. Figure 3 shows that the declining pattern of the sibling correlation between the mid-20s and the early-30s persists even for brothers born at least five, eight or ten years apart. This pattern suggests that the source of convex evolution of sibling correlations in Figures 2 and 3 is in the long-term component of earnings.

Figure 4 shows the correlation of earnings for community peers who are neighbors residing in the same parish, or schoolmates who attend the same school. To obtain the between-peers correlation of earnings (at each relevant age), we first compute the within-community correlation and then we average between communities using the weighting scheme of Page and Solon (2003, pp. 841), which gives more importance to more populated communities and makes inference person-representative. These empirical correlations pick-up all sources of peer similarity, which include correlated family effects within communities but also influences independent of the family. The magnitude of the earnings correlation of community peers is roughly one tenth of the correlation of sibling earnings and higher at the beginning of the life-cycle (up to age 30) but negligible thereafter. Figure 4 also shows that the correlation of earnings for "unrelated" individuals – who are not siblings or community peers – is zero for all ages.[10] This contrast suggests that the evolution of sibling and community peer correlations over the life-cycle is not simply an artifact of aging but is picking up factors attributable to families and communities.

4. Econometric model

The aim of the paper is to assess the relative influence of family and community background on earnings inequality over the life-cycle. Motivated by the empirical facts presented in Section 3, we exploit the linked earnings records of siblings and community peers within a model of multi-person earnings dynamics where we distinguish permanent from transitory earnings and allow for heterogeneous earnings growth. The model extends the joint earnings dynamics model of Bingley and Cappellari (2017) for three persons (a father and two sons) to multi-person groups. We use the parameter estimates from this extended model to decompose the sibling correlation of life-cycle earnings into family and community influences.

4.1 The model of earnings dynamics

To separate life-cycle effects from calendar-time trends we consider the distribution of earnings within three-year birth cohorts. In particular, we assume that residual log earnings (w) – after regressing log real gross annual earnings on year dummies and a quadratic age trend by birth cohort group – are the sum of two components: (i) a permanent component (y) and (ii) a transitory component (v), which are orthogonal by definition and we write as

[10] We compute this correlation by randomly matching each individual in the sample with 1,000 unrelated individuals born in the same year.

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

where the indices *i, f, c* and *a* stand for individual, family, community and age, respectively.[11]

Since our model allows for a transitory component in earnings and life-cycle effects, we can tackle the two well-known biases in the estimation of correlations in permanent earnings between persons due to measurement error. The first source of bias 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 longitudinal data. The second source of bias 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).

4.2 Specification of permanent earnings

We allow the permanent component of earnings (y) in equation (1) to depend on both *shared* and *idiosyncratic* factors. Shared factors capture the determinants of permanent earnings that are common between siblings and community peers. The idiosyncratic factors represent individual-specific sources of variation in permanent earnings.

We model life-cycle dynamics of shared factors using a specification based on *heterogeneous income profiles* (HIP), which is also known as a *random growth* model. The HIP specification for the shared factors is consistent with human capital models in which differential investments generate heterogeneity of initial earnings and earnings growth (Mincer, 1958; Ben-Porath, 1967; Baker and Solon, 2003). In the model of Becker and Tomes (1979), parents influence the human

[11] We measure age in deviation from 24, which we set as the life-cycle starting point.

capital of their offspring by transmitting abilities, preferences and resources, and thereby affecting 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. Human capital models predict that these heterogeneous investments induce an inverse relationship 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 initial earnings and growth rates generates a U-shaped evolution of earnings dispersion by age due to the 'Mincerian cross-over' of earnings profiles. These observations motivate the specification for the determinants of shared earnings, which reflects the idea that cross-person resemblance of earnings stems from similarities in social background and human capital investments. The life-cycle patterns of earnings correlations between siblings and community peers shown in Section 3 are consistent with these mechanisms.

Besides the earnings profile shared by siblings and peers, we allow for idiosyncratic permanent shocks (ω_{ia}) to capture persistent individual deviations from the shared profile. To model this, we add a *random walk* process starting at age 24 (a *restricted income profile* – RIP – model), which captures the effects idiosyncratic ability over time.

Overall, our permanent earnings model is specified as follows:

$$y_{ifca} = \pi_t[(\mu_f + \mu_c) + (\gamma_f + \gamma_c)a + \omega_{ia}]; \tag{2}$$

$$\omega_{ia} = \omega_{i(a-1)} + \xi_{ia};\ t = b(i) + 24 + a,$$

where $b(i)$ is the birth cohort of person i and π_t is a calendar time shifter that allows for aggregate changes of the permanent earnings process over time. We factor the intercept and the slope of the individual-specific linear profile of earnings into two zero-mean components, where their variances capture family (f) and community (c) heterogeneity in *initial earnings* (denoted by μ_f, μ_c) and life-cycle *earnings growth* (denoted by γ_f, γ_c).

To summarize, the assumptions on the variance-covariance structure of permanent earnings are the following:

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

$$\left(\mu_f, \gamma_f\right) \sim \left(0,0; \sigma^2_{\mu \mathrm{F}}, \sigma^2_{\gamma \mathrm{F}}, \sigma_{\mu\gamma \mathrm{F}}\right); \tag{3.b}$$

$$(\mu_c, \gamma_c) \sim \left(0,0; \sigma^2_{\mu \mathrm{C}}, \sigma^2_{\gamma \mathrm{C}}, \sigma_{\mu\gamma \mathrm{C}}\right), \tag{3.c}$$

where we denote the specific dimensions of heterogeneity of the variance-covariance parameters by F (for family) and C (for community). Assumption (3a) allows the idiosyncratic parameters to vary by sibling birth order, which we denote by s, and we include singletons among the first born. Assumptions (3.b) and (3.c) specify the distribution of shared factors and allow for an unrestricted covariance of initial earnings and earnings growth heterogeneity within each factor, which we denote by $\sigma_{\mu\gamma \mathrm{F}}$ and $\sigma_{\mu\gamma \mathrm{C}}$, respectively. We also model the sorting of families across communities by allowing for the covariance between family and community effects through the intercept of the individual-specific profiles:

$$cov\left(\mu_f, \mu_c\right) = \sigma_{\mathrm{FC}}\ . \tag{3.d}$$

The covariance (σ_{FC}) is non-zero if families sort themselves across communities.

4.3 Specification of transitory earnings

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

$$v_{ifca} = \eta_t u_{ifca};\ u_{ifca} = \rho_s u_{ifc(a-1)} + \varepsilon_{ifca}; \tag{4}$$

$$\varepsilon_{ifca} \sim \left(0, \sigma_{\varepsilon s}^2 \exp\left(g_s(a)\right)\right), \qquad u_{ifc24} \sim \left(0, \sigma_{u_{24}s}^2\right),$$

where η_t is a time loading factor and u_{ifca} is the birth-order-specific AR(1) process. The autoregressive process begins at age 24 and we specify the variance of the initial condition ($\sigma_{u_{24}s}^2$). The process evolves through the arrival of white noise shocks (ε_{ifca}) whose variance is age-and-birth-order-specific ($\sigma_{\varepsilon s}^2 \exp\left(g_s(a)\right)$, where $g_s(a)$ denotes a linear spline in age for brother *s* with knots at 28, 33, 38 and 43.

We also allow for cross-person correlation of transitory shocks because they may be correlated not only across time but also between individuals. For siblings, the birth-order-specific distribution of shocks enables identification of the contemporaneous correlation of AR(1) innovations. For two individuals i and i', the sibling covariance of AR(1) innovations is specified as follows:

$$E\left(\varepsilon_{ifca}\varepsilon_{i'fc'a'}\right) = \sigma_f,\ \ \forall\ c, c', a = a' \pm |b(i) - b(i')|. \tag{5}$$

That is, for siblings observed in the same time period (at different ages) the innovations of transitory earnings are allowed to co-vary with parameter σ_f. This covariance of shocks between siblings is transmitted over time through the autoregressive structure of the model. For community peers, we follow a different approach to that used for pairs of siblings due to the high dimensionality that would result from parameterizing the covariance of transitory shocks between numerous peers belonging to different families (f and f'). Specifically, we allow for a catch-all “mass-point” covariance (λ) collapsing all the parameters of the underlying stochastic processes, and allow the covariance to fade away over time. For any two (not necessarily different) ages a and a', the covariance of transitory shocks across community peers is specified as follows:

$$E\left(u_{ifca}\, u_{i'f'ca'}\right) = \lambda^{1+|t-t'|}, \quad |\lambda| < 1. \tag{6}$$

4.4 Identification of permanent earnings decomposition

Identification of the parameters determining permanent earnings relies on three sets of moment restrictions: for a given individual over time, and cross-person moment restrictions for siblings and for community peers. Compared to previous studies in the sibling literature which consider separately sibling and peer correlations, the modeling approach we propose has the following advantages. First, we can identify family effects *net of any* community influences because we exploit *jointly* the moment restrictions for siblings and community peers. Second, we show that it is possible to separately identify sorting from community and family effects by exploiting between-sibling community variation.[12]

Earnings covariances for an individual are a function of all sources of earnings heterogeneity which include: (i) family influences, (ii) community influences, (iii) the sorting of families into communities and (iv) the idiosyncratic component. Individual moment restrictions for two (not necessarily different) ages, a and a', can be written as follows:

$$E\left(y_{ifca}, y_{ifca'}\right) = \tag{7}$$

[12] In Page and Solon (2003), due to the sampling design in the PSID, siblings always share the community. Raaum et al. (2006) use a linear projection of earnings on neighborhood characteristics and neighborhood fixed effects to derive an approximation for the contextual term. Oreopoulos (2003) accounts for sorting of families into neighborhoods by using quasi-random assignment of neighbors.

$$\{\sigma_{\mu\mathrm{F}}^2 + \sigma_{\mu\mathrm{C}}^2 + (\sigma_{\gamma\mathrm{F}}^2 + \sigma_{\gamma\mathrm{C}}^2)aa' + (\sigma_{\mu\gamma\mathrm{F}} + \sigma_{\mu\gamma\mathrm{C}})(a + a') + 2\sigma_{\mathrm{FC}}$$
$$+ \sigma_{\omega_{24}s}^2 + \sigma_{\xi s}^2 min(a, a')\}\pi_t\pi_{t'}.$$

Cross-person moments, such as those between siblings and between community peers, do not depend on idiosyncratic heterogeneity. Moment restrictions for siblings (different *i* but same *f*) depend on family, community and sorting effects and can be written as follows:

$$E(y_{ifca}, y_{i'fc'a'}) = \{\sigma_{\mu\mathrm{F}}^2 + \sigma_{\gamma\mathrm{F}}^2 aa' + \sigma_{\mu\gamma\mathrm{F}}(a + a') + \tag{8}$$
$$I(c = c')[\sigma_{\mu\mathrm{C}}^2 + \sigma_{\gamma\mathrm{C}}^2 aa' + \sigma_{\mu\gamma\mathrm{C}}(a + a')] + 2\sigma_{\mathrm{FC}}\}\pi_t\pi_{t'} ,$$

where $I(.)$ is an indicator function. For community peers the covariance function depends only on community and sorting effects, but not on family effects, and can be written as follows:

$$E(y_{ifca}, y_{i'f'ca'}) = [\sigma_{\mu\mathrm{C}}^2 + \sigma_{\gamma\mathrm{C}}^2 aa' + \sigma_{\mu\gamma\mathrm{C}}(a + a') + 2\sigma_{\mathrm{FC}}]. \tag{9}$$

Combining the moment restrictions defined in equations (7)-(9), we can identify community effects including sorting from equation (9), family effects from equation (8) and idiosyncratic effects from equation (7). Because we exploit sibling and peer moments jointly in the model we can identify family effects *net of any* community and sorting effects.

However, because families sort into communities, the estimated community influences will be biased upward according to the extent of sorting. Although this does not affect the estimated family effects, to identify separately the sorting parameter (σ_{FC}) from community effects we need an additional moment restriction. One possible source for the additional moment restriction is to consider community variation between siblings. Equation (8) nests moment restrictions for two types of siblings: (i) those who share the community, that is, $I(c = c') = 1$ and (ii) those who do not share the community, that is, $I(c = c') = 0$. Unlike the previous discussion where we considered siblings who only share the community, with between-sibling community variation the additional moment restriction permits the identification of community effects separately from sorting. To illustrate this identification argument, consider the covariance function for siblings sharing the community, which depends on family, sorting, and community effects. Whereas, for siblings who do not share the community, the covariance function depends only on family and sorting effects. The difference in the covariance functions between these two types of siblings identifies the community influences. Because community effects are identified by the moment restrictions for siblings, moment restrictions in (9) effectively identify sorting of families across communities. Finally, we can identify family effects by combining the moment restrictions of equation (8) and equation (9).

Siblings can be exposed to different communities at any given age because of family mobility. For example, when we measure community at age 15, family mobility after brother 1 turns 15 (but before brother 2 turns 15) generates between-sibling community variation because at that age the two brothers reside in different neighborhoods or attend different schools. Instead, for stayer families the two brothers share the community at that age. This between-sibling community variation allows estimating the sorting parameter separately from community effects.

The between-sibling community variation based on family mobility rests on the assumption that families who move are comparable to stayer families. However, these two types of families may be different due to underlying unobserved characteristics that may also affect earnings. To address possible biases coming from the comparison of moving families with stayer families, we also estimate the model using only moving families and exploit the timing of family mobility as a source of between-sibling community variation. For this robustness check, we focus on the neighborhood definition of community because we can observe community affiliation from age 11 only for the parish of residence and not for the school. We exclude from the analysis families for which the parish of the first brother remained the same between ages 11 and 15. After excluding these families we compare families moving before brother 1 turns 15 and families who move after brother 1 turns 15. These are all families who move, so it is only the difference in the timing of mobility that exposes siblings to different environments at that specific age. We argue that this source of between-sibling community variation is less prone to selection than contrasting movers and stayers. The findings we present in Section 5 are unchanged when we restrict the analysis to movers and exploit the timing of family mobility.

4.5 Estimation and decomposition of the sibling correlation

We estimate parameters by Minimum Distance where we match moment restrictions implied by the model to the empirical moments derived from the data, excluding empirical moments based on fewer than 100 observations.[13] There are three types of empirical moments entering into the estimation. First, there are individual moments, which include the variances and intertemporal covariances of individual earnings. Second, there are sibling moments, which are defined in our sample only for the first two brothers in a family. This implies that each family contributes at most once in the estimation of sibling empirical moments, while families with singletons do not contribute. To match the two different moment restrictions nested in equation (8) we estimate separate empirical moments for siblings depending on whether they share the community. Finally, there are empirical moments for community peers who by definition share the community. In contrast to families, the number of peers varies over communities. We account for such varying importance of communities using the weighting scheme we described in Section 3.

Using parameter estimates from the model we predict the contributions of family and community to the sibling correlation of permanent earnings over the life cycle. Specifically, we

[13] 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 (see, for example, Haider, 2001).

use the moment conditions of equations (8) and (9) and attribute the sorting parameter in equal parts to family and to communities as follows:

$$r^F(a) = \frac{E\left(y_{ifca}, y_{i'fc'a}\right) - \pi_t \pi_{t'}(\sigma_{\mathrm{FC}})}{E\left(y_{ifca}, y_{ifca}\right)} \; ;$$

$$r^C(a) = \frac{E\left(y_{ifca}, y_{i'f'ca}\right) - \pi_t \pi_{t'}(\sigma_{\mathrm{FC}})}{E\left(y_{ifca}, y_{ifca}\right)}, \tag{10}$$

where *r* denotes correlation coefficients of permanent earnings. It is worth noting 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 for brothers sharing the community is the sum of the two components:

$$r^S(a) = r^F(a) + r^C(a). \tag{11}$$

5. Results

In Section 5.1 we discuss the 'core' parameter estimates of the permanent and transitory components; we report estimates of calendar time shifters of the two components in an Appendix Table. In Section 5.2, we decompose the sibling correlation of earnings into family and community effects. In Section 5.3 we present checks of robustness to various alternative community definitions, to different sources of community variation between siblings, to different measures of community, and in Section 5.4 we compare the main findings with the existing evidence in the literature.

5.1 Parameter estimates

Permanent earnings in equation (2) depend on shared factors and on idiosyncratic determinants of earnings. Panel A of Table 3 shows that family is the most relevant shared factor determining inequality of long-term earnings, both for initial earnings (intercept) and for earnings growth rates (slope). Column 1 shows this feature for the baseline model where community is defined as sharing the neighborhood, the school or both community dimensions. Columns 2 and 3 show that this general pattern is repeated even when community is defined only based on neighborhoods or schools, respectively. It is worth noting however that for the school-based definition of community the variance of intercepts and slopes is lower.

Table 3 shows also for all community definitions a negative covariance between intercepts and slopes of earnings profiles ($\sigma_{\mu\gamma \mathrm{F}}, \sigma_{\mu\gamma \mathrm{C}}$), which suggests that families or communities associated with low initial earnings (at age 24) are also associated with faster growth in life-cycle earnings. That is, shared determinants of long-term earnings display the "Mincerian cross-over" property, which implies that the variance of permanent earnings across these factors is U-shaped in age because it falls in the years of catch-up and increases after the point of cross-over. The point of cross-over is the year the earnings variance is minimized, which is located – for the estimates in Column 1 – at age 33 for the between-family earnings distribution and at age 35 for the between-community earnings distribution.[14]

Following the discussion in Section 4.4, for the estimates reported in Table 3, to estimate the covariance between the two shared determinants of earnings (σ_{FC}), which captures sorting of families into communities, we exploit between-sibling community variation comparing moving to stayer families. We find that sorting is positive and statistically significant, which implies that a high draw from the distribution of family effects in permanent earnings is associated with a similarly high draw in the distribution of community effects.

[14] Taking into account that sorting contributes to the variance of intercepts, the *correlation* between intercept and slope for the baseline estimates equals -0.841. Estimating a model imposing no sorting we can compute this correlation separately for the family and community factors, which equal -0.861 and -0.840, respectively.

Panel B of Table 3 reports the estimates of the idiosyncratic source of permanent inequality in earnings. This reveals interesting birth-order effects, such that dispersion of the initial condition of the random walk is larger for elder brothers, while the dispersion of life-cycle shocks is larger for younger brothers.

Table 4 shows the parameter estimates of transitory earnings where there is a clear age pattern of transitory shocks whose variance decreases between the mid-20s and the mid-30s, while the decrease slows down around age 35. This sharp decline followed by a leveling-off is consistent with the patterns reported by Baker and Solon (2003) who find that the variance of transitory shocks declines at decreasing rate between the ages of 25 and 45. The age pattern of transitory shocks, as well as the autoregressive coefficients, are very similar between siblings and across all community definitions. Finally, Table 4 also shows that the correlation of transitory shocks between siblings is positive and significant. For community peers the correlation of transitory shocks is generally negative, but not always significant when the community definition includes the neighborhood, and is positive and significant when community is based only on schools.

5.2 Decomposition of sibling correlation

To assess the relative importance of family and community effects in explaining life-cycle earnings inequality we first use the baseline parameter estimates of the model to decompose the sibling correlation of permanent earnings over the life cycle. We generate predictions of the sibling correlation and its decomposition based on the formulae provided in section 4.5 (equations 10 and 11). In particular, we consider the scenario represented by equation (11) of two brothers who share the community at age 15. The resulting sibling correlation is the sum of family and community effects, where we impute the estimated sorting parameter to the two factors in equal parts.

Figure 5 shows that the life-cycle pattern of the sibling correlation is U-shaped in age with an estimate equal to 0.622 (s.e. 0.013) at age 25, which drops to 0.174 (s.e. 0.016) at age 35 and rises back to 0.336 (s.e. 0.020) by age 45 – the last age for which we observe younger brothers. As discussed earlier, the U-shape pattern is the result of the "Mincerian cross-over" of earnings profiles, which implies that the sibling correlation first shrinks and then fans out over the life cycle.[15] The decomposition of the sibling correlation in Figure 5 shows that family is the most important factor influencing the dispersion of permanent earnings. Column 1 of Table 5 (Panel A) shows that the average sibling correlation over the life cycle equals 0.313 (s.e. 0.014), which is in line with previous estimates for Denmark.[16] The average community correlation of earnings equals 0.023 (s.e. 0.012), which implies that community accounts for only 7.4 percent of the sibling correlation of earnings (C/S = 0.023/0.313).

Figure 5 also shows that community effects are relatively more important at the beginning of the working life, but their influence in explaining earnings dispersion diminishes over time. These results indicate that there is not much room for community effects in shaping the sibling correlation in the long run. The family is the only factor that generates a substantial correlation in permanent earnings between brothers throughout the life cycle. Furthermore, measuring earnings at relatively young ages exaggerates the relevance of community effects. Column 1 of Table 5 (Panel B) shows that if we measure earnings only up to the beginning of the working life (age 25), the share of sibling correlation of earnings accounted for by community effects is 21 percent (C/S=0.14/0.66). Instead, if we measure earnings up to age 30 this share reduces to about 16 percent (C/S=0.079/0.487) and by age 35 it reduces further to about 11 percent (C/S=0.041/0.355). This

[15] The same U-shaped pattern is also a feature of the raw cross-person correlations shown in Figures 2 to 4, and especially in Figure 3, which depicts the earnings correlation for widely-spaced brothers.
[16] Björklund et al. (2002, p. 765) report for men aged 25-42 a sibling correlation of 0.29 for a model without community effects. We obtain also an average estimate of 0.29 if we limit our sample in the same age range.

evidence highlights the importance of analyzing earnings beyond the early part of the working life.[17]

5.3 Robustness checks

5.3.1 Alternative community definitions

Figure 6 shows a U-shaped pattern of sibling correlation also for the neighborhood-only (Panel A) and school-only (Panel B) definitions of community, and that family remains the most important factor explaining earnings inequality throughout the life cycle. Column 2 in Table 5 (Panel A) shows that the share of sibling correlation accounted for by neighborhoods equals 5.6 percent (C/S=0.017/0.308), while the share accounted for by schools is lower at 2.8 percent (C/S=0.008/0.297). Similarly to the baseline estimates, Columns 2 and 3 in Table 5 (Panel B) show for both alternative community definitions that the average community correlation diminishes as we measure earnings for a larger part of the life cycle. In both cases, the share of sibling correlation of earnings accounted for by community effects (C/S) declines below 10 percent when earnings are measured up to age 35, which is similar to the pattern for the baseline estimates.

5.3.2 Alternative between-sibling community variation

To test the robustness of the baseline estimates to the source of between-sibling community variation which we exploit to separate community from sorting effects, instead of comparing movers to stayers we re-estimate the model restricting the sample of siblings only to those from moving families. Because we can perform this robustness check only for the neighborhood-based community definition, the proper comparison with the baseline results is with the decomposition

---

[17] The findings of the baseline model are robust to several additional sensitivity checks related to sample selection, including estimating the model for different family sizes (up to 2 or up to 3 children) and excluding singletons. These estimates are not reported but are available from the authors.

in Figure 6 (Panel A) and the correlations in Table 5 (column 2). We find that the sibling correlation is still U-shaped (Figure 7 – Panel A) and that family accounts for most of the correlation of sibling earnings, with a diminishing importance of community effects as earnings are measured closer to the middle of the life cycle (Table 5 – column 4). The share of sibling correlation accounted for by community – on average over the life cycle – increases to 10.3 percent (C/S=0.032/0.309), but it still remains relatively small.

Although our main findings remain robust, in the absence of a random assignment of families to communities we cannot entirely rule out any bias due to endogenous family mobility. However, as we noted in Section 4.4, family mobility is necessary only if we aim to identify community effects separately from sorting. If not, we can still estimate within our model family effects net of any community influences using only siblings who always share the community (stayer families). We expect in this case to estimate community effects which are biased upward because they measure both the pure community effect and the sorting of families into communities. This would give us an upper bound of the possible community influences. Figure 7 (Panel B) and Column 5 in Table 5 report the predicted sibling correlation and its decomposition over the life cycle from the stayers model; they confirm our general finding that family accounts for most the sibling correlation and that community effects do not persist in the long run. Compared to the baseline estimates, the share of the sibling correlation accounted for by community in the stayers model is 12.4 percent (C/S=0.038/0.31), which as expected is biased upward but nevertheless explains a very small portion of the resemblance between siblings.[18]

5.3.3 Alternative measures of community affiliation

[18] Parameter estimates from the estimation of the model restricted to movers or stayers are not reported but are available from the authors.

It is possible that the community effects we report above may appear low because of measurement error, which tends to reduce their importance relative to family effects. By measuring communities at a single age (e.g. age 15) we might miss part of the community effects due to potentially limited exposure (for a similar discussion see also Chetty and Hendren, 2015). To check the sensitivity of the estimated community correlation to different community measures we estimate a community-only model in which we ignore family ties and allow for community as the only factor determining cross-person correlations in permanent earnings. For this sensitivity exercise we vary the age we measure community from 11 to 15, and we also consider different age intervals. Table 6 shows that for all different age levels and age intervals the estimated average community correlation over the life cycle is very similar and equals either 0.057 or 0.058. This provides evidence that the community estimates are not sensitive to the specific age we measure community affiliation.

5.4 Discussion

Our estimated community effects are smaller than those found in observational studies and closer to quasi-random assignment estimates. Oreopoulos (2003) finds a zero correlation of earnings between neighbors after accounting for sorting of families into neighborhoods by using quasi-random assignment of neighbors. Page and Solon (2003), without taking sorting into account, find that neighborhoods account for 50 percent of the estimated sibling correlation (C/S=0.16/0.32). Raaum et al. (2006) report for Norway an earnings correlation of youth neighbors of 0.06 and a sibling correlation of 0.2, which implies an incidence of 30 percent of neighborhood effects over the total sibling correlation. The share of sibling correlation accounted for by community effects we find for Denmark, a country in many respects similar to Norway, is substantially lower – between 7 to 12 percent.

Within our model, because we consider both factors jointly we estimate community net of family effects. Estimates of community effects in previous studies instead pick up also the influence of families because they compare the sibling correlation of earnings with the correlation of earnings among neighbors. To demonstrate this confounding, we return to the estimates from the community-only model in Table 6, which is the closest equivalent to the ones reported in the sibling correlation literature, where community is defined as neighborhood-only and includes both community and family influences. Compared to the baseline, the estimates of Table 6 show that community effects are consistently overestimated throughout the life cycle when we do not account for family effects. In particular, the community correlation of earnings accounts for 19 percent of the baseline sibling correlation (C/S=0.058/0.308). This share is 3 times larger than the share accounted for in the baseline estimates in Column 2 of Table 5, where community effects are estimated net of family and sorting. In addition, this share is closer to that reported for Norway.

Finally, our long follow-up period – beyond age 35 – also helps reconcile our estimated community effects with those in the literature. Tables 5 and 6 show that only observing earnings for the early part of the working life inflates the importance of community. Taken together these findings provide strong evidence that through the proposed model we can isolate a pure community influence which is lower than most previous estimates.

6. Conclusion

Exploiting population-based administrative data for Denmark, by virtue of which we can link earnings records of siblings, schoolmates and parish neighbors, we analyze the relative influence of family and youth community on earnings inequality. We develop and estimate a model which accounts for the joint earnings dynamics of multiple groups of individuals and we are the first to decompose the sibling correlation of earnings into family and community effects over the life cycle.

Modelling jointly the earnings of siblings and peers we identify family effects net of any community effects and we show that it is possible to identify community influences separately from sorting of families into communities.

We find that the sibling correlation of earnings is U-shaped; consistent with the prediction from human capital models that heterogeneous investments in human capital induce an inverse relationship between initial earnings and earnings growth rates. Decomposing the sibling correlation of earnings we find that within the youth environment, family is the most important factor in accounting for the inequality of permanent earnings over the life cycle. Community background explains a modest share of the sibling correlation of earnings early in the working life, but its importance diminishes over time and becomes negligible after age 30. On average, community does not account for more than 12 percent of the sibling correlation of earnings. These findings are robust to the measurement of youth communities and to various sample selection choices. The diminishing community influence over the life cycle highlights the importance of observing long earnings histories beyond the first years of the working life.

Our findings are based on data from Denmark with a welfare system promoting equality of opportunity. However, as highlighted recently by Landersø and Heckman (2016), there is much less educational mobility than income mobility in Denmark, with low private financial returns to schooling discouraging educational investments among the children of less educated parents. These family influences are consistent with our finding that family is the most important determinant of long run earnings similarities across siblings. Communities seem to affect earnings early in the working life, for example through peers influencing educational choices or youth behaviors, but these influences are short lived deviations from an earnings profile that – apart from idiosyncratic factors – mainly reflects characteristics and choices of the family. As administrative datasets and cohort studies mature in other countries, our approach to modeling group-wise dynamics could be applied to measure family and community effects on long run outcomes in other contexts.

REFERENCES

Baker, Michael, and Gary Solon. 2003. "Earnings Dynamics and Inequality among Canadian Men, 1976-1992: Evidence from Longitudinal Income Tax Records." *Journal of Labor Economics*, 21 (2): 267-88.

Becker, Gary S., and Nigel Tomes. 1979. "An Equilibrium Theory of the Distribution of Income and Intergenerational Mobility." *Journal of Political Economy*, 87 (6): 1153-89.

Ben-Porath, Yoram. 1967. "The Production of Human Capital and the Life Cycle of Earnings." *Journal of Political Economy*, 75 (4): 352-65.

Bingley, Paul, and Lorenzo Cappellari. 2017. "Correlations of Brothers' Earnings and Intergenerational Transmission." IZA Discussion Paper No. 10761.

Björklund, Anders, and Markus Jännti. 2009. "Intergenerational Income Mobility and the Role of Family Background." in *Oxford Handbook of Economic Inequality*, edited by Wiemer Salverda, Brian Nolan, and Timothy Smeeding, 491-521. Oxford: Oxford University Press.

Björklund, Anders, Markus Jäntti, and Matthew J. Lindquist. 2009. "Family Background and Income during the Rise of the Welfare State: Brother Correlations in Income for Swedish Men Born 1932–1968." *Journal of Public Economics* 93 (5-6): 671-80.

Björklund, Anders, Tor Eriksson, Markus Jännti, Oddbjrön Raaum and Eva Österbacka. 2002. "Brother Correlations in Earnings in Denmark, Finland, Norway and Sweden Compared to the United States." *Journal of Population Economics*, 15:757–72.

Black, Sandra E., Paul J. Devereux. 2011. "Recent Developments in Intergenerational Mobility." in *Handbook of Labor Economics, Vol. 4A*, edited by Orley Ashenfelter and David Card, 1487-541. Amsterdam: Elsevier Science, North Holland.

Blundell, Richard, Luigi Pistaferri, and Ian Preston. 2008. "Consumption Inequality and Partial Insurance." *American Economic Review*, 98 (5): 1887-1921.

Bohlmark, Anders, and Matthew J. Lindquist. 2006. "Life-Cycle Variations in the Association between Current and Lifetime Income: Replication and Extension for Sweden." *Journal of Labor Economics*, 24 (4): 879-900.

Chetty, Raj, and Nathalien Hendren. 2015. "The Impacts of Neighborhoods on Intergenerational Mobility: Childhood Exposure Effects and County-Level Estimates." Harvard University, mimeo.

Chetty, Raj, Nathalien Hendren, and Lawrence F. Katz. 2016. "The Effects of Exposure to Better Neighborhoods on Children: New Evidence from the Moving to Opportunity Experiment." *American Economic Review*, 106(4): 855-902.

Chetty, Raj, John N, Friedman, Nathaniel Hilger, Emmanuel Saez, Diane Whitmore Schanzenbach, and Danny Yagan. 2011. "How Does Your Kindergarten Classroom Affect Your Earnings? Evidence from Project STAR." *Quarterly Journal of Economics*, 126 (4): 1593-660.

Francesconi, Marco, and James J. Heckman. 2016. "Symposium on Child Development and Parental Investment: Introduction." Institute for the Study of Labor Discussion Paper No. 9977.

Fredriksson, Peter, Björn Öckert, and Hessel Oosterbeek. 2013. "Long-Term Effects of Class Size." *Quarterly Journal of Economics*, 128 (1): 249-85.

Haider, Steven J. 2001. "Earnings Instability and Earnings Inequality of Males in the United States: 1967-1991." *Journal of Labor Economics*, 19 (4): 799-836.

Haider, Steven J., and Gary Solon. 2006. "Life-Cycle Variation in the Association between Current and Lifetime Earnings." *American Economic Review*, 96 (4): 1308-20.

Hanushek, Erik A. 2006. "School Resources." In *Handbook of the Economics of Education, Volume* 2, ed. Eric A. Hanushek, and Finis Welch, 865-908. Amsterdam: Elsevier Science, North Holland.

Jenkins, Stephen J. 1987. "Snapshots vs. Movies: 'Lifecycle biases' and the Estimation of Intergenerational Earnings Inheritance." *European Economic Review*, 31 (5): 1149–58.

Landersø, Rasmus and James J. Heckman. 2016. "The Scandinavian Fantasy: The Sources of Intergenerational Mobility in Denmark and the U.S." Forthcoming, *Scandinavian Journal of Economics*.

Mazumder, Bhashkar. 2005. "Fortunate Sons: New Estimates of Intergenerational Mobility in the United States Using Social Security Earnings Data." *Review of Economics and Statistics* 87 (2): 235–55.

Mincer, Jacob. 1958. "Investment in Human Capital and Personal Income Distribution" *Journal of Political Economy*, 66 (4): 281-302.

Nybom, Martin, and Jan Stuhler. 2016. "Heterogeneous Income Profiles and Life-Cycle Bias in Intergenerational Mobility Estimation." *Journal of Human Resources*, 51 (1): 239-68.

Oreopoulos, Philip. 2003. "The Long-Run Consequences of Living in a Poor Neighborhood." *Quarterly Journal of Economics*, 118 (4): 1533-75.

Page, Marianne, and Gary Solon. 2003. "Correlations between Brothers and Neighboring Boys in their Adult Earnings: The Importance of Being Urban." *Journal of Labor Economics*, 21 (4): 831-56.

Pedersen, Carsten Bøcker, Heine Gøtzsche, Jørgen Østrup Møller and Preben Bo Mortensen 2006. "The Danish Civil Registration System. A cohort of eight million persons." *Danish Medical Bulletin*, 53 (4): 441-9.

Raaum, Oddbjrön, Erik Sörensen, and Kjell G. Salvanes 2006. "The Neighbourhood Is Not What It Used to Be." *Economic Journal*, 116 (1): 200-22.

Solon, Gary. 1992. "Intergenerational Income Mobility in the United States." *American Economic Review* 82 (3): 393–408.

Solon, Gary. 1999. "Intergenerational Mobility in the Labor Market." In *Handbook of Labor Economics, Vol. 3A*, ed. Orley Ashenfelter, and David Card, 1761-1800. Amsterdam: Elsevier Science, North Holland.

Wilson, William J. 1987. "The Truly Disadvantaged." Chicago: Chicago University Press.

Appendix.

Moment restrictions for transitory earnings

Considering two (not 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:

$$E\left(v_{ifca}v_{ifca'}\right) = [I(a = a' = 24)\sigma_{24s}^2 + \\ I(a = a' > 24)\left(\exp\left(g_s(a)\right) + var\left(u_{ifc(a-1)}\right)\rho_s^2\right) + \\ I(a \neq a')\left(E\left(u_{ifc(a-1)}u_{ifca'}\right)\rho_c\right)]\eta_t\eta_{t'} \ . \tag{A.1}$$

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

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

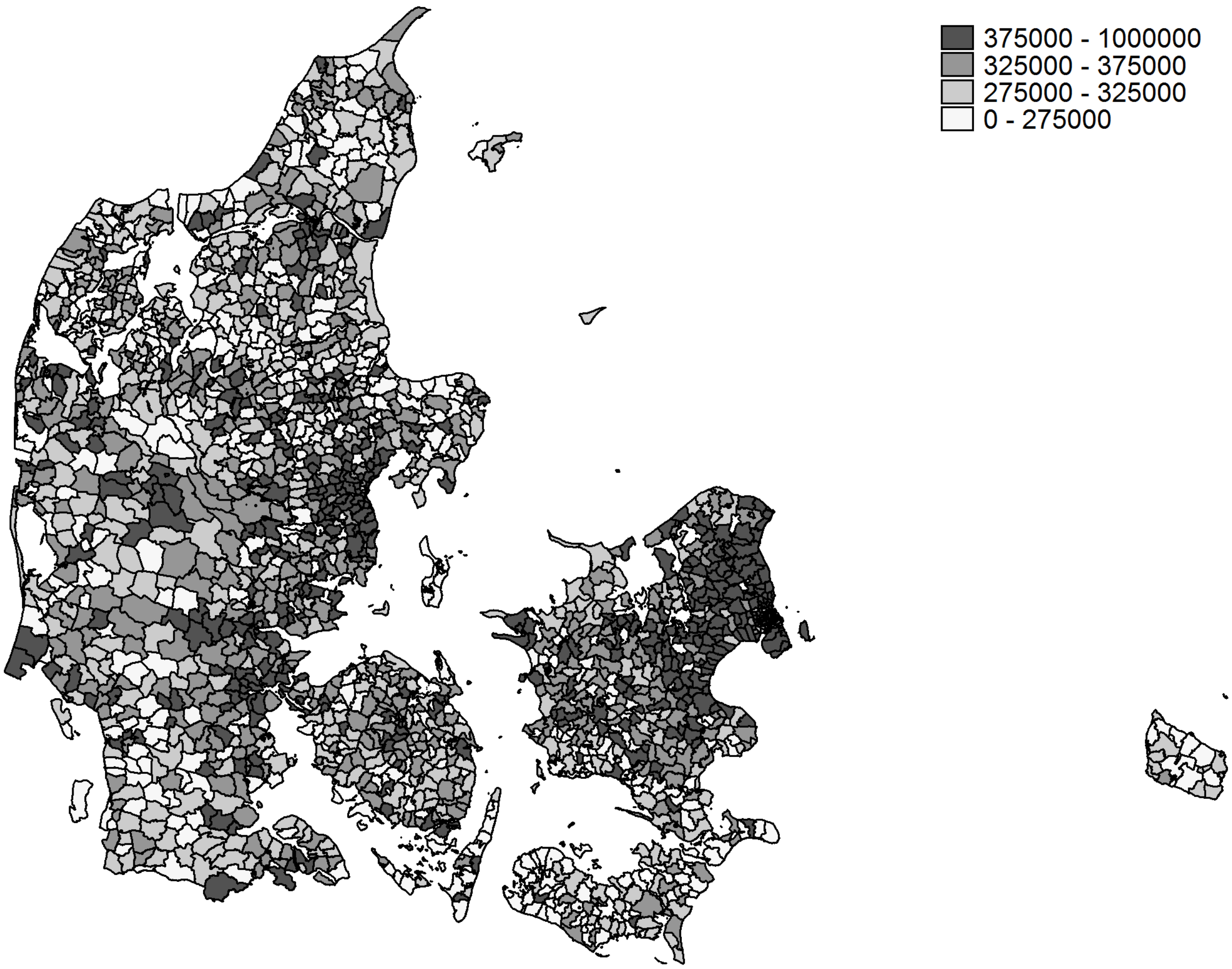
where P is the number of overlapping years the two brothers are observed in the data.

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 (not necessarily different) age levels a and a', covariances of transitory earnings across non-sibling peers are as follows:

$$E\left(v_{ifca}, v_{i'f'ca'}\right) = \lambda^{1+|t-t'|}\eta_t\eta_{t'} \tag{A.3}$$

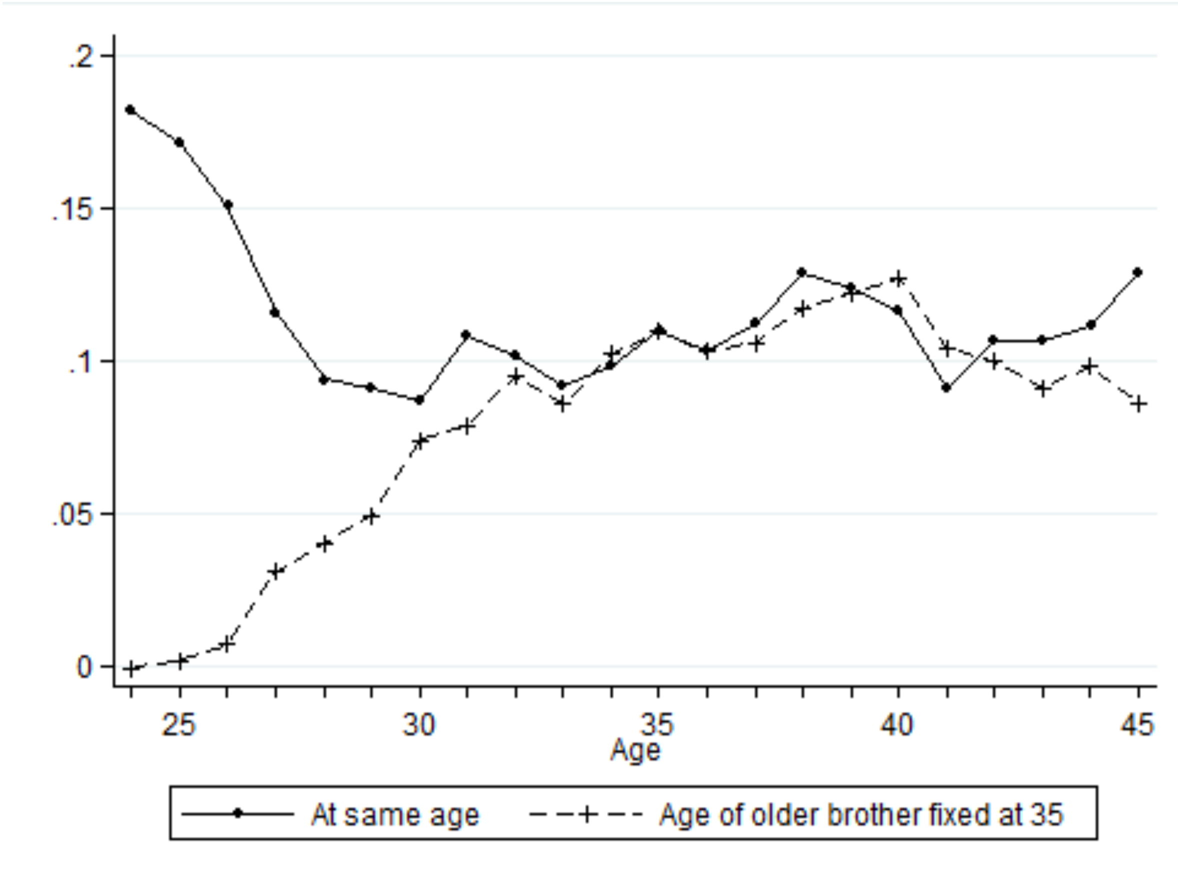
The moment restrictions above characterize the inter-temporal distribution of transitory earnings for each individual and between siblings and peers. The orthogonality assumption between permanent and transitory earnings in equation (1) implies that moment restrictions of the full model are the sum of moment restrictions for permanent and transitory earnings, the former being discussed in Section 2.3 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.

Figure 1. Mean fathers' earnings when son is age 15.



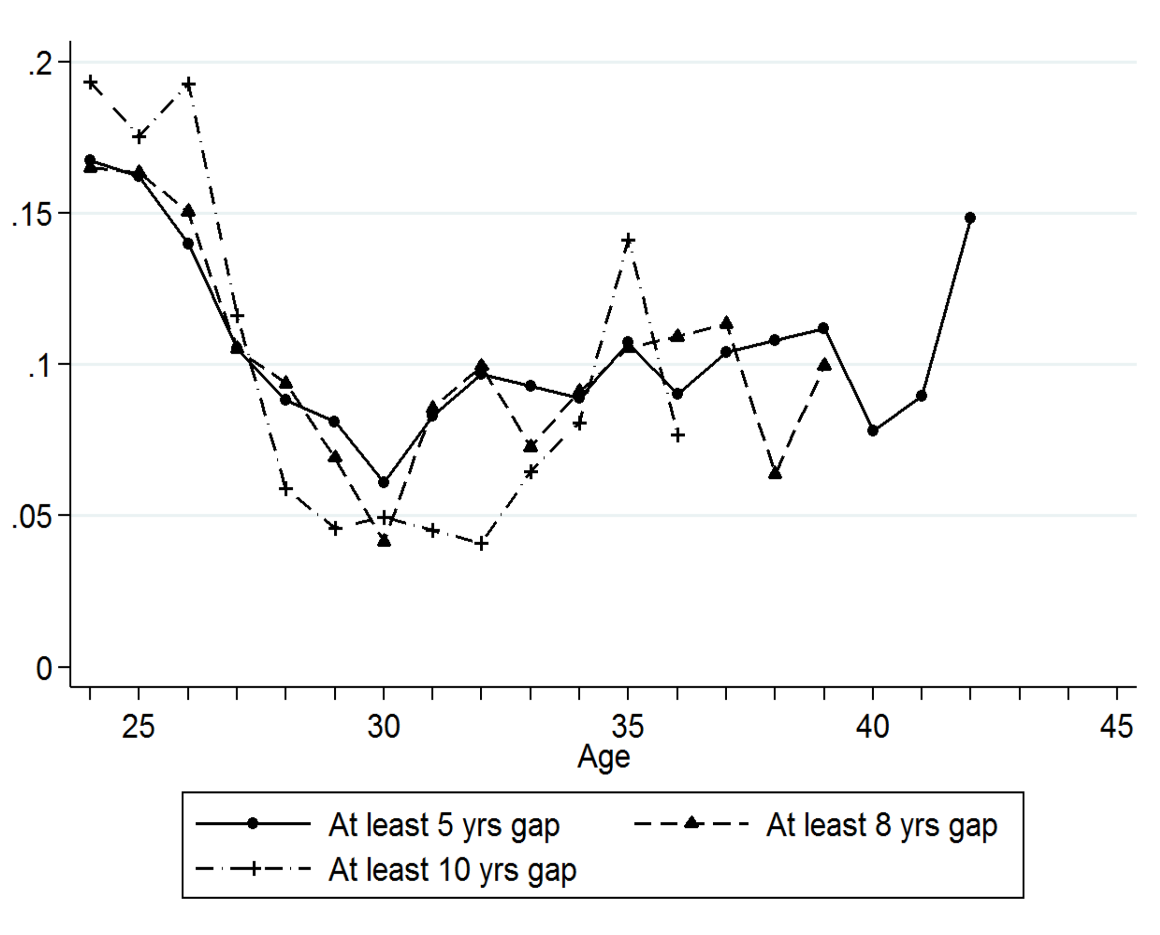
Note: Paternal annual labor earnings (DKK 2012 prices) across Danish parishes when the son is age 15. Shading indicates different mean earnings with groupings approximately corresponding to earnings quartiles. The scale of the map is 300km from east to west and 200km from south to north.

Figure 2. Sibling correlation of annual earnings.



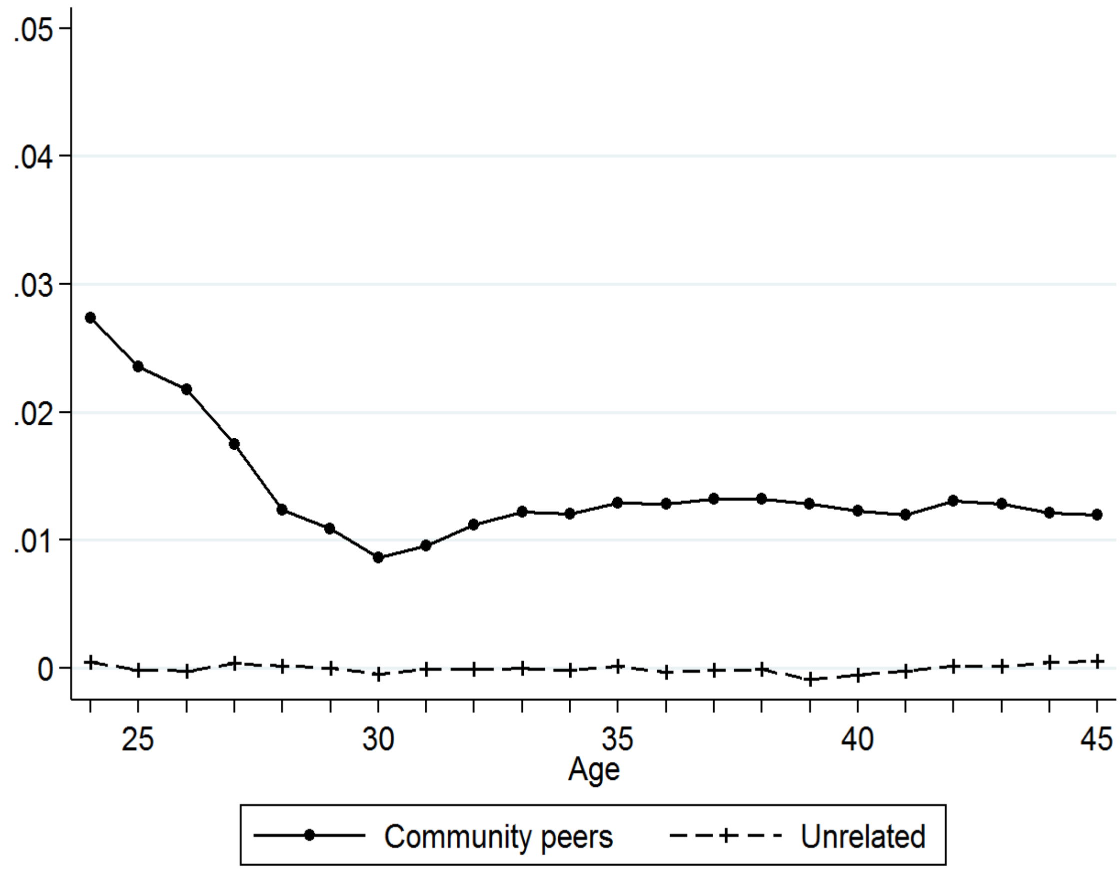
Note: The figure shows raw sibling correlations of earnings over the life cycle based on 89,738 sibling pairs born between 1965 and 1985. The solid line shows the sibling correlation when the brothers are at the same point in their life cycle, while the dashed line shows the sibling correlation when we fix the age of the elder brother at 35.

Figure 3. Sibling correlation of annual earnings by siblings' age gap.



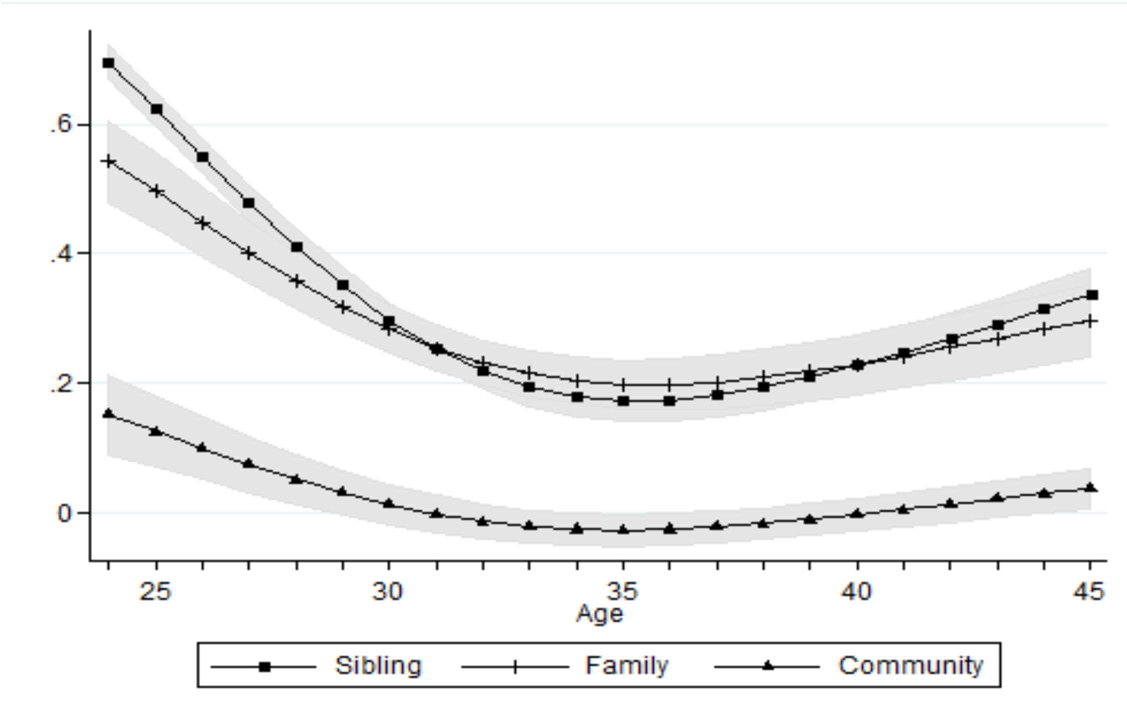
Note: The figure shows raw sibling correlations of earnings over the life cycle when brothers are at the same point in their life cycle, and refer to sibling pairs with an age gap of 5, 8 and 10 years born between 1965 and 1985.

Figure 4. Correlation of annual earnings among community peers.



Note: The figure shows raw correlations of earnings for community peers born between 1965 and 1985 over the life cycle. Community peers are defined as neighbors who reside in the same parish at age 15, or schoolmates who attend the same school at age 15. Unrelated individuals share neither the family nor the community. We compute this correlation by randomly matching each individual in the sample with 1000 unrelated individuals of the same age.

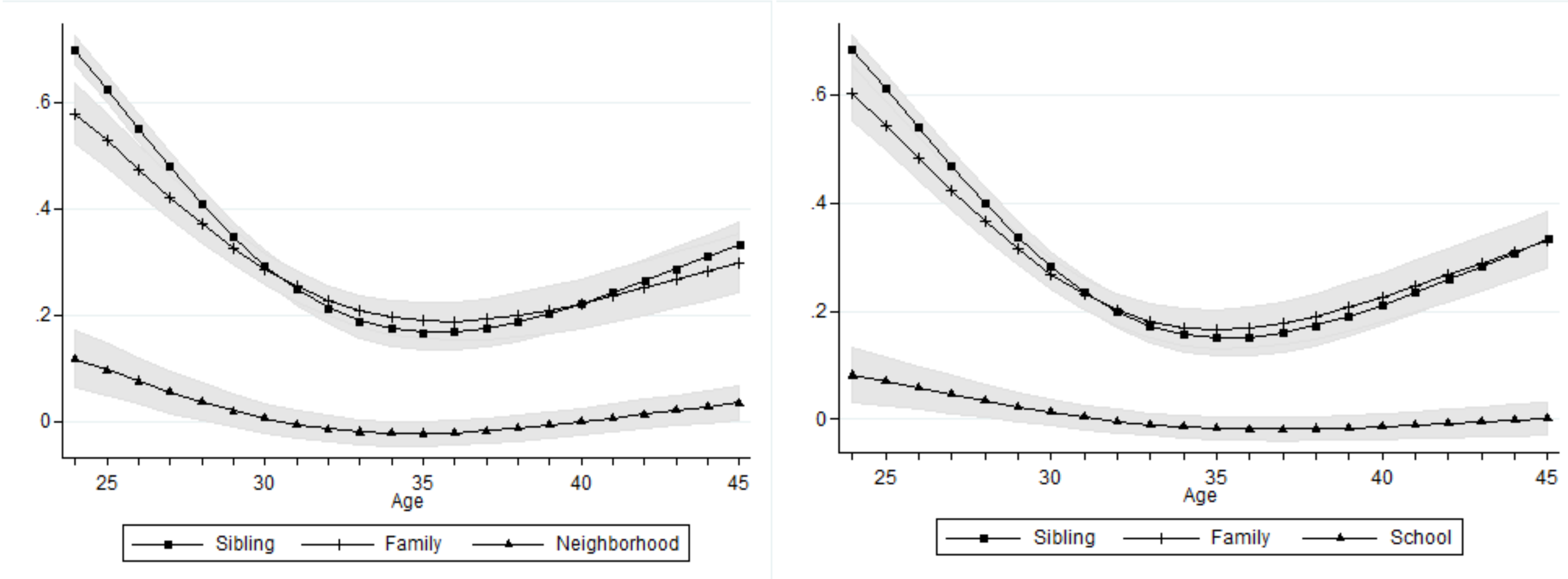
Figure 5. Predicted sibling correlation of permanent earnings and factor decomposition: baseline model.



Note: The figure shows the predicted sibling correlation over the life cycle and its decomposition into family and community effects using the baseline estimates in Tables 3 and 4, where community is defined using both the neighborhood and the school at age 15. The sorting parameter is estimated using between-sibling variation of community comparing moving to stayer families. Predictions are generated using the formulae provided in Section 4.5 for the case of siblings sharing the community**.** The resulting sibling correlation is the sum of family and community effects, where we impute the estimated sorting parameter to the two factors in equal parts.

Figure 6. Predicted sibling correlation of permanent earnings and factor decomposition: alternative community definitions.

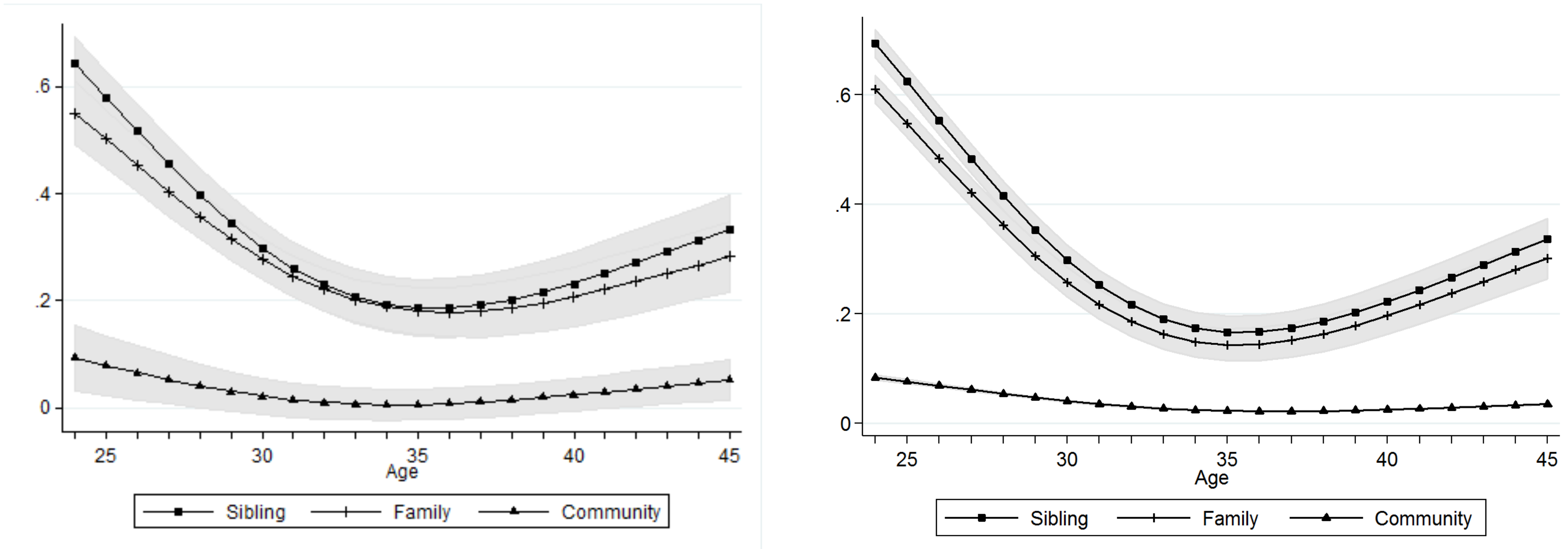
Panel A. Only neighborhood. **Panel B. Only school.**



Note: The figure shows the predicted sibling correlation over the life cycle and its decomposition into family and community effects. The definition of community in the left panel is based only on neighborhoods using the estimates of Column 2 in Tables 3 and 4. The definition of community in the right panel is based only on schools using the estimates of Column 3 in Tables 3 and 4. In both cases community is measured at age 15. The sorting parameter is estimated using between-sibling variation of community comparing moving to stayer families. Predictions are generated using the formulae provided in Section 4.5 for the case of siblings sharing the community**.** The resulting sibling correlation is the sum of family and community effects (neighborhood or school, respectively), where we impute the estimated sorting parameter to the two factors in equal parts.

Figure 7. Predicted sibling correlation of permanent earnings and factor decomposition: alternative between-sibling community variation.

Panel A. Movers. **Panel B. Stayers.**



Note: The figure shows the predicted sibling correlation over the life cycle and its decomposition into family and community effects for alternative between-sibling community variation. The definition of community in the left panel (movers) is based on neighborhoods measured at age 15. The sorting parameter is estimated using between-sibling variation of community based on moving families. Compared to Figure 5 (left panel), we exclude families for which the parish of the first brother remained the same between ages 11 and 15, so we compare families moving before brother 1 turns 15 and families who move after brother 1 turns 15. The definition of community in the right panel (stayers) is based on both neighborhoods and schools at age 15 and the model is estimated using only brothers from stayer families for which the parish of the first brother remained the same between ages 11 and 15. Because for stayers there is no between-sibling community variation the sorting parameter cannot be estimated separately from community effects. Therefore, compared to Figure 4, the community effects are upward biased. Predictions are generated using the formulae provided in Section 4.5 for the case of siblings sharing the community. The resulting sibling correlation is the sum of family and community effects, where in left panel we impute the estimated sorting parameter to the two factors in equal parts.

Table 1. 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
1965-67	1990	25	48	2,234,572	103,774	1,484	2,112
1968-70	1993	22	45	1,748,750	91,297	1,497	2,108
1971-73	1996	19	42	1,566,608	93,529	1,539	2,105
1974-76	1999	16	39	1,245,362	87,498	1,540	2,103
1977-79	2002	13	36	888,691	76,228	1,514	2,100
1980-82	2005	10	33	606,580	66,752	1,530	2,091
1983-85	2008	7	30	393,008	60,395	1,550	2,092
1965-85	1990-2008	7-25	30-48	8,683,571	579,473	10,654	14,711

Note: The table reports sample characteristics by birth cohort for men born 1965-1985. Schools are defined using school of enrollment at age 15; neighborhoods are defined using the parish of residence at age 15. Column 7 reports the number of year-of-birth-by-school clusters within each birth cohort; Column 8 reports the number of year-of-birth-by-parish clusters within each birth cohort.

Table 2. Neighborhood and long run earnings – key study characteristics.

	(1) Page and Solon (2003)	(2) Raaum, et.al. (2006)	(3) Oreopoulos (2003)	(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	44,124
#Men observed	443	228,700	4,060	579,473
Men/cluster	4	14	50	13
Others/cluster	86	450	1,036	2,672
Exposures				
Birth cohorts	1952-62	1946-65	1963-70	1965-1985
Years	1968	1960 and 1970	1978-86	1976-2002
Ages	6-16	5-15	8-16	11-15
Duration	snapshot	snapshot	1-9 years	1-5 years
Outcomes				
Measure	Earnings	Residual earnings	Income	Residual earnings
Duration (years)	5	6	3	3-25 (mean 15)
Transformation	total mean	total mean	total mean	untransformed
Years observed	1987-91	1990-95	1997-99	1990-2014
Ages observed	25-39	25-50	27-36	23-49

Table 3. Parameter estimates of permanent earnings.

	(1) Baseline		Baseline with alternative community definitions: (2) Only neighborhood		(3) Only school	
Panel A. Shared components (heterogeneous income profile –random growth)						
	Coeff.	s.e.	Coeff.	s.e.	Coeff.	s.e.
	Variance of intercepts					
Family ($\sigma^2_{\mu F}$)	0.0758	0.0119	0.0756	0.0101	0.0786	0.0132
Community ($\sigma^2_{\mu C}$)	0.0163	0.0065	0.0112	0.0052	0.0053	0.0044
	Variance of slopes					
Family ($\sigma^2_{\gamma F}$)	0.00054	0.00009	0.00053	0.00008	0.00062	0.00011
Community ($\sigma^2_{\gamma C}$)	0.00021	0.00005	0.00016	0.00004	0.00007	0.00003
	Covariance intercepts-slopes					
Family ($\sigma^2_{\mu\gamma F}$)	-0.0051	0.0008	-0.0052	0.0007	-0.0061	0.0010
Community ($\sigma^2_{\mu\gamma C}$))	-0.0024	0.0005	-0.0018	0.0004	-0.0010	0.0004
	Covariance between components					
Family-Community (σ_{FC})	0.0069	0.0022	0.0053	0.0018	0.0062	0.0017
Panel B. Idiosyncratic components (restricted income profile-random walk)						
	Coeff.	s.e.	Coeff.	s.e.	Coeff.	s.e.
	Initial condition (age 24)					
Brother 1 ($\sigma^2_{\omega 24,1}$)	0.0596	0.0089	0.0544	0.0072	0.0569	0.0095
Brother 2 ($\sigma^2_{\omega 24,2}$)	0.0337	0.0060	0.0304	0.0049	0.0324	0.0062
	Variance of innovations					
Brother 1 ($\sigma^2_{\xi 1}$)	0.0081	0.0014	0.0075	0.0011	0.0067	0.0012
Brother 2 ($\sigma^2_{\xi 2}$)	0.0097	0.0016	0.0090	0.0013	0.0083	0.0015

Note: The table reports Equally-Weighted Minimum Distance estimates for the parameters of the permanent component of the earnings process. Panel A reports parameter estimates for the earnings components shared by siblings, whereas Panel B reports parameter estimates for sibling-specific components. In the baseline estimates of column (1) the community is defined as siblings sharing either the neighborhood, the school or both. In columns (2) and (3) siblings share only the neighborhood, or only the school, respectively. For all estimates there are two types of siblings: those who share the community (stayers) and those who do not share the community (movers). Estimates in the three columns are derived using 14012, 15059 and 15702 empirical variances and covariances (from left to right).

Table 4. Parameter estimates of transitory earnings.

	(1) Baseline		Baseline with alternative community definitions (2) Only neighborhood		(3) Only school	
	Coeff.	s.e.	Coeff.	s.e.	Coeff.	s.e.
	Initial condition (age 24)					
Brother 1 ($\sigma^2_{24,1}$)	0.7810	0.0299	0.7972	0.0246	0.7977	0.0312
Brother 2 ($\sigma^2_{24,2}$)	0.7976	0.0325	0.8147	0.0273	0.8166	0.0338
	Variance of innovations at age 25					
Brother 1 ($\sigma^2_{\varepsilon 1}$)	0.5710	0.0225	0.5863	0.0191	0.5950	0.0237
Brother 2 ($\sigma^2_{\varepsilon 2}$)	0.5534	0.0237	0.5666	0.0202	0.5754	0.0247
	Age splines in variance of innovations					
Brother 1						
26-28	-0.1380	0.0034	-0.1389	0.0034	-0.1368	0.0034
29-33	-0.1040	0.0027	-0.1039	0.0027	-0.1028	0.0027
34-38	-0.0337	0.0034	-0.0338	0.0035	-0.0333	0.0034
39-43	-0.0406	0.0064	-0.0386	0.0063	-0.0342	0.0062
44-51	-0.0248	0.0099	-0.0234	0.0095	-0.0210	0.0090
Brother 2						
26-28	-0.1614	0.0063	-0.1625	0.0063	-0.1611	0.0064
29-33	-0.1172	0.0054	-0.1174	0.0054	-0.1165	0.0054
34-38	-0.0358	0.0076	-0.0351	0.0076	-0.0326	0.0076
39-43	-0.0528	0.0145	-0.0515	0.0144	-0.0477	0.0139
44-51	0.0271	0.0490	0.0288	0.0482	0.0316	0.0453
	Autoregressive coefficient					
Brother 1 (ρ_1)	0.5000	0.0036	0.4979	0.0036	0.4895	0.0040
Brother 2 (ρ_2)	0.5239	0.0042	0.5238	0.0042	0.5175	0.0043
	Cross-person associations in transitory earnings					
Sibling covariance of Innovations (σ_f)	0.0098	0.0018	0.0108	0.0020	0.0127	0.0021
Peers covariance of transitory earnings (mass point, λ)	-0.0020	0.0010	-0.0011	0.0009	0.0024	0.0010

Note: The table reports Equally-Weighted Minimum Distance estimates for the parameters of the transitory component of the earnings process. Community definitions for each column are similar to the notes of Table 3. Estimates in the three columns are derived using 14012, 15059 and 15702 empirical variances and covariances (from left to right).

Table 5. Decomposition of sibling correlation into family and community effects – average over the life cycle and by age.

	(1) Baseline		Baseline with alternative community definitions: (2) Neighborhood-only		Baseline with alternative community definitions: (3) School-only		Alternative between-sibling community variation: (4) Movers		Alternative between-sibling community variation: (5) Stayers	
Panel A. Average decomposition with earnings measured over the life cycle (age 24-45).										
	Corr.	s.e.	Corr.	s.e	Corr.	s.e.	Corr.	s.e.	Corr.	s.e.
Siblings (S)	0.313	0.014	0.308	0.015	0.297	0.015	0.309	0.024	0.310	0.013
Family (F)	0.289	0.017	0.291	0.015	0.289	0.015	0.277	0.020	0.271	0.013
Community (C)	0.023	0.012	0.017	0.011	0.008	0.010	0.032	0.014	0.038	0.001
C/S	0.074		0.056		0.028		0.103		0.124	
Panel B. Average decomposition with earnings measured over parts of the life cycle (age 24 up to age 25, 27, 30, 35).										
	Corr.	s.e.	Corr.	s.e	Corr.	s.e.	Corr.	s.e.	Corr.	s.e.
Siblings										
Age 25	0.661	0.013	0.663	0.013	0.651	0.013	0.614	0.025	0.661	0.013
Age 27	0.544	0.024	0.544	0.012	0.533	0.012	0.513	0.023	0.544	0.012
Age 30	0.487	0.013	0.485	0.014	0.475	0.014	0.462	0.024	0.488	0.013
Age 35	0.355	0.012	0.352	0.013	0.341	0.013	0.344	0.022	0.354	0.012
Family										
Age 25	0.521	0.031	0.555	0.028	0.575	0.025	0.527	0.029	0.581	0.013
Age 27	0.437	0.026	0.462	0.023	0.473	0.020	0.445	0.024	0.477	0.012
Age 30	0.407	0.024	0.427	0.021	0.429	0.018	0.408	0.023	0.427	0.013
Age 35	0.313	0.018	0.323	0.015	0.315	0.014	0.309	0.018	0.308	0.012
Community										
Age 25	0.140	0.029	0.108	0.026	0.076	0.024	0.086	0.029	0.080	0.002
Age 27	0.107	0.012	0.082	0.022	0.060	0.020	0.068	0.025	0.067	0.002
Age 30	0.079	0.022	0.059	0.020	0.047	0.018	0.054	0.023	0.062	0.001
Age 35	0.041	0.016	0.029	0.014	0.025	0.013	0.034	0.017	0.046	0.001

Note: The table reports the predicted sibling correlation and its decomposition into family and community effects. Panel A shows the average decomposition over the life cycle (24-45), where C/S reports the share of the community effects within the sibling correlation. Panel B shows the predicted sibling correlation and its decomposition averaging up to the reported age. The decomposition in columns (1)-(3) refer to the parameters reported in Table 3. The decomposition in column (4) is based on parameter estimates from moving families with community defined as neighborhood. The decomposition in column (5) is based on parameter estimates from stayer families; in this case the sorting parameter is not identified separately from community effects. Predictions are generated using the formulae provided in Section 4.5.

Table 6. Community correlation of earnings – sensitivity to measurement of community affiliation by level and age intervals.

Panel A. Average community correlation of earnings for community measured at various age levels.

	Age 11		**Age 12**		**Age 13**		**Age 14**		**Age 15**	
	Corr.	s.e.	Corr.	s.e	Corr.	s.e.	Corr.	s.e.	Corr.	s.e.
Earnings measured over ages 24-45	0.057	0.001	0.057	0.001	0.057	0.001	0.058	0.001	0.058	0.001
Earnings measured up to										
Age 25	0.209	0.003	0.211	0.003	0.210	0.003	0.212	0.003	0.213	0.003
Age 27	0.177	0.002	0.180	0.002	0.178	0.002	0.180	0.002	0.181	0.002
Age 30	0.132	0.002	0.134	0.002	0.133	0.002	0.134	0.002	0.135	0.002
Age 35	0.075	0.001	0.076	0.001	0.075	0.001	0.076	0.001	0.077	0.001

Panel B. Average community correlation of earnings for community measured over various age intervals.

	Age 11-15		**Age 12-15**		**Age 13-15**		**Age 14-15**	
	Corr.	s.e.	Corr.	s.e	Corr.	s.e.	Corr.	s.e.
Earnings measured over ages 24-45	0.057	0.001	0.057	0.001	0.057	0.001	0.058	0.001
Earnings measured up to								
Age 25	0.214	0.003	0.215	0.003	0.215	0.003	0.214	0.003
Age 27	0.182	0.003	0.183	0.002	0.182	0.002	0.182	0.002
Age 30	0.135	0.002	0.136	0.002	0.136	0.002	0.135	0.002
Age 35	0.076	0.001	0.077	0.001	0.077	0.001	0.077	0.001

Note: The table reports the estimated average community correlation of earnings over the life cycle and for different segments of the life cycle from the community-only model in which we allow for community as the only factor determining permanent earnings. Community peers are defined as parish neighbors born in the same year and residing in the parish at the given age level or age interval.

Appendix Table. Parameter estimates of time effects (1990=1).

	Permanent Component (π_t)		Transitory Component (η_t)	
	Coeff.	s.e.	Coeff.	s.e.
t=				
1991	1.0314	0.0721	0.9825	0.0186
1992	1.0472	0.0856	1.0087	0.0230
1993	1.1210	0.0980	1.0535	0.0247
1994	1.0723	0.0923	1.0303	0.0245
1995	1.0629	0.0900	0.9653	0.0243
1996	1.1228	0.0908	0.9601	0.0221
1997	1.0606	0.0895	0.9590	0.0230
1998	1.0888	0.0901	0.9526	0.0235
1999	1.1075	0.0879	0.9797	0.0217
2000	1.1633	0.0930	0.9668	0.0226
2001	1.1258	0.0889	1.0172	0.0233
2002	1.2036	0.0930	1.0278	0.0223
2003	1.2073	0.0945	1.0869	0.0239
2004	1.1363	0.0892	1.0774	0.0237
2005	1.1469	0.0899	1.0493	0.0226
2006	1.0450	0.0832	1.0162	0.0224
2007	1.0315	0.0833	0.9965	0.0229
2008	0.9951	0.0807	1.0001	0.0224
2009	0.9982	0.0821	1.1160	0.0250
2010	1.0135	0.0835	1.1829	0.0267
2011	0.9756	0.0810	1.1938	0.0276
2012	0.9195	0.0769	1.2267	0.0284
2013	0.8811	0.0735	1.2487	0.0290
2014	0.8695	0.0718	1.2588	0.0285

Note: The table reports Equally-Weighted Minimum Distance estimates for the time shifters from the baseline model. Estimates in the three columns are derived using 14012, empirical variances and covariances.