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Executive summary

This study explores how economic status is passed down through generations within families in the Netherlands. The researchers reconstructed family trees using Dutch municipal records and linked these to tax data to analyse earnings and wealth across multiple generations.

Key Findings:

1. Intergenerational Transmission of Wealth:

    ◦ The study shows that economic advantages or disadvantages are significantly passed from parents to children.

    ◦ Families at the lower end of the income distribution exhibit stronger intergenerational persistence, meaning that children born into poorer families are more likely to remain poor.

2. Heterogeneous Mobility:

    ◦ The transmission of wealth and income is not uniform across different families. Poorer families tend to have lower economic mobility, suggesting potential poverty traps.

    ◦ Conversely, those from wealthier families have higher chances of retaining their economic status across generations.

3. Latent Factor Models:

    ◦ The researchers used a latent factor model to estimate the underlying mechanisms of economic transmission. This model suggests that hidden factors, such as genetic traits or family culture, play a significant role in the economic outcomes of individuals.

    ◦ The latent factor model indicates that the degree of economic inequality transmitted across generations is higher than traditional models suggest.

4. Sibling and Cousin Correlations:

    ◦ By comparing siblings and cousins, the study highlights that family background significantly influences economic outcomes.

    ◦ Sibling correlations in income are higher than cousin correlations, indicating that immediate family has a stronger impact on economic status.

Implications:

- Policy Context:

    ◦ The findings suggest that policy interventions aimed at increasing social mobility should focus on breaking the cycle of poverty. This could involve targeted educational programs and financial support for low-income families.

    ◦ Redistributive educational policies could mitigate the disadvantages faced by children from poorer families, thereby enhancing economic mobility.

Heterogenous latent factor models using horizontal kinship

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Abstract

We reconstruct the genealogical tree of all individuals ever appearing in Dutch municipalities records since 1995. Using microdata from tax authorities, we compute a measure of their permanent earnings and assess the degree to which the intergenerational transmission process is heterogeneous. Our analysis relies on traditional estimates as well as model assuming a latent transmission of family endowments. In both cases, we show that offspring born into families belonging to the lowest percentiles of the income distribution show a higher degree of intergenerational persistence. The same applies when looking at heterogeneity in intergenerational mobility along the grandparental wealth, potentially suggesting the existence of poverty traps.

Keywords: intergenerational mobility; sibling correlations; inequality.
JEL codes: J62; I24.

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1 Introduction

The degree of association between earnings of different members of the same household has been extensively used in the literature to investigate the role of family background on the cross-distribution of economic outcomes. A large degree of attention has been devoted to the analysis of vertical relations, i.e., the parent-to-offspring (and beyond) transmission of social status. Scholars have debated the theoretical mechanisms behind intergenerationally transmitted inequalities (e.g., Becker & Tomes, 1976, 1979, 1986; Loury, 1981) as well as between- and within-country differences in intergenerational mobility (e.g., Solon, 2002; Hertz et al., 2007; Chetty et al., 2014) and their underlying drivers (e.g., Durlauf, 1994; Borjas, 1992; Dustmann, 2004).[1]

More recently, thanks to the increased availability of administrative records which allow recreating family linkages (both horizontally and vertically), a growing number of contributions exploit data on extended families to measure the parameters of the intergenerational process by comparing different degrees of kinship within the same generation (e.g., Adermon et al., 2021; Collado et al., 2023). The use of extended family linkages not only avoids the usual caveats of a steady state assumption (Nybom & Stuhler, 2019), but also allows testing for the transmission of latent advantage across generations.[2]

In this paper, we use administrative data from the Netherlands to establish the family tree of all citizens ever appearing in the Dutch municipality records starting in 1995. Using individual tax records, we construct a measure of permanent income for individuals at generation t (siblings and cousins, born in the 1980s) and at generation t_{-1} (their parents, born in the 1950s). In addition, we exploit information on household wealth to characterise the social status of their grandparents (generation t_{-2}). Using this information, we assess the degree to which inequalities are transmitted across families and generations.

We start from the seminal models by Becker & Tomes (1979) and Becker & Tomes (1986). We show that models of intergenerational transmission having different underlying assumptions, such as a latent factor transmission (Clark & Cummins, 2015; Braun & Stuhler, 2018), have different implications with regards to the interpretation of hor-

[1] The literature examines extensively three main determinants behind variations in intergenerational mobility: the role of educational systems and early-track choice (e.g., Dustmann, 2004; Pekkarinen et al., 2009); that of early childhood accessibility and childcare (e.g., Havnes & Mogstad, 2015; Felfe & Lalive, 2018), as early-state learning facilitate learning at later stages (Cunha & Heckman, 2007); and neighborhoods effects, both in terms of residential segregation (Chetty et al., 2014) and school quality and social capital (Chetty et al., 2016; Bingley et al., 2021).

[2] Markovian models of social status persistence across two generations yield lower estimates than the observed persistence across three (or more) generations (e.g., Lindahl et al., 2015; Braun & Stuhler, 2018; Neidhöfer & Stockhausen, 2018; Colagrossi et al., 2020).

izontal and vertical correlations (Lundberg, 2020). We then discuss the potential bias arising when the transmission process is assumed to be homogeneous (i.e., linear) across families of different socio-economic background. In particular, we show that an homogeneous transmission process implies that group-specific mechanisms of intergenerational transmission are independent from the (latent) endowments of their fathers.

Yet, the literature long-discussed the existence of non-linearities in the transmission process through, e.g., credit market constraints (Becker & Tomes, 1986), poverty traps and neighborhood effects (Durlauf, 1994; Durlauf & Seshadri, 2018) or through the redistributional effects of education policies (Bratsberg et al., 2007). Solon (1992), Durlauf et al. (2017) and Kourtellos et al. (2020) suggest a higher degree of persistence at the bottom of the distribution, whereas Corak & Heisz (1999), Björklund et al. (2012) and Bratsberg et al. (2007) show the opposite. Others find a J-shaped (Gregg et al., 2019) or a U-shaped (Barone & Mocetti, 2021) distribution.

Our results confirm the existence of an heterogeneous transmission process, which varies across the distribution of parental income and of grandparental wealth, and this is true for both vertical and horizontal moments. In all cases, individuals at the bottom of the distribution exibit a lower degree of intergenerational mobility than those in the middle or at the top.

Recent literature suggests that when estimating a latent factor intergenerational transmission model, the degree to which inequalities are passed across generations is higher than traditional estimates suggest (e.g., Braun & Stuhler, 2018; Neidhöfer & Stockhausen, 2018). This finding is shown for the specific case of the Netherlands in Colagrossi et al. (2023). In this paper we report novel results derived from estimating the parameters of a heterogeneous latent factor model. To the best of our knowledge, this evidence is being introduced for the first time. Our estimates confirm the existence of heterogeneities across the distribution of both parental income and grandparental wealth, with those being at the bottom characterized by a substantially lower degree of mobility. As these individuals are also those having lower earnings and wealth, this implies that they end up transmitting their economic disadvantages to their offspring. Thus, our results also speak to the literature investigating intergenerational poverty and its consequences (e.g., Harper et al., 2003; Lesner, 2018) and, at large, to that studying poverty traps (e.g., Barham et al., 1995).

The remainder of this paper is structured as follows: Section 2 introduces the theoretical framework, its implication for sibling and cousin's correlation, the potential mechanisms behind the heterogeneity as well as the bias arising when this is unaccounted for; Section 3 details the data used and our empirical approach; Section 4 discusses our findings; and Section 5 offers some concluding remarks.

2 Models of intergenerational transmission

In a recent contribution, Lundberg (2020) provides a statistical representation of the generic socio-economic outcome for individual i from generation t: $y_{i,t} = \eta^s_{i,t} + \delta^c_{i,t} + \alpha_{i,t}$, where η^s and δ^c summarize the drivers of socio-economic outcomes shared by siblings and cousins, respectively. Sibling and cousin correlations correspond to the fraction of the total variance σ^2_y that is explained by the variances of the η^s and δ^c components.

These correlations can be interpreted in light of theoretical models of intergenerational transmission of economic outcomes across multiple generations. The starting point is the theoretical framework in Becker & Tomes (1979). In the Becker-Tomes model (BT hereafter), parents choose the optimal level of investment in children's earning capacity to maximize a utility function that depends on children's earnings, own consumption, and intergenerational preferences. As a result, the child's lifetime earnings $y_{i,t}$ depend on parental lifetime earnings $y_{i,t-1}$ and the child's unobservable endowment of earnings ability $e_{i,t}$. The latter is assumed to follow an AR process, where h represents the degree of heritability of endowments:

$$\begin{aligned} y_{i,t} &= \mu + \theta y_{i,t-1} + pe_{i,t} \\ e_{i,t} &= \delta + he_{i,t-1} + v_{i,t} \end{aligned} \tag{1}$$

Parameter θ is the product of two terms: earnings return to human capital and the marginal product of parental investment in the child's human capital.

In this model, both $y_{i,t-1}$ and $e_{i,t}$ depend on $e_{i,t-1}$ (Solon, 2014), thus the correlation between $y_{i,t}$ and $y_{i,t-1}$ would be such that:

$$\text{Corr}(y_{i,t}, y_{i,t-1}) = \beta^{BT}_{-1} = \frac{(\theta + h)}{(1 + h\theta)}. \tag{2}$$

Becker & Tomes (1986), however, argue that the degree of heritability of endowments h is negligible, which implies that the term $pe_{i,t}$ in Equation (1) does not depend on endowments of the parent generation, hence on parental lifetime earnings. As a consequence, for $h \to 0$, the correlation between $y_{i,t}$ and $y_{i,t-1}$ becomes $\text{Corr}(y_{i,t}, y_{i,t-1}) = \beta^{BT}_{-1} = \theta$. Under the assumption that $0 < \theta < 1$, the intergenerational correlation in earnings β^{BT}_{-m}

rapidly decreases in a few generations, because $\text{Corr}(y_{i,t}, y_{i,t-m}) = \theta^m$. As a consequence, "almost all the earnings advantages or disadvantages of ancestors are wiped out in three generations" (Becker & Tomes, 1986, p. 32).

The BT model integrates previous "mechanical" approaches to the analysis of income distributions and mobility by providing an economic theoretical framework based on optimizing behavior. The estimating equations aim at isolating structural parameters. Importantly, the key parameter θ identifies the earnings returns to parental investment in the child's human capital (Solon, 2014). Like any theoretical model of optimizing behavior, the BT model is a stylized representation of reality, which entails simplifying assumptions and could be subject to critiques (see Goldberger, 1989). In this case, the main causal pathway linking parental and offspring resources is parental investment in children's earnings ability, and the technology transforming the investments in observable economic outcomes. The advantage of the behavioral interpretation comes at the cost of the model's flexibility to encompass a variety of mechanisms governing the intergenerational transmission process (Stuhler, 2012).

Building on previous work by Clark & Cummins (2015) and Stuhler (2012), Braun & Stuhler (2018) propose a representation of the intergenerational transmission process based on a simple latent factor model. The core idea of their approach is that parents transmit their status via a latent factor that encompasses various inheritance mechanisms, including ability, investments, genetic traits, and other relevant determinants. Using the authors' notation, the model can be summarized as:

$$\begin{aligned} y_{i,t} &= \rho e_{i,t} + u_{i,t} \\ e_{i,t} &= \lambda e_{i,t-1} + v_{i,t} \end{aligned} \tag{3}$$

where $y_{i,t}$ is the observable outcome in generation t for family i, $e_{i,t}$ is the unobservable endowment which is transmitted from one generation to the next, $u_{i,t}$ and $v_{i,t}$ are noise terms. This representation, although not formally derived from utility-maximizing conditions, has many similarities with the implications of the BT model. $u_{i,t}$ and $v_{i,t}$ remind the market and endowment luck terms in Becker & Tomes (1979). Also, endowments follow the same dynamics as the BT model. However, there are two fundamental differences. First, in the latent factor model (LF hereafter), the transmission of endowments, via its governing parameter λ, is the key mechanism linking two consecutive generations. This is because, differently from the parameter h of the BT model, which is usually thought to be (or estimated as) zero, λ is always positive. Second, in the LF model endowments are only partially transformed into observable outcomes according to the transferability coefficient ρ. Thus, the correlation between $y_{i,t}$ and $y_{i,t-1}$ would be such that:

$$\text{Corr}(y_{i,t}, y_{i,t-1}) = \beta_{-1}^{LF} = \rho^2\lambda, \tag{4}$$

while the generic intergenerational correlation between outcomes of generation t and generation $t-m$ is equal to $\beta_{-m}^{LF} = \text{Corr}(y_{i,t}, y_{i,t-m}) = \rho^2\lambda^m$.

The main implication of the LF model is that with imperfect transferability of endowments the degree of intergenerational persistence should be higher than what can be computed by iteration across generations of β_{-1}^{LF}, i.e. $\beta_{-m}^{LF} > (\beta_{-1}^{LF})^m$ (Braun & Stuhler, 2018). Conversely, in the BT model this yields a geometric decay of social status across generations, as $\beta_{-m}^{BT} = (\beta_{-1}^{BT})^m$.

2.1 Implications for sibling and cousin correlations

Following the remarks by Becker & Tomes (1979, 1986) and the assumption that h is equal to zero in the BT model, income correlations among siblings and cousins correspond to:

$$\beta_{sibings}^{BT} = \text{Corr}(y'_{i,t}, y''_{i,t}) = \theta^2$$
$$\beta_{cousins}^{BT} = \text{Corr}(y'_{i,t}, y'_{j,t}) = \theta^4,$$

where $y'_{i,t}$ and $y''_{i,t}$ are the outcomes of two siblings from the same family i and $y'_{j,t}$ is the outcome of an individual in family j, with i and j sharing the same ancestor at generation $t-2$. Notably, $\beta_{cousins}^{BT} = (\beta_{siblings}^{BT})^2$. Empirical evidence against this implied relationship, as well as against the implied multigenerational correlation coefficient θ^m, should then cast doubts against the validity of the assumptions of the restricted BT model. Similarly, in light of the LF model, estimates of the sibling and cousin correlation would be:

$$\beta_{sibings}^{LF} = \rho^2\lambda^2$$
$$\beta_{cousins}^{LF} = \rho^2\lambda^4,$$

where $\beta_{cousins}^{LF} \geq (\beta_{siblings}^{LF})^2$. It is important to notice that classical intergenerational elasticity estimates using data for two generations would not be sufficient to separately identify the parameters ρ and λ. Braun & Stuhler (2018) use data on three generations (t, t_{-1}, t_{-2}) to achieve identification. Similarly, the parameter λ can be identified using the square root of the ratio $\beta_{cousins}^{LF}/\beta_{siblings}^{LF}$.

2.2 Heterogeneity in the transmission process

While most empirical contributions in the literature on the intergenerational transmission of economic outcomes provide a single measure of the parameter(s) governing the transmission process, in principle there is no reason to assume that such parameters and the underlying mechanisms are constant across the distribution of parental and/or offspring earnings.

The model by Becker & Tomes (1986) explains the potential existence of non-linearities in the transmission process via credit market imperfections. In the absence of credit constraints families can optimally invest in their children's human capital. When credit constraints are binding, however, low-income families might not be able to optimally invest leading to higher intergenerational persistence in the lower tail of the income distribution.[3]

Han & Mulligan (2001) observe that the effect of credit constraints is likely to be mitigated because high-income families are more likely to have children with higher ability. If returns to human capital increase with ability, these families are more likely to be credit-constrained when education is costly. Bratsberg et al. (2007) discuss a similar argument and consider a setup where all families are borrowing constrained because the optimal level of investment increases with ability. In this case, the slope coefficient of the son-to-father earnings regression would be higher than the parameter governing the transmission of endowment (the h coefficient in the BT model). Then, redistributive educational policies granting access to education services to low-income families would make the son-to-father earnings regression *flatter* in the lower tail of the income distribution, hence generating convexity rather than concavity.[4]

Becker et al. (2018) revisit economic models of intergenerational mobility building on the recent literature on complementarities in the formation of skills (e.g., Heckman & Mosso, 2014). They show that even considering a setup without credit constraints and no intergenerational transmission of endowments, complementarity between parental human capital and parental investment in the production of children's skills can generate nonlinearities in intergenerational mobility across the distribution because productivity

[3] The so-called "Becker-Tomes conjecture" has been the starting point for several empirical and theoretical contributions in the literature on non-linearities in intergenerational elasticities (e.g., Solon, 1992; Mulligan, 1999; Corak & Heisz, 1999; Mazumder, 2005). Evidence of concavity in the son-to-father relationship consistent with this conjecture is mixed in these early studies.

[4] Their analysis of intergenerational mobility in the European Nordic countries provides evidence of higher persistence at the top of the income distribution, consistent with their convexity conjecture. Grawe (2004) shows that the existence of credit constraints is not sufficient to generate non-linearities in the intergenerational transmission process. Using simulations, the author shows that any nonlinear pattern can be generated under different assumptions about the earnings function transforming ability into earnings.

in parental investment is increasing in parental human capital.

Another potential determinant of heterogeneity in the transmission process is explored by models of poverty traps generated by neighborhood effects (e.g., Durlauf, 1994, 1996; Durlauf & Seshadri, 2018). In these models, individuals endogenously sort into neighborhoods based on their resources. Neighborhood membership has a crucial role in the development of human capital during childhood and in the transformation of human capital into earnings during adulthood (Durlauf et al., 2022) due to heterogeneity in the quality of education (through differences in local public financing) as well as to social interactions within neighborhoods. As a result, the predicted relationship between children's and parents' earnings is homogeneous within and heterogeneous across neighborhoods.

Finally, Bingley & Cappellari (2019) study the decomposition of the sibling correlation in its intergenerational and residual components. They suggest that if the literature finds a residual role for parent-child transmission in explaining sibling correlation, this is due to the assumption of homogeneous intergenerational transmission across families. They consider the extreme case in which the parameters of the standard BT model are family-specific, such that the generic family j is characterized by a family-specific intergenerational transmission process λ_j. When reconciling their findings with the previous literature, the authors underline the important role of the correlation between λ_j and parental income $y_{j,t-1}$. They suggest that the existence of such correlation is likely to induce an omitted variable bias in standard intergenerational elasticities (IGE) estimates.

2.3 Estimating heterogeneous models

Based on the above considerations, a number of scholars provide estimates of heterogeneous (i.e., non-linear) intergenerational parameters.[5] To the best of our knowledge, there have been not yet attempts to estimate a latent factor model accounting for heterogeneous transmission mechanisms.

There are reasons to believe that the pathways linking parental ability to that of the

[5] Solon (1992), Couch & Lillard (2004) and Bratsberg et al. (2007) include higher-order terms of fathers' earning in OLS estimates of IGE to account for non-linearities. Mulligan (1999) and Mazumder (2005) split the sample based on bequest values and financial net worth in the USA, respectively. Corak & Heisz (1999) employ nearest neighbour estimator using a sample of Canadian men. Eide & Showalter (1999), Grawe (2004) and Bratberg et al. (2005) consider Conditional Quantile Regression (CQR) to estimate non-linear IGE in the USA, Canada and Norway, respectively. Schnitzlein (2016), Gregg et al. (2019) and Palomino et al. (2018) consider Unconditional Quantile Regression (UQR) estimates in the USA and Germany, UK and US, respectively. Durlauf et al. (2017) investigate the existence of social status trap in the US using threshold regression models. Finally, Kourtellos et al. (2020) device a Varying Coefficient Model (VCM) to uncover non-linearities in IGE in the US.

offspring might be heterogeneous also in this statistical representations, as λ encompasses various inheritance mechanisms, including ability, investments and community effects. The importance of cross-sectional heterogeneity in the latent factor can be seen re-writing Equation 3 as follows:

$$
\begin{aligned}
y_{ig,t} &= (\overline{\rho} + \rho_g)e_{ig,t} + u_{gi,t} \\
e_{ig,t} &= (\overline{\lambda} + \lambda_g)e_{ig,t-1} + \upsilon_{gi,t}
\end{aligned}
$$

where the subscript g indicates one of the G groups of the population of interest with potentially different transmission mechanisms such as families (Bingley & Cappellari, 2019), neighborhoods (Durlauf, 1994, 1996; Chetty et al., 2014) or parental income (Björklund & Jäntti, 2009; Grawe, 2004; Bratsberg et al., 2007). $\overline{\rho}$ and $\overline{\lambda}$ are the population average parameters, while ρ_g and λ_g are the group-specific deviations from population averages. Importantly, ρ_g and λ_g are now random variables with mean zero and variance σ^2_ρ and σ^2_λ, respectively. Consider the observable outcome of two siblings from family i, $y'_{ig,t}$ and $y''_{ig,t}$:

$$
\begin{aligned}
y'_{ig,t} &= \underbrace{\overline{\rho}\overline{\lambda}e_{ig,t-1}}_{a'} + \underbrace{(\overline{\rho}\lambda_g + \overline{\lambda}\rho_g + \rho_g\lambda_g)e_{ig,t-1}}_{b'} + \underbrace{\overline{\rho}\upsilon'_{gi,t}}_{c'} + \underbrace{\rho_g\upsilon'_{gi,t}}_{d'} + \underbrace{u'_{ig,t}}_{e'} \\
y''_{ig,t} &= \underbrace{\overline{\rho}\overline{\lambda}e_{ig,t-1}}_{a''} + \underbrace{(\overline{\rho}\lambda_g + \overline{\lambda}\rho_g + \rho_g\lambda_g)e_{ig,t-1}}_{b''} + \underbrace{\overline{\rho}\upsilon''_{gi,t}}_{c''} + \underbrace{\rho_g\upsilon''_{gi,t}}_{d''} + \underbrace{u''_{ig,t}}_{e''}
\end{aligned}
$$

In this context, the probability limit of $\text{Corr}(y'_{ig,t}, y''_{ig,t})$ would be:

$$
\overline{\rho^2\lambda^2} + 2\text{Cov}(a', b'') + 2\text{Cov}(a', d'') + 2\text{Cov}(b', d'') + \text{Cov}(b', b'') + \text{Cov}(d', d'')
$$

which is equal to $\overline{\rho^2\lambda^2}$ only if λ_g and ρ_g are independent from $e_{ig,t-1}$, and independent of each other. Put differently, this requires that the parameters governing the group-specific intergenerational transmission mechanisms are independent from the $e_{ig,t-1}$ latent factors.

3 Data and methods

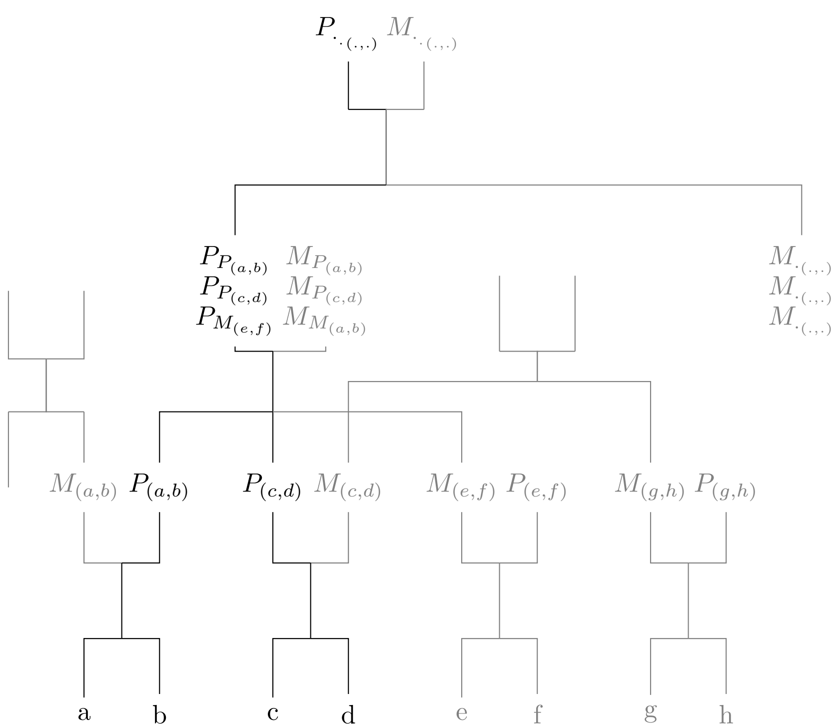
3.1 Data

We use administrative data from the Dutch *Centraal Bureau voor de Statistiek* (CBS). CBS collects information on all individuals residing (or that have resided) in the Netherlands. We use their 2020 municipal population registers, which contains anonymised demographic information on all persons ever appearing in the municipal population registers since 1 January 1995. By merging these data to information on the legal parent(s) of each individual, we recreate the family lineages of the entire Dutch population up to their earlier ancestors available.

We select only the full patrilineal lineages (see Figure 1). This means that we select only sons, their father, their uncle(s) and their grandfather(s). This choice stems from the recognition that, in a society where female labor market participation is lower than that of males, female earnings might be an unreliable indicator of their socio-economic status (Chadwick & Solon, 2002). While this is less of a concern nowadays, as the Netherlands now has one of the highest female labour market participation rates (about 80% in 2019), in the early 80s only about 36% of women were participating to the labour market.[6]

We acknowledge that looking at the patrilineal lineage only has limitations. Besides ignoring the role of women in the transmission of socio-economic status, it severely reduces

Figure 1: The patrilineal lineage



Note: darker lines represent the patrilineal lineage which contributes to our sample. "P" and "M" represent the paternal and maternal kinship, respectively. Those at the bottom represents the generation at time t, while their parents the generation at t_{-1}. The parents of the latter are defined as generation t_{-2}

[6] See https://stats.oecd.org/index.aspx

the sample size as compared to looking at the matrilineal lineage or at mixed lineages, as men generally have a shorter life expectancy, and single parents are typically women. Further, life expectancy is positively associated with earnings (Cristia, 2009; Bagchi, 2019). Given the data structure, we can recreate family lineages only for those families where the male ancestor was old enough to ever appear in CBS registers. Therefore, by following patrilineal lineages only, our sample is potentially skewed towards the right-hand side of the distribution.

We then match individuals appearing in family lineages with information on income, which is available from 2003. Income microdata are collected from Dutch public administrations, of which the most important data provider is the Tax and Customs Administration, and provide information on the persons belonging to the population of the Netherlands on January 1st of each year. Our analysis is based on what CBS defines as gross personal income, which includes income from employment, income from own business, income insurance benefits and social security benefits. It excludes income from property, child-related transfers and housing benefits.

Modelling intergenerational income dynamics can give rise to measurement issues. Annual income data are a mixture of permanent and transitory components (Jenkins, 1987; Solon, 1992; Zimmerman, 1992). For this reason, researchers should proxy permanent earnings by taking several annual observations. On the other hand, sons and fathers are at different points of their life-cycle, which usually leads to underestimating offspring permanent income and overestimating that of parents (Haider & Solon, 2006; Nybom & Stuhler, 2016). We address these issues by selecting only individuals aged between 28 and 60 and having at least three non-missing annual income observations within the window 2003–2020. Income is deflated at 2003 constant prices to avoid overestimating the earnings observed in the last years available (which are those observed mostly for generation t) due to inflationary processes.

For the grandparents' generation (i.e., generation t_{-2}), we match individuals with their household wealth. As information on income is available starting in 2003, we do not rely on income streams because for them these largely reflect pension income. Wealth microdata is collected from Dutch tax authorities and concerns both declaration and assessment data of all the households belonging to the population of the Netherlands on January 1st of each year. We consider what CBS defines as total household wealth, which comprises the total value of bank and savings balances and securities, bonds and shares, real estate assets (including the primary residence), business assets and other possessions of the household.

3.2 The estimation framework

In this paper, we provide estimates of the intergenerational transmission parameter under both the BT and the LF models. In the case of the BT model, when heritability of endowments $h \to 0$, this coincides with θ (see Equation 2) and is typically estimated as the coefficient of a linear regression model of the offspring labour market outcome (usually earnings) on that of the parent. We label this coefficient θ^{BT}. Conversely, when a latent factor representation as the one illustrated in Equation 4 is assumed, identifying the intergenerational transmission parameter λ^{LF} requires estimating two separate correlations. To do so, we exploit horizontal moments, i.e., sibling and cousin correlations.

Following the discussion on the potential role of cross-sectional heterogeneity (Section 2.2), we provide estimates of all parameters across the income and wealth distribution of the family. Previous literature deals with potential non-linearities in the functional form of the intergenerational transmission parameters using polynomials of the parental outcome (e.g., $y^2_{i,t-1}$, $y^3_{i,t-1}$), by locally estimating this relation with non-parametric techniques (e.g., local linear regressions), or using quantile regression techniques. Our aim is to estimate sibling and cousin correlations conditional on the positioning on the family distribution; i.e.:

$$\beta(x) = \text{Corr}\left(y_{if}, y_{jf} | x_f = x\right)$$

where y_{if} and y_{jf} are the outcomes of the individuals i and j belonging to family f, and x_f is a conditioning variable measuring the relative position of family f in some relevant distribution. Importantly, we define the family as a set of individuals across different generations who share a common ancestor at t_{-2} (see Figure 1).

Put differently, we do not restrict the support of y_{if} and y_{jf} but keep the value of x_f fixed. Since the conditioning is not on y_{if} nor on y_{jf} – the two arguments of the correlation – we cannot rely on standard non-linear techniques like LOESS or quantile regression methods. Our approach is close in spirit to LOESS estimation in that we compute each value of $\widehat{\beta}(x)$ using all observations in an interval $[x - k; x + k]$ of the conditioning variable, where k is a fixed bandwidth value.[7] Thus, each value of $\widehat{\beta}(x)$ is the estimated OLS coefficient of the regression of y_{if} on y_{jf}:

$$\widehat{\alpha}(x); \widehat{\beta}(x) = \underset{\alpha(x),\beta(x)}{\arg\min} \sum_{f:x_f \in [x-k;x+k]} \left(y_{if} - \alpha(x) - \beta(x) y_{jf}\right)^2 .$$

[7] In our main specifications, we use a bandwidth of 7.5, in order to roughly include the 15% of the sample. Robustness to this choice is provided in the Appendix.

In all cases, $\widehat{\beta}(x)$ is estimated using rank-rank regressions. This allows capturing changes in the relative position in the income distribution, an important property when comparing the mobility of sub-samples of the population (Mazumder, 2014). In addition, rank correlations are robust to measurement error issues (Mazumder, 2015; Nybom & Stuhler, 2017).[8]

When estimating θ^{BT}, y_{if} and y_{jf} are the income percentile of sons and fathers from family f, while the conditioning variable x_f is the percentile of the average income of family f members of generation t_{-1}. In this case, the estimated values of $\widehat{\beta}(x)$ correspond to estimates of the intergenerational parameter θ^{BT} across the t_{-1} income distribution.

When estimating λ^{LF}, y_{if} and y_{jf} are income percentile of family f members from generation t. In the case of sibling correlations the generic pair (if, jf) corresponds to a pair of siblings. In the case of cousin correlations the generic pair (if, jf) corresponds to a pair of cousins. As above, the conditioning variable x_f is the percentile of the average gross income of family f members from generation t_{-1}. We also consider an alternative conditioning variable, the percentile of grandfather's wealth.[9] After estimating sibling and cousin correlations for each value of x_f, we retrieve the implied value of λ^{LF} using:

$$\sqrt{\frac{\widehat{\beta}^{LF}_{cousins}}{\widehat{\beta}^{LF}_{siblings}}}.$$

To estimate the standard errors of the parameter λ^{LF} we use a block bootstrap procedure. In each step, we extract a random (bootstrap) sample of families and we estimate $\widehat{\beta}^{LF}_{siblings}$ and $\widehat{\beta}^{LF}_{cousins}$ using pairs of siblings and cousins that belong to the same randomly selected families. We then compute the ratio between the two quantities. This procedure is repeated 100 times to compute the standard errors of the bootstrap estimates.

3.3 Descriptive statistics

Figure 2 shows the average gross income by income percentile across two generations, t (the offspring, solid line) and t_{-1} (their parents, dashed line). Generations t and t_{-1} exhibit very similar averages at the lower end of the income distribution. At the 10th

[8] For a detailed comparison of the difference between rank-rank correlations and intergenerational elasticities, see Chetty et al. (2014). For an analysis of all different approaches used in the literature to asses intergenerational mobility, see Deutscher & Mazumder (2023).

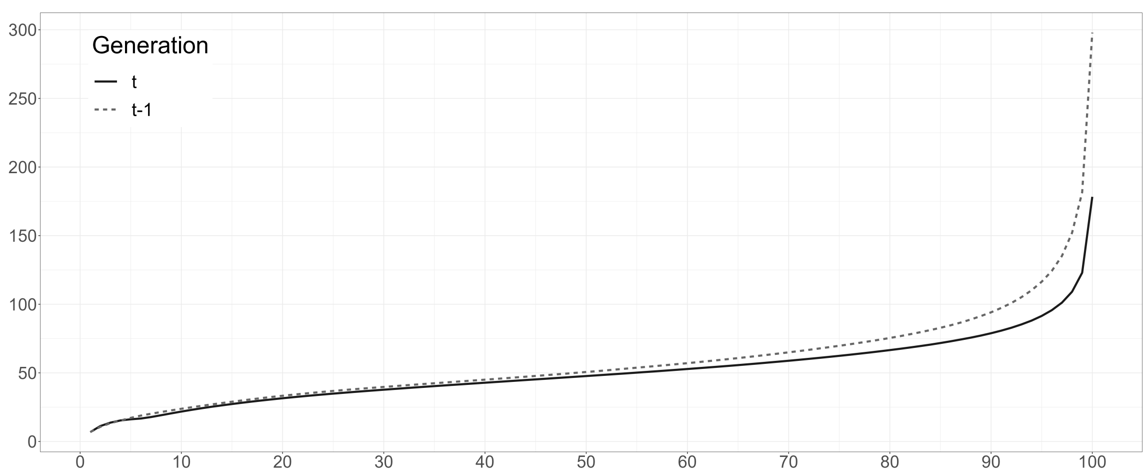
[9] After excluding from our sample those having missing records and institutional households, we compute the wealth percentile of each household. To avoid time dynamics in wealth accumulation, percentile are computed by 5 years cohorts.

percentile, the average deflated income of generation t is 21,790 Euros, while that of their parents is 23,800 Euros. Similar and relatively small differences persist up until the median of the distribution, where the offspring report an average income of about 47,650 Euros and the parents of about 3,000 Euros larger (i.e., 50,600 Euros). Differences in average earnings increase on the right side of the distribution. At the 75th percentile, parents report an average income of 7,500 Euros higher than that of their children (69,700 and 62,400 Euros, respectively). The difference becomes increasingly larger in the highest percentiles: at the 90th, generation t reports an average of 78,870 Euros while generation t_{-1} an average of about 94,100 Euros.

There are two potential explanations. First, Atkinson et al. (2017) show evidence suggesting a reduction of inequality over time in the Netherlands. This might reflect changes in the distribution of cross-sectional inequalities across generations in our sample. Indeed, the $p90/p10$ ratio (the ratio between the 90th and 10th percentiles) is lower at generation t (3.62) than at generation t_{-1} (3.95). The same, however, does not apply to the $p50/p10$ ratio (the ratio between the median and 10th percentile), which is similar across generation t (2.18) and t_{-1} (2.10).

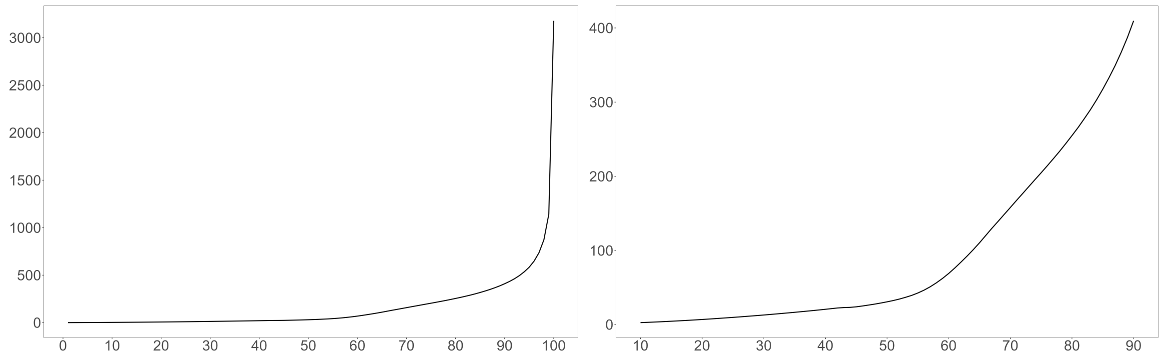
The second potential explanation is that the differences on the right side of Figure 2 are driven by a residual life-cycle bias. In other words, it is more likely that individuals reach high-earning positions later in life rather than earlier. Due to data limitations, as

Figure 2: Average gross income by generation and income percentile



Note: Average gross income by income percentile. The solid line refers to the offspring (generation t); the dashed line to the parents (generation t_{-1}). Individuals aged 28 to 60 only. Those with less than three non-missing years of observations from 2003 to 2020 are excluded from the sample. The y-axis is expressed as thousands of Euros.

Figure 3: Average wealth of generation t_{-2} by wealth percentile



(a) Full distribution (b) Excluding top and bottom 10%

Note: Average wealth of generation t_{-2} by wealth percentile. Panel (a) plots the full distribution, panel (b) excludes individuals in the bottom and top 10 percentiles. The y-axis is expressed as thousands of Euros.

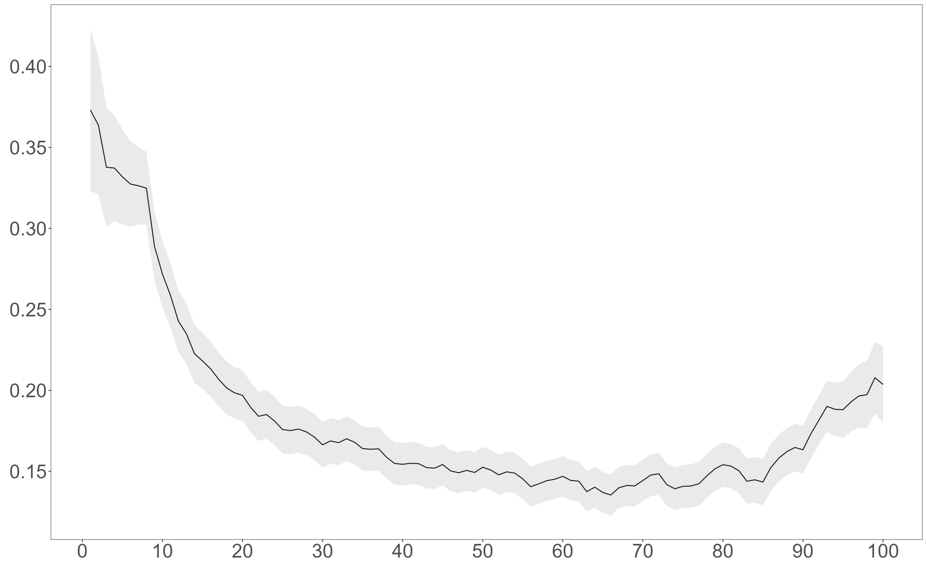
explained in Section 3, we select only individuals aged 28 to 60 having at least three non-missing annual income observations. Yet, since income microdata is only available since 2003, this results in having income from an earlier career stage for generation t than for generation t_{-1}. While this is not a concern for our results, as we use rank-rank correlations (and thus the relative positioning within each generation), the differences in Figure 2 might arise from this issue.

As for generation t_{-2}, in Figure 3 we provide information on average household wealth by wealth percentile. In particular, Figure 3a (left panel) shows the full distribution. Figure 3b (right panel) shows the same distribution excluding the bottom and top 10 percentiles. The wealth distribution follows a quasi-exponential form, likely due to wealth accumulation dynamics (e.g., bequests and transfers). Indeed, at 10th percentile the average household wealth is about 2,600 Euros, at the median percentile it increases to 30,600 Euros and then surges to about 205,000 Euros at the 75th percentile and 410,000 Euros at the 90th percentile. This yields measures of cross-sectional inequality higher than those observed in income. The $p90/p10$ ratio is 156, while $p50/p10$ ratio is about 11.7.

4 Results

We start by following the procedure described in Section 3.2 to estimate father-to-son rank correlations (i.e., the parameter θ^{BT}) across the distribution of parental income.

Figure 4: Estimates of θ^{BT} along the income distribution of generation t_{-1}



Note: Estimates of θ^{BT} for each percentile are obtained as the OLS coefficient of the son-to-father rank-rank regression using the sub-sample of families whose t_{-1} members' average income falls in a fixed neighbourhood around the given percentile of the t_{-1} income distribution across all families. Point estimates and standard errors are reported in Table A.1.

Figure 4 shows that the intergenerational persistence is decreasing along the distribution of parental income, following a mirrored J-shaped pattern. The average rank-correlation coefficient in the first ten percentile is above 0.30. It then flattens at around 0.15 between the 40th and the 90th percentiles and increases again to 0.20 in the last decile of the distribution.

Recent estimates of intergenerational correlation in income using Dutch microdata report an average of 0.22, ranging between 0.20 for younger cohorts to 0.25 for older cohorts (Colagrossi et al., 2023). The pattern described above suggests a marked degree of heterogeneity in intergenerational persistence across the income distribution.

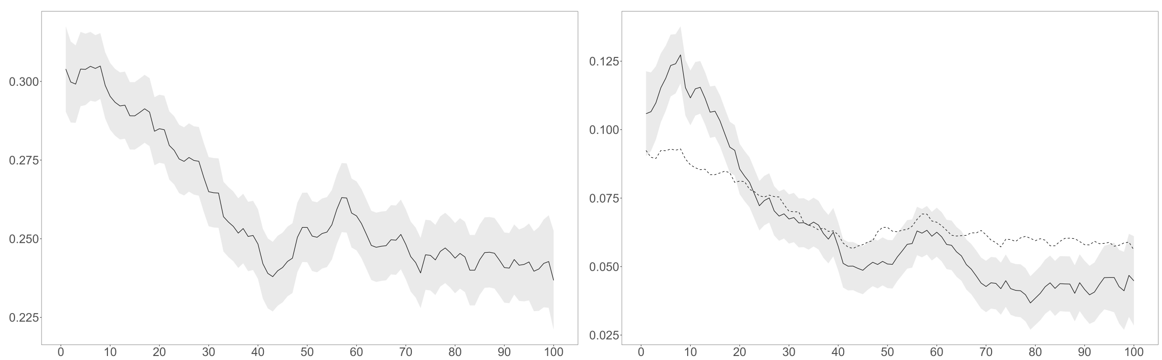
While there are no previous estimates of heterogeneous intergenerational persistence for the Netherlands, we can assess these results in light of the literature referred to other countries. Overall, our findings are in line with those by Solon (1992), Eide & Showalter (1999), Palomino et al. (2018), Durlauf et al. (2017) and Kourtellos et al. (2020) for the USA, Grawe (2004) for Canada and Bratberg et al. (2005) for Norway. They all find a higher degree of intergenerational persistence at the bottom of the distribution, and, in the case of Palomino et al. (2018), a mirrored J-shaped pattern. Interestingly, this pattern does not seem to apply to income only. In Norway, offspring from parents with particularly low earnings fall behind in various quality-of-life outcomes (Markussen & Roed, 2017).

Our results diverge from Corak & Heisz (1999), Couch & Lillard (2004), Bratsberg et al. (2007), Björklund et al. (2012), Schnitzlein (2016) and Barone & Mocetti (2021), who document a higher persistence at the top of the distribution.[10] Finally, Gregg et al. (2019) show evidence of a J-shaped distribution in the UK, where parental income is a strong predictor of earnings at the bottom of the distribution and to an even greater extent for those at the top of the distribution.

To estimate the heterogeneous parameter of the latent factor model λ^{LF} we first need to estimate sibling and cousin rank-rank correlations along the income distribution of generation t_{-1}. These are reported in Figures 5a and 5b. In both cases, estimated correlations follow a similar pattern to the one uncovered for the son-to-father correlation in Figure 4, with the degree of income similarities between siblings and between cousins decreasing with the position of their parents along the distribution.

Finally, we compute the intergenerational parameter of the latent factor model λ^{LF}. Figure 6 shows our results. First, we note that the values of λ^{LF} are, on average, sensibly

Figure 5: $\widehat{\beta}^{LF}_{siblings}$ and $\widehat{\beta}^{LF}_{cousins}$ along the income distribution of generation t_{-1}

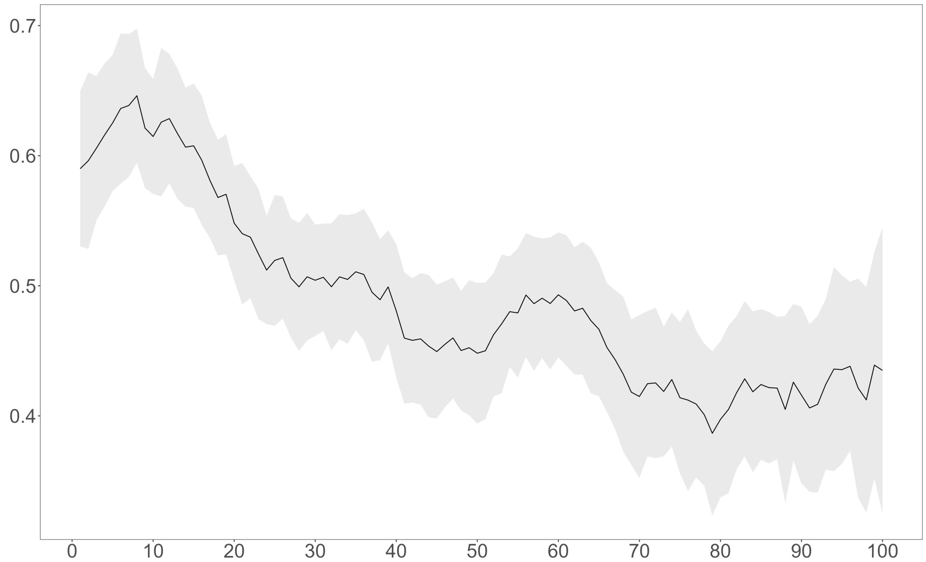


(a) Sibling correlation (b) Cousin correlation

Note: Estimates of $\widehat{\beta}^{LF}_{siblings}$ and $\widehat{\beta}^{LF}_{cousins}$ for each percentile of the parental income distribution are obtained as the OLS coefficient of the sibling-to-sibling (panel a) and cousin-to-cousin (panel b) rank-rank regression using the sub-sample of families whose t_{-1} members' average income falls in a fixed neighborhood around the given percentile of the t_{-1} income distribution across all families. The dotted line in panel b represents the theoretical moments as implied in Section 2.1.

[10] These studies use data from Canada, Denmark, Germany, Norway, Sweden, the USA, the UK and Italy. Barone & Mocetti (2021) show evidence of higher persistence both at the top and at the bottom of the distribution. In their analysis of long-run intergenerational mobility in the city of Florence, "more than two-fifths of descendants from the lower class" remain at the bottom of the distribution even after five centuries (Barone & Mocetti, 2021, p. 15).

Figure 6: λ^{LF} along the income distribution of generation t_{-1}



Note: Estimates of λ^{LF} for each percentile of the parental income distribution are obtained as $\sqrt{\widehat{\beta}^{LF}_{cousins}/\widehat{\beta}^{LF}_{siblings}}$ using the sub-sample of families whose t_{-1} members' average income falls in a fixed neighborhood around the given percentile of the t_{-1} income distribution across all families. Standard errors are obtained through block-bootstrap, 100 replications.

higher than those of θ^{BT}, in line with previous findings (Braun & Stuhler, 2018; Neidhöfer & Stockhausen, 2018; Colagrossi et al., 2023). In addition, we present novel evidence of heterogeneity in the latent factor estimates. In particular, we show a higher persistence of social status at the bottom of the distribution, with values ranging from above 0.6 in the first decile to around 0.4 in the top three deciles. While shifted upwards in comparison to the estimates of θ^{BT}, this pattern resembles the one reported in Figure 4 for the standard heterogeneous intergenerational correlation. However, estimates of λ^{LF} show a less pronounced decline moving away from the lower tail of the distribution. Indeed, while θ^{BT} drops by about 50% going from the first decile to those above the median (i.e., from 0.30 to 0.15), the decrease is limited to around 30% in the case of λ^{LF}.

There are several potential mechanisms discussed in the literature that can explain the larger persistence in income and social status at the bottom of the distribution. One is the existence of borrowing constraints, where low-income families cannot access credit to optimally invest in their children's education (Becker & Tomes, 1986). However, it is unlikely that these differences are exclusively due to credit constraints (Black et al., 2011), also given that in the Netherlands primary and secondary education is free and higher education is relatively cheap compared to other EU countries.

Another possibility is the existence of poverty traps generated by neighborhood effects (Durlauf, 1994, 1996). While there is evidence in this regard for the USA (Chetty et al., 2014), Dutch cities are, on average, less segregated. However, immigration from Turkey and Morocco in the late 1970s and early 1980s has generated some degree of income and ethnic segregation in Dutch cities, so it is not possible to completely reject this hypothesis.

A third factor worth considering is the role of education. Bratsberg et al. (2007) argue that low-income families in Nordic countries (i.e., Denmark, Norway, and Sweden) have a lower degree of intergenerational persistence due to the features of the educational system. This is because when equal access to high-skill formation is provided to all families, this exert a re-distributional role that decreases the stickiness at the bottom of the income distribution (Hægeland et al., 2005). However, educational policies can also have opposite effects and yield higher intergenerational persistence. Previous works show that separating children by ability into different paths at an early age (i.e., early tracking) can reduce intergenerational mobility (Dustmann, 2004). Similarly, Pekkarinen et al. (2009) show that the Finnish reform that postponed the tracking of students from age 11 to age 16 decreased intergenerational persistence by about 20%. As the Netherlands has an early tracking system that divides children by ability at age 12 into three highly divergent tracks, such a mechanism might explain, to some extent, our evidence of a higher persistence at the bottom of the income distribution.

Finally, persistent segmentation into high-mobility and low-mobility groups might arise from poverty traps. Earnings of offspring of parents with low income follow a different transmission process than those having high-income parents (Durlauf et al., 2017). These different regimes might arise from different processes – e.g., neighborhood effects with endogenous stratification (Durlauf, 1994) or complementaries in the technology of human capital formation (Becker et al., 2018).

4.1 Grouping families based on grandparental wealth

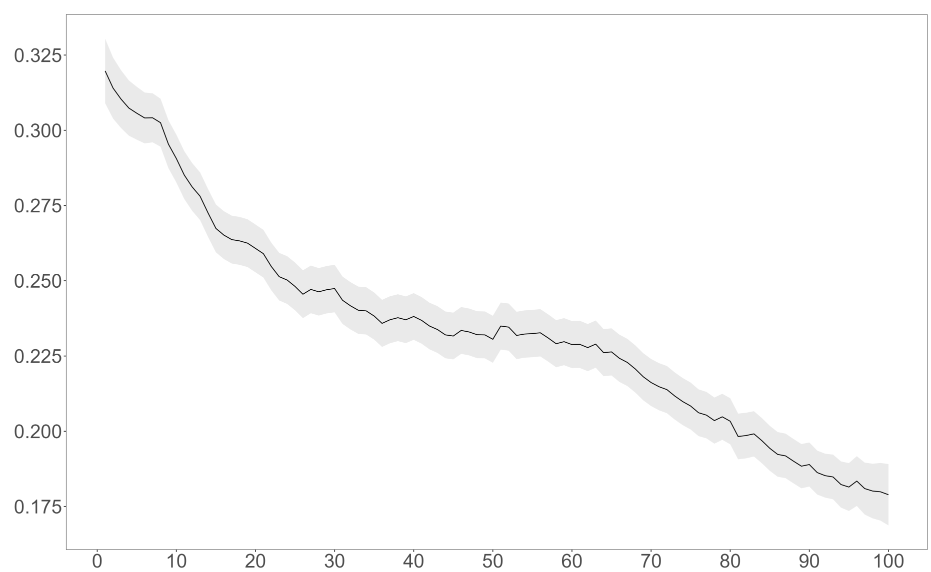
A natural question is whether the mechanisms discussed above, and especially poverty traps, extend beyond a single generation. Given our definition of family – all individuals sharing a common ancestor, we can replicate our analysis grouping families based on grandparental wealth rather than parental income. In this case, the conditioning variable is the position of the family along the wealth distribution of generation t_{-2}.

We start by estimating the father-to-son θ^{BT} parameter based on the wealth distribution of grandparents. Figure 7 shows that in this case θ^{BT} follows a linear and less steep decay compared to the same estimate based on the distribution of parental income reported in Figure 4. Interestingly, at the very low end of the distribution (below 10th percentile) the estimated θ^{BT} is always at its highest (above 0.30), regardless of being based on the positioning of the parental income or the grandparental wealth. The inverted-J shape is no longer visible in Figure 7, suggesting that the father-to-child correlation persists much less for those having very wealthy grandparents.

Then, in Figure 8 we replicate the analysis of the heterogeneous latent factor model grouping cousins and siblings along the percentile of their grandparent's wealth. Similarly to the findings shown along the income distribution of generation t_{-1} (Figure 5), siblings and cousins whose grandparent belongs to the lowest wealth percentiles exhibit higher degrees of associations in income. In particular, while the average at the first deciles is well above 0.30 and 0.13 for brothers and cousins, the top deciles display values around 0.270 and 0.80, respectively.

Two other observations arise. The first is that, as in Figure 5b, the theoretical moments implied by the *naive* version of the BT model underestimate the association in cousins' income greatly than when conditioning on parental income, potentially informing about a longer-term (i.e., non-Markovian) intergenerational transmission of ability and endowments, as suggested by Mare (2011) and Lindahl et al. (2015). Second, cousin correlations (Figure 8b), display a different pattern than those shown so far, as they

Figure 7: Estimates of θ^{BT} along the wealth distribution of generation t_{-2}



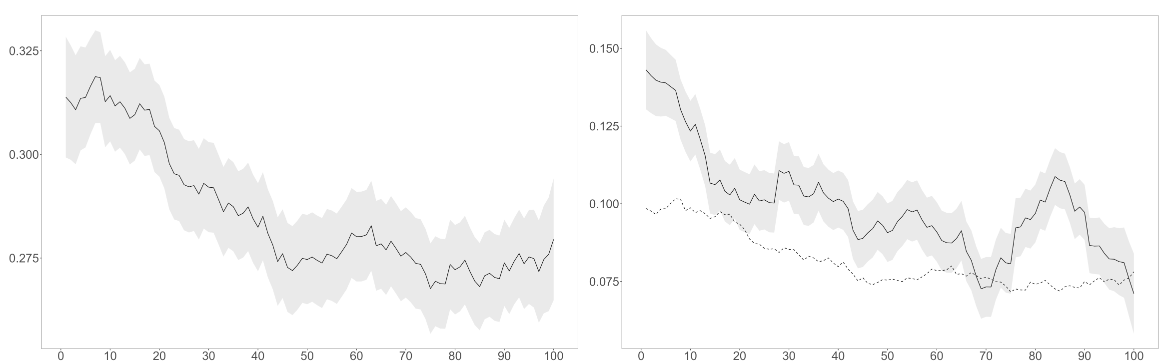
Note: Estimates of θ^{BT} for each percentile are obtained as the OLS coefficient of the son-to-father rank-rank regression using the sub-sample of families whose t_{-2} members' wealth falls in a fixed neighbourhood around the given percentile of the t_{-2} wealth distribution across all families.

display a pronounced increase in intergenerational transmission for those cousins having wealthy ancestors belonging to the 7th and 8th decile of the distribution. Overall, this finding confirms the importance of estimating heterogeneous parameters of intergenerational transmission.

Finally, 9 shows the latent factor model along the distribution of the grandparent's wealth. Compared to the results based on the distribution of parental income (Figure 6), differences in intergenerational correlation across the distribution are less pronounced, i.e., estimates of λ^{LF} here are less steep than those in Figure 6. Offspring in the first decile have an average persistence of 0.65 whereas those in the highest decile show figures around 0.55. Nonetheless, as in the case of θ^{BT}, for individuals whose parents or grandparents belong to the first decile of the corresponding distribution, persistence in parental income transmission is highest.

Our finding convey three important messages. First, the intergenerational transmission process estimated through a latent factor representation is always higher than traditional estimates, regardless of whether we condition on parental income or grandparental wealth. Second, even after two generations, the offspring coming from disadvantaged families seem to pass on their (mis)fortunes to their heirs more than those coming from wealthier families, and the degree of persistence is very similar across generations. Third, the intergenerational correlation is flatter, hence less heterogeneous, when based on the positioning of the previous generation $(t-2)$, and this is true both when we consider the

Figure 8: $\widehat{\beta}^{LF}_{siblings}$ and $\widehat{\beta}^{LF}_{cousins}$ along the wealth distribution of generation t_{-2}

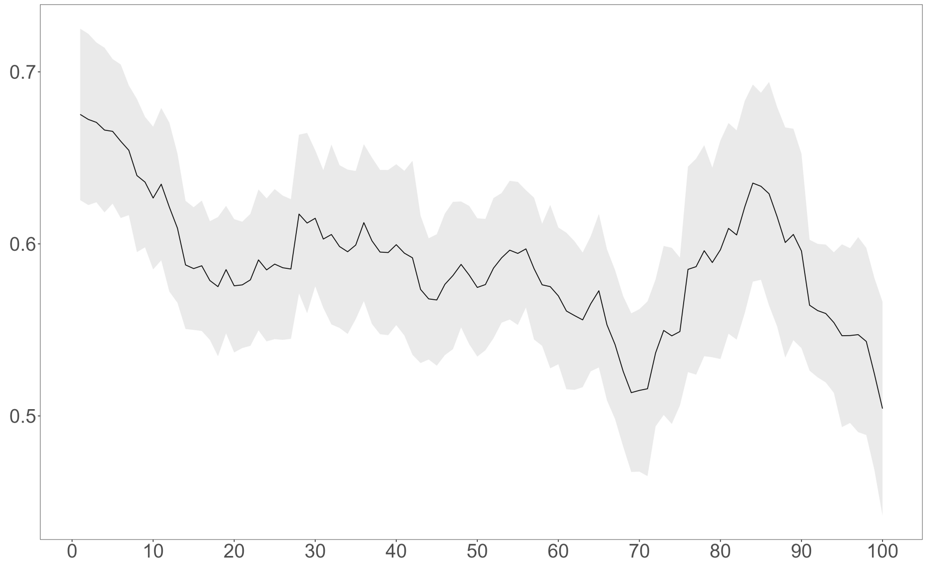


(a) Sibling correlation

(b) Cousin correlation

Note: Estimates of $\widehat{\beta}^{LF}_{siblings}$ and $\widehat{\beta}^{LF}_{cousins}$ for each percentile of the grandparent's wealth distribution are obtained as the OLS coefficient of the sibling-to-sibling (panel a) and cousin-to-cousin (panel b) rank-rank regression using the sub-sample of families whose t_{-2} members' wealth falls in a fixed neighborhood around the given percentile of the t_{-2} wealth distribution across all families. The dotted line in panel 8b represents the theoretical moments as implied in Section 2.1.

Figure 9: λ^{LF} along the wealth distribution of generation t_{-2}



Note: Estimates of λ^{LF} for each percentile of the grandparent's wealth distribution are obtained as $\sqrt{\widehat{\beta}^{LF}_{cousins}/\widehat{\beta}^{LF}_{siblings}}$ using the sub-sample of families whose t_{-2} members' wealth falls in a fixed neighborhood around the given percentile of the t_{-2} wealth distribution across all families. Standard errors are obtained through block-bootstrap, 100 replications.

BT or the LF model. Poverty traps (Durlauf et al., 2017) and longer-term intergenerational dynamics (Mare, 2011) might help explain low levels of mobility for those born in low-income, low-wealth families.

5 Conclusions

Understanding the degree to which family members resemble each other in labor market outcomes is the subject of a vast literature in social science. Standard models of intergenerational mobility find evidence of substantial heterogeneities in the transmission process. To the best of our knowledge, however, the existence of non-linearities has never been addressed using a model of latent transmission.

Our contribution to the literature is threefold. We use administrative data spanning three generations to construct the genealogical tree of all individuals ever appearing in the Dutch municipal records since 1995. We confirm that the intergenerational transmission process, as estimated through a latent factor representation, consistently yields higher results than traditional estimates. This holds true irrespective of whether the conditioning factor is parental income or grandparental wealth. We show that the intergenerational transmission process is heterogeneous, and is characterized by increased persistence (indicating reduced mobility) at the lower end of the parental income distribution. This pattern persists when analyzing traditional parent-to-son estimates of mobility and remains consistent when considering a latent transmission of family endowments. Notably, the latter finding represents a novel contribution to the current literature on intergenerational mobility.

We exploit the richness of our data and assess the degree to which siblings and cousins resemble each other in income as well as latent factor estimates along the wealth distribution of their shared ancestor (i.e., their grandparent). Even after two generations, disadvantaged families seem to transmit their (mis)fortunes to their descendants to a greater extent than those from more affluent backgrounds.

Finally, from a methodological perspective, we propose a method to compute intergenerational measures across family members that allows conditioning on a grouping variable – i.e., horizontal and vertical intergenerational parameters conditioning on the positioning of the family along some relevant distribution.

Overall, the availability of rich administrative data allows a deeper analysis of the role of family background in explaining the intergenerational transmission of inequalities than it is possible with survey data. In the context of the Netherlands, the identification of an increased persistence at the bottom of the distribution of parental income and grandparental wealth emerges as an important feature of intergenerational mobility. Future research may be able to isolate the role of potential mechanisms behind this heterogeneous transmission.

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Appendix

Table A.1: Estimates of θ^{BT} across the income distribution of generation t_{-1}

Pct	$k=5$		$k=7.5$		$k=10$		Pct	$k=5$		$k=7.5$		$k=10$	
	β	S.E.	β	S.E.	β	S.E.		β	S.E.	β	S.E.	β	S.E.
1	0.367	(0.043)	0.373	(0.026)	0.344	(0.018)	51	0.152	(0.008)	0.151	(0.006)	0.151	(0.005)
2	0.339	(0.034)	0.364	(0.022)	0.329	(0.016)	52	0.144	(0.008)	0.148	(0.006)	0.154	(0.005)
3	0.352	(0.028)	0.338	(0.019)	0.327	(0.014)	53	0.139	(0.008)	0.15	(0.006)	0.153	(0.005)
4	0.368	(0.024)	0.337	(0.017)	0.33	(0.013)	54	0.145	(0.008)	0.149	(0.006)	0.149	(0.005)
5	0.351	(0.02)	0.332	(0.015)	0.324	(0.012)	55	0.146	(0.008)	0.145	(0.006)	0.148	(0.005)
6	0.322	(0.018)	0.327	(0.013)	0.32	(0.011)	56	0.143	(0.008)	0.141	(0.006)	0.151	(0.005)
7	0.273	(0.017)	0.326	(0.012)	0.317	(0.01)	57	0.142	(0.008)	0.142	(0.006)	0.152	(0.005)
8	0.26	(0.016)	0.325	(0.011)	0.316	(0.009)	58	0.143	(0.008)	0.144	(0.006)	0.148	(0.005)
9	0.255	(0.015)	0.289	(0.011)	0.312	(0.009)	59	0.136	(0.008)	0.145	(0.006)	0.15	(0.005)
10	0.24	(0.014)	0.272	(0.01)	0.307	(0.008)	60	0.137	(0.008)	0.147	(0.006)	0.147	(0.005)
11	0.233	(0.013)	0.259	(0.01)	0.287	(0.008)	61	0.14	(0.008)	0.144	(0.006)	0.145	(0.005)
12	0.225	(0.012)	0.243	(0.01)	0.27	(0.008)	62	0.147	(0.008)	0.144	(0.006)	0.144	(0.005)
13	0.224	(0.012)	0.235	(0.009)	0.259	(0.008)	63	0.144	(0.008)	0.137	(0.006)	0.142	(0.005)
14	0.216	(0.011)	0.223	(0.009)	0.247	(0.008)	64	0.139	(0.008)	0.14	(0.006)	0.143	(0.005)
15	0.202	(0.011)	0.218	(0.009)	0.236	(0.007)	65	0.138	(0.008)	0.137	(0.006)	0.143	(0.005)
16	0.197	(0.011)	0.213	(0.009)	0.232	(0.007)	66	0.138	(0.008)	0.135	(0.006)	0.144	(0.005)
17	0.201	(0.011)	0.207	(0.008)	0.22	(0.007)	67	0.134	(0.008)	0.14	(0.006)	0.145	(0.006)
18	0.192	(0.01)	0.202	(0.008)	0.217	(0.007)	68	0.13	(0.008)	0.141	(0.006)	0.147	(0.006)
19	0.184	(0.01)	0.199	(0.008)	0.212	(0.007)	69	0.139	(0.008)	0.141	(0.007)	0.145	(0.006)
20	0.181	(0.01)	0.197	(0.008)	0.207	(0.007)	70	0.141	(0.008)	0.144	(0.007)	0.146	(0.006)
21	0.181	(0.01)	0.19	(0.008)	0.204	(0.007)	71	0.139	(0.008)	0.148	(0.007)	0.145	(0.006)
22	0.175	(0.01)	0.184	(0.008)	0.199	(0.007)	72	0.138	(0.008)	0.148	(0.007)	0.143	(0.006)
23	0.172	(0.01)	0.185	(0.008)	0.192	(0.006)	73	0.143	(0.008)	0.142	(0.007)	0.144	(0.006)
24	0.175	(0.009)	0.181	(0.008)	0.187	(0.006)	74	0.145	(0.008)	0.139	(0.007)	0.146	(0.006)
25	0.177	(0.009)	0.176	(0.008)	0.186	(0.006)	75	0.15	(0.008)	0.141	(0.007)	0.145	(0.006)
26	0.179	(0.009)	0.175	(0.007)	0.18	(0.006)	76	0.147	(0.008)	0.141	(0.007)	0.146	(0.006)
27	0.172	(0.009)	0.176	(0.007)	0.179	(0.006)	77	0.147	(0.009)	0.142	(0.007)	0.147	(0.006)
28	0.169	(0.009)	0.174	(0.007)	0.176	(0.006)	78	0.151	(0.009)	0.147	(0.007)	0.149	(0.006)
29	0.169	(0.009)	0.171	(0.007)	0.178	(0.006)	79	0.147	(0.009)	0.152	(0.007)	0.15	(0.006)
30	0.168	(0.009)	0.166	(0.007)	0.178	(0.006)	80	0.143	(0.009)	0.154	(0.007)	0.155	(0.006)
31	0.163	(0.009)	0.169	(0.007)	0.179	(0.006)	81	0.139	(0.009)	0.153	(0.007)	0.155	(0.006)
32	0.164	(0.009)	0.168	(0.007)	0.172	(0.006)	82	0.142	(0.009)	0.15	(0.007)	0.154	(0.006)
33	0.163	(0.009)	0.17	(0.007)	0.171	(0.006)	83	0.139	(0.009)	0.144	(0.007)	0.161	(0.006)
34	0.161	(0.009)	0.168	(0.007)	0.172	(0.006)	84	0.14	(0.009)	0.145	(0.007)	0.166	(0.006)
35	0.166	(0.009)	0.164	(0.007)	0.169	(0.006)	85	0.141	(0.009)	0.143	(0.007)	0.167	(0.006)
36	0.164	(0.009)	0.164	(0.007)	0.166	(0.006)	86	0.142	(0.009)	0.152	(0.007)	0.164	(0.006)
37	0.152	(0.008)	0.164	(0.007)	0.165	(0.006)	87	0.142	(0.009)	0.158	(0.007)	0.165	(0.006)
38	0.155	(0.008)	0.159	(0.007)	0.165	(0.006)	88	0.151	(0.009)	0.162	(0.007)	0.167	(0.006)
39	0.158	(0.008)	0.155	(0.007)	0.162	(0.006)	89	0.166	(0.009)	0.165	(0.007)	0.176	(0.006)
40	0.155	(0.008)	0.154	(0.007)	0.162	(0.006)	90	0.168	(0.009)	0.163	(0.008)	0.184	(0.006)
41	0.152	(0.008)	0.155	(0.007)	0.159	(0.006)	91	0.168	(0.009)	0.173	(0.008)	0.185	(0.007)
42	0.151	(0.008)	0.155	(0.007)	0.16	(0.006)	92	0.166	(0.01)	0.182	(0.008)	0.185	(0.007)
43	0.153	(0.008)	0.152	(0.007)	0.156	(0.006)	93	0.172	(0.01)	0.19	(0.008)	0.186	(0.007)
44	0.15	(0.008)	0.152	(0.007)	0.156	(0.006)	94	0.181	(0.01)	0.188	(0.008)	0.187	(0.008)
45	0.146	(0.008)	0.154	(0.006)	0.156	(0.006)	95	0.196	(0.01)	0.188	(0.009)	0.187	(0.008)
46	0.144	(0.008)	0.15	(0.006)	0.158	(0.006)	96	0.203	(0.011)	0.193	(0.009)	0.189	(0.008)
47	0.154	(0.008)	0.149	(0.006)	0.153	(0.006)	97	0.204	(0.012)	0.197	(0.01)	0.188	(0.009)
48	0.149	(0.008)	0.151	(0.006)	0.152	(0.005)	98	0.199	(0.013)	0.197	(0.011)	0.192	(0.009)
49	0.146	(0.008)	0.149	(0.006)	0.153	(0.005)	99	0.189	(0.014)	0.208	(0.011)	0.192	(0.01)
50	0.144	(0.008)	0.153	(0.006)	0.153	(0.005)	100	0.185	(0.016)	0.204	(0.012)	0.196	(0.01)

Note: Point estimates and standard errors as reported in Figure 4 ($k = 7.5$) and its robustness ($k = 5$ and $k = 10$), where k defines the interval $[x - k; x + k]$ of the conditioning variable.

Table A.2: Estimates of $\widehat{\beta}^{LF}_{siblings}$ across the income distribution of generation t_{-1}

Pct	$k=5$		$k=7.5$		$k=10$		Pct	$k=5$		$k=7.5$		$k=10$	
	β	S.E.	β	S.E.	β	S.E.		β	S.E.	β	S.E.	β	S.E.
1	0.308	(0.008)	0.304	(0.007)	0.302	(0.006)	51	0.254	(0.007)	0.251	(0.006)	0.252	(0.005)
2	0.313	(0.008)	0.3	(0.007)	0.303	(0.006)	52	0.256	(0.007)	0.25	(0.006)	0.253	(0.005)
3	0.306	(0.007)	0.299	(0.006)	0.304	(0.006)	53	0.259	(0.007)	0.252	(0.006)	0.254	(0.005)
4	0.301	(0.007)	0.304	(0.006)	0.304	(0.005)	54	0.256	(0.007)	0.252	(0.006)	0.253	(0.005)
5	0.3	(0.006)	0.304	(0.006)	0.304	(0.005)	55	0.264	(0.007)	0.254	(0.006)	0.256	(0.005)
6	0.298	(0.006)	0.305	(0.006)	0.304	(0.005)	56	0.262	(0.007)	0.259	(0.006)	0.255	(0.005)
7	0.292	(0.007)	0.304	(0.005)	0.305	(0.005)	57	0.261	(0.007)	0.263	(0.006)	0.253	(0.005)
8	0.293	(0.007)	0.305	(0.005)	0.305	(0.005)	58	0.26	(0.007)	0.263	(0.006)	0.254	(0.005)
9	0.291	(0.007)	0.299	(0.005)	0.306	(0.005)	59	0.262	(0.007)	0.258	(0.006)	0.255	(0.005)
10	0.292	(0.007)	0.295	(0.005)	0.305	(0.005)	60	0.259	(0.007)	0.257	(0.006)	0.256	(0.005)
11	0.293	(0.007)	0.293	(0.005)	0.301	(0.005)	61	0.255	(0.007)	0.255	(0.006)	0.254	(0.005)
12	0.286	(0.007)	0.292	(0.005)	0.296	(0.005)	62	0.248	(0.007)	0.251	(0.006)	0.254	(0.005)
13	0.291	(0.007)	0.292	(0.005)	0.296	(0.005)	63	0.246	(0.007)	0.248	(0.006)	0.253	(0.005)
14	0.296	(0.007)	0.289	(0.005)	0.293	(0.005)	64	0.251	(0.007)	0.247	(0.006)	0.253	(0.005)
15	0.292	(0.007)	0.289	(0.005)	0.293	(0.005)	65	0.247	(0.007)	0.248	(0.006)	0.249	(0.005)
16	0.29	(0.007)	0.29	(0.005)	0.292	(0.005)	66	0.244	(0.007)	0.248	(0.006)	0.25	(0.005)
17	0.289	(0.007)	0.291	(0.006)	0.285	(0.005)	67	0.246	(0.007)	0.25	(0.006)	0.248	(0.005)
18	0.288	(0.007)	0.29	(0.006)	0.289	(0.005)	68	0.243	(0.007)	0.25	(0.006)	0.248	(0.005)
19	0.284	(0.007)	0.284	(0.006)	0.288	(0.005)	69	0.243	(0.007)	0.251	(0.006)	0.249	(0.005)
20	0.282	(0.007)	0.285	(0.006)	0.287	(0.005)	70	0.239	(0.007)	0.248	(0.006)	0.246	(0.005)
21	0.282	(0.007)	0.285	(0.006)	0.284	(0.005)	71	0.243	(0.007)	0.244	(0.006)	0.248	(0.005)
22	0.278	(0.007)	0.28	(0.006)	0.282	(0.005)	72	0.248	(0.007)	0.242	(0.006)	0.247	(0.005)
23	0.28	(0.007)	0.278	(0.006)	0.28	(0.005)	73	0.248	(0.007)	0.239	(0.006)	0.246	(0.005)
24	0.275	(0.007)	0.275	(0.006)	0.279	(0.005)	74	0.247	(0.007)	0.245	(0.006)	0.245	(0.005)
25	0.276	(0.007)	0.275	(0.006)	0.277	(0.005)	75	0.243	(0.007)	0.245	(0.006)	0.243	(0.005)
26	0.272	(0.007)	0.276	(0.006)	0.275	(0.005)	76	0.25	(0.007)	0.243	(0.006)	0.242	(0.005)
27	0.269	(0.007)	0.275	(0.006)	0.274	(0.005)	77	0.248	(0.007)	0.246	(0.006)	0.244	(0.005)
28	0.268	(0.007)	0.275	(0.006)	0.271	(0.005)	78	0.248	(0.007)	0.247	(0.006)	0.245	(0.005)
29	0.272	(0.007)	0.27	(0.006)	0.268	(0.005)	79	0.245	(0.007)	0.246	(0.006)	0.246	(0.005)
30	0.269	(0.007)	0.265	(0.006)	0.267	(0.005)	80	0.247	(0.007)	0.244	(0.006)	0.246	(0.005)
31	0.265	(0.007)	0.265	(0.006)	0.262	(0.005)	81	0.24	(0.007)	0.245	(0.006)	0.245	(0.005)
32	0.267	(0.007)	0.265	(0.006)	0.26	(0.005)	82	0.238	(0.007)	0.244	(0.006)	0.247	(0.005)
33	0.261	(0.007)	0.257	(0.006)	0.258	(0.005)	83	0.241	(0.007)	0.24	(0.006)	0.247	(0.005)
34	0.258	(0.007)	0.255	(0.006)	0.261	(0.005)	84	0.242	(0.007)	0.24	(0.006)	0.247	(0.005)
35	0.256	(0.007)	0.254	(0.006)	0.258	(0.005)	85	0.246	(0.007)	0.243	(0.006)	0.247	(0.005)
36	0.25	(0.007)	0.252	(0.006)	0.254	(0.005)	86	0.239	(0.007)	0.246	(0.006)	0.245	(0.005)
37	0.248	(0.007)	0.253	(0.006)	0.255	(0.005)	87	0.242	(0.007)	0.246	(0.006)	0.243	(0.005)
38	0.245	(0.007)	0.251	(0.006)	0.251	(0.005)	88	0.243	(0.007)	0.245	(0.006)	0.242	(0.005)
39	0.248	(0.007)	0.251	(0.006)	0.248	(0.005)	89	0.246	(0.007)	0.243	(0.006)	0.245	(0.005)
40	0.245	(0.007)	0.248	(0.006)	0.247	(0.005)	90	0.242	(0.007)	0.241	(0.006)	0.245	(0.005)
41	0.241	(0.007)	0.242	(0.006)	0.246	(0.005)	91	0.246	(0.007)	0.241	(0.006)	0.243	(0.005)
42	0.24	(0.007)	0.239	(0.006)	0.246	(0.005)	92	0.247	(0.007)	0.243	(0.006)	0.242	(0.005)
43	0.239	(0.007)	0.238	(0.006)	0.247	(0.005)	93	0.239	(0.007)	0.242	(0.006)	0.242	(0.005)
44	0.235	(0.007)	0.24	(0.006)	0.246	(0.005)	94	0.244	(0.007)	0.242	(0.006)	0.241	(0.006)
45	0.236	(0.007)	0.241	(0.006)	0.248	(0.005)	95	0.241	(0.007)	0.243	(0.006)	0.24	(0.006)
46	0.24	(0.007)	0.243	(0.006)	0.248	(0.005)	96	0.244	(0.007)	0.24	(0.006)	0.242	(0.006)
47	0.243	(0.007)	0.244	(0.006)	0.25	(0.005)	97	0.239	(0.008)	0.24	(0.007)	0.244	(0.006)
48	0.246	(0.007)	0.25	(0.006)	0.25	(0.005)	98	0.236	(0.008)	0.242	(0.007)	0.241	(0.006)
49	0.241	(0.007)	0.254	(0.006)	0.247	(0.005)	99	0.232	(0.009)	0.243	(0.008)	0.242	(0.007)
50	0.251	(0.007)	0.254	(0.006)	0.251	(0.005)	100	0.235	(0.01)	0.237	(0.008)	0.241	(0.007)

Note: Point estimates and standard errors as reported in Figure 5a ($k = 7.5$) and its robustness ($k = 5$ and $k = 10$), where k defines the interval $[x - k; x + k]$ of the conditioning variable.

Table A.3: Estimates of $\widehat{\beta}^{LF}_{cousins}$ across the income distribution of generation t_{-1}

Pct	$k=5$		$k=7.5$		$k=10$		Pct	$k=5$		$k=7.5$		$k=10$	
	β	S.E.	β	S.E.	β	S.E.		β	S.E.	β	S.E.	β	S.E.
1	0.11	(0.01)	0.106	(0.008)	0.116	(0.007)	51	0.054	(0.005)	0.051	(0.004)	0.057	(0.004)
2	0.105	(0.009)	0.107	(0.007)	0.119	(0.006)	52	0.057	(0.006)	0.054	(0.004)	0.055	(0.004)
3	0.107	(0.008)	0.11	(0.007)	0.12	(0.006)	53	0.062	(0.006)	0.056	(0.004)	0.056	(0.004)
4	0.106	(0.008)	0.115	(0.006)	0.124	(0.006)	54	0.057	(0.006)	0.058	(0.005)	0.058	(0.004)
5	0.108	(0.007)	0.119	(0.006)	0.126	(0.005)	55	0.062	(0.005)	0.058	(0.004)	0.058	(0.004)
6	0.107	(0.007)	0.123	(0.006)	0.126	(0.005)	56	0.064	(0.005)	0.063	(0.005)	0.058	(0.004)
7	0.104	(0.007)	0.124	(0.006)	0.127	(0.005)	57	0.064	(0.006)	0.062	(0.004)	0.058	(0.004)
8	0.105	(0.006)	0.127	(0.005)	0.127	(0.005)	58	0.065	(0.006)	0.063	(0.005)	0.061	(0.004)
9	0.111	(0.006)	0.115	(0.005)	0.132	(0.005)	59	0.062	(0.006)	0.061	(0.005)	0.06	(0.004)
10	0.112	(0.006)	0.112	(0.005)	0.129	(0.004)	60	0.063	(0.006)	0.063	(0.005)	0.06	(0.004)
11	0.108	(0.006)	0.115	(0.005)	0.123	(0.004)	61	0.059	(0.006)	0.061	(0.005)	0.06	(0.004)
12	0.109	(0.006)	0.115	(0.005)	0.116	(0.004)	62	0.055	(0.006)	0.058	(0.005)	0.059	(0.004)
13	0.107	(0.006)	0.111	(0.005)	0.114	(0.004)	63	0.057	(0.006)	0.058	(0.005)	0.056	(0.004)
14	0.115	(0.006)	0.106	(0.005)	0.112	(0.004)	64	0.06	(0.006)	0.055	(0.005)	0.053	(0.004)
15	0.105	(0.006)	0.107	(0.005)	0.107	(0.004)	65	0.053	(0.006)	0.054	(0.005)	0.054	(0.004)
16	0.1	(0.006)	0.103	(0.005)	0.105	(0.004)	66	0.052	(0.006)	0.051	(0.005)	0.051	(0.004)
17	0.095	(0.006)	0.098	(0.005)	0.102	(0.004)	67	0.051	(0.006)	0.049	(0.005)	0.047	(0.004)
18	0.092	(0.006)	0.094	(0.005)	0.098	(0.004)	68	0.045	(0.006)	0.047	(0.005)	0.047	(0.004)
19	0.087	(0.006)	0.092	(0.005)	0.097	(0.004)	69	0.041	(0.006)	0.044	(0.005)	0.05	(0.004)
20	0.08	(0.006)	0.086	(0.005)	0.091	(0.004)	70	0.042	(0.006)	0.043	(0.005)	0.049	(0.004)
21	0.084	(0.006)	0.083	(0.005)	0.085	(0.004)	71	0.04	(0.006)	0.044	(0.005)	0.047	(0.004)
22	0.078	(0.006)	0.081	(0.005)	0.082	(0.004)	72	0.036	(0.006)	0.044	(0.005)	0.047	(0.004)
23	0.076	(0.006)	0.076	(0.005)	0.083	(0.004)	73	0.035	(0.006)	0.042	(0.005)	0.046	(0.004)
24	0.066	(0.006)	0.072	(0.005)	0.081	(0.004)	74	0.037	(0.006)	0.045	(0.005)	0.044	(0.004)
25	0.067	(0.006)	0.074	(0.005)	0.079	(0.004)	75	0.043	(0.006)	0.042	(0.005)	0.042	(0.004)
26	0.061	(0.006)	0.075	(0.005)	0.079	(0.004)	76	0.042	(0.006)	0.041	(0.005)	0.041	(0.004)
27	0.06	(0.006)	0.07	(0.005)	0.076	(0.004)	77	0.041	(0.006)	0.041	(0.005)	0.039	(0.004)
28	0.066	(0.006)	0.068	(0.005)	0.075	(0.004)	78	0.045	(0.006)	0.04	(0.005)	0.039	(0.004)
29	0.068	(0.006)	0.069	(0.005)	0.068	(0.004)	79	0.045	(0.006)	0.037	(0.005)	0.039	(0.004)
30	0.069	(0.006)	0.067	(0.005)	0.067	(0.004)	80	0.041	(0.006)	0.038	(0.005)	0.043	(0.004)
31	0.07	(0.006)	0.068	(0.005)	0.067	(0.004)	81	0.04	(0.006)	0.04	(0.005)	0.04	(0.004)
32	0.067	(0.006)	0.066	(0.005)	0.068	(0.004)	82	0.041	(0.006)	0.043	(0.005)	0.04	(0.004)
33	0.068	(0.006)	0.066	(0.005)	0.066	(0.004)	83	0.042	(0.006)	0.044	(0.005)	0.043	(0.004)
34	0.066	(0.006)	0.065	(0.005)	0.065	(0.004)	84	0.04	(0.006)	0.042	(0.005)	0.044	(0.004)
35	0.062	(0.006)	0.066	(0.005)	0.064	(0.004)	85	0.039	(0.006)	0.044	(0.005)	0.045	(0.004)
36	0.067	(0.006)	0.065	(0.005)	0.062	(0.004)	86	0.035	(0.006)	0.044	(0.005)	0.047	(0.004)
37	0.069	(0.006)	0.062	(0.005)	0.061	(0.004)	87	0.034	(0.006)	0.044	(0.005)	0.048	(0.005)
38	0.061	(0.006)	0.06	(0.005)	0.059	(0.004)	88	0.037	(0.006)	0.04	(0.005)	0.047	(0.005)
39	0.057	(0.006)	0.063	(0.004)	0.058	(0.004)	89	0.037	(0.006)	0.044	(0.005)	0.045	(0.005)
40	0.055	(0.006)	0.057	(0.004)	0.056	(0.004)	90	0.042	(0.006)	0.042	(0.005)	0.042	(0.005)
41	0.05	(0.005)	0.051	(0.005)	0.058	(0.004)	91	0.05	(0.006)	0.04	(0.005)	0.042	(0.005)
42	0.05	(0.005)	0.05	(0.005)	0.058	(0.004)	92	0.052	(0.007)	0.041	(0.006)	0.041	(0.005)
43	0.047	(0.005)	0.05	(0.004)	0.054	(0.004)	93	0.048	(0.007)	0.043	(0.006)	0.04	(0.005)
44	0.047	(0.005)	0.049	(0.004)	0.054	(0.004)	94	0.044	(0.007)	0.046	(0.006)	0.04	(0.005)
45	0.046	(0.005)	0.049	(0.004)	0.053	(0.004)	95	0.042	(0.007)	0.046	(0.006)	0.042	(0.006)
46	0.047	(0.005)	0.05	(0.004)	0.054	(0.004)	96	0.044	(0.007)	0.046	(0.006)	0.046	(0.006)
47	0.044	(0.005)	0.052	(0.004)	0.055	(0.004)	97	0.046	(0.008)	0.043	(0.007)	0.047	(0.006)
48	0.045	(0.005)	0.051	(0.004)	0.055	(0.004)	98	0.045	(0.009)	0.041	(0.007)	0.045	(0.006)
49	0.048	(0.005)	0.052	(0.004)	0.053	(0.004)	99	0.043	(0.01)	0.047	(0.008)	0.044	(0.007)
50	0.048	(0.005)	0.051	(0.004)	0.055	(0.004)	100	0.034	(0.011)	0.045	(0.008)	0.042	(0.007)

Note: Point estimates and standard errors as reported in Figure 5b ($k = 7.5$) and its robustness ($k = 5$ and $k = 10$), where k defines the interval $[x - k; x + k]$ of the conditioning variable.

Table A.4: Estimates of λ^{LF} across the income distribution of generation t_{-1}

Pct	$k=5$		$k=7.5$		$k=10$		Pct	$k=5$		$k=7.5$		$k=10$	
	β	S.E.	β	S.E.	β	S.E.		β	S.E.	β	S.E.	β	S.E.
1	0.597	(0.047)	0.59	(0.03)	0.619	(0.03)	51	0.462	(0.031)	0.45	(0.027)	0.475	(0.021)
2	0.58	(0.038)	0.596	(0.035)	0.628	(0.028)	52	0.471	(0.031)	0.462	(0.024)	0.465	(0.022)
3	0.59	(0.037)	0.606	(0.028)	0.629	(0.028)	53	0.488	(0.031)	0.471	(0.027)	0.47	(0.021)
4	0.592	(0.036)	0.616	(0.028)	0.639	(0.027)	54	0.471	(0.032)	0.48	(0.022)	0.478	(0.022)
5	0.599	(0.036)	0.625	(0.027)	0.644	(0.026)	55	0.483	(0.027)	0.479	(0.025)	0.474	(0.02)
6	0.6	(0.034)	0.636	(0.029)	0.642	(0.026)	56	0.495	(0.026)	0.493	(0.024)	0.475	(0.023)
7	0.597	(0.033)	0.639	(0.028)	0.644	(0.024)	57	0.497	(0.029)	0.486	(0.026)	0.479	(0.023)
8	0.597	(0.028)	0.646	(0.026)	0.645	(0.021)	58	0.499	(0.027)	0.49	(0.023)	0.492	(0.022)
9	0.617	(0.031)	0.621	(0.023)	0.656	(0.022)	59	0.487	(0.029)	0.486	(0.026)	0.486	(0.02)
10	0.621	(0.031)	0.615	(0.023)	0.651	(0.02)	60	0.493	(0.029)	0.493	(0.024)	0.483	(0.02)
11	0.607	(0.035)	0.626	(0.029)	0.638	(0.02)	61	0.483	(0.026)	0.489	(0.026)	0.484	(0.022)
12	0.617	(0.031)	0.629	(0.025)	0.626	(0.022)	62	0.471	(0.035)	0.481	(0.025)	0.482	(0.023)
13	0.607	(0.033)	0.617	(0.026)	0.62	(0.019)	63	0.48	(0.03)	0.483	(0.026)	0.471	(0.02)
14	0.624	(0.029)	0.607	(0.023)	0.617	(0.024)	64	0.488	(0.028)	0.473	(0.029)	0.457	(0.022)
15	0.599	(0.029)	0.608	(0.024)	0.604	(0.022)	65	0.465	(0.032)	0.467	(0.026)	0.465	(0.022)
16	0.588	(0.026)	0.597	(0.025)	0.6	(0.021)	66	0.46	(0.037)	0.453	(0.025)	0.451	(0.021)
17	0.574	(0.025)	0.581	(0.023)	0.597	(0.019)	67	0.456	(0.031)	0.443	(0.027)	0.436	(0.023)
18	0.565	(0.027)	0.568	(0.023)	0.582	(0.021)	68	0.43	(0.034)	0.432	(0.03)	0.434	(0.022)
19	0.553	(0.027)	0.57	(0.024)	0.579	(0.022)	69	0.409	(0.037)	0.418	(0.028)	0.449	(0.023)
20	0.532	(0.028)	0.548	(0.022)	0.563	(0.018)	70	0.42	(0.039)	0.415	(0.032)	0.444	(0.023)
21	0.545	(0.024)	0.54	(0.028)	0.547	(0.018)	71	0.406	(0.032)	0.425	(0.028)	0.436	(0.028)
22	0.53	(0.03)	0.537	(0.024)	0.54	(0.022)	72	0.38	(0.042)	0.425	(0.03)	0.438	(0.024)
23	0.522	(0.029)	0.524	(0.026)	0.543	(0.02)	73	0.378	(0.045)	0.419	(0.025)	0.431	(0.026)
24	0.491	(0.031)	0.512	(0.021)	0.539	(0.02)	74	0.387	(0.039)	0.428	(0.026)	0.422	(0.026)
25	0.494	(0.028)	0.519	(0.026)	0.533	(0.018)	75	0.419	(0.037)	0.414	(0.03)	0.415	(0.024)
26	0.474	(0.034)	0.522	(0.024)	0.536	(0.02)	76	0.409	(0.034)	0.412	(0.036)	0.412	(0.026)
27	0.474	(0.031)	0.506	(0.023)	0.527	(0.021)	77	0.408	(0.045)	0.409	(0.029)	0.401	(0.027)
28	0.497	(0.032)	0.499	(0.025)	0.526	(0.017)	78	0.425	(0.04)	0.401	(0.028)	0.399	(0.028)
29	0.502	(0.028)	0.507	(0.025)	0.505	(0.021)	79	0.431	(0.041)	0.387	(0.032)	0.399	(0.027)
30	0.507	(0.022)	0.504	(0.022)	0.501	(0.02)	80	0.408	(0.042)	0.397	(0.031)	0.417	(0.027)
31	0.512	(0.029)	0.507	(0.021)	0.504	(0.021)	81	0.407	(0.039)	0.405	(0.033)	0.406	(0.029)
32	0.502	(0.026)	0.499	(0.025)	0.509	(0.019)	82	0.416	(0.04)	0.418	(0.03)	0.402	(0.029)
33	0.509	(0.028)	0.507	(0.025)	0.507	(0.019)	83	0.416	(0.035)	0.429	(0.03)	0.418	(0.023)
34	0.506	(0.03)	0.505	(0.025)	0.498	(0.019)	84	0.405	(0.045)	0.419	(0.032)	0.424	(0.031)
35	0.491	(0.032)	0.511	(0.023)	0.497	(0.02)	85	0.397	(0.039)	0.424	(0.03)	0.425	(0.027)
36	0.516	(0.03)	0.509	(0.026)	0.494	(0.023)	86	0.382	(0.044)	0.422	(0.03)	0.437	(0.027)
37	0.53	(0.03)	0.495	(0.027)	0.488	(0.02)	87	0.377	(0.047)	0.421	(0.028)	0.444	(0.027)
38	0.5	(0.03)	0.489	(0.024)	0.486	(0.019)	88	0.39	(0.04)	0.405	(0.037)	0.44	(0.028)
39	0.479	(0.032)	0.499	(0.022)	0.484	(0.021)	89	0.387	(0.042)	0.426	(0.031)	0.427	(0.027)
40	0.472	(0.031)	0.481	(0.026)	0.476	(0.022)	90	0.419	(0.04)	0.416	(0.035)	0.414	(0.034)
41	0.457	(0.035)	0.46	(0.026)	0.485	(0.021)	91	0.452	(0.038)	0.406	(0.033)	0.414	(0.033)
42	0.456	(0.032)	0.458	(0.024)	0.484	(0.022)	92	0.458	(0.037)	0.409	(0.035)	0.414	(0.031)
43	0.443	(0.038)	0.459	(0.026)	0.469	(0.023)	93	0.446	(0.047)	0.424	(0.033)	0.409	(0.035)
44	0.447	(0.031)	0.454	(0.028)	0.467	(0.02)	94	0.422	(0.039)	0.436	(0.04)	0.408	(0.035)
45	0.44	(0.033)	0.449	(0.026)	0.463	(0.021)	95	0.417	(0.046)	0.436	(0.037)	0.417	(0.033)
46	0.441	(0.033)	0.455	(0.025)	0.465	(0.023)	96	0.423	(0.043)	0.438	(0.033)	0.436	(0.031)
47	0.424	(0.034)	0.46	(0.024)	0.468	(0.022)	97	0.44	(0.05)	0.421	(0.043)	0.441	(0.036)
48	0.428	(0.039)	0.45	(0.023)	0.471	(0.024)	98	0.436	(0.052)	0.412	(0.044)	0.434	(0.042)
49	0.447	(0.031)	0.452	(0.026)	0.464	(0.022)	99	0.431	(0.06)	0.439	(0.044)	0.425	(0.041)
50	0.437	(0.03)	0.448	(0.028)	0.47	(0.021)	100	0.383	(0.083)	0.435	(0.056)	0.417	(0.049)

Note: Point estimates and standard errors as reported in Figure 6 ($k = 7.5$) and its robustness ($k = 5$ and $k = 10$), where k defines the interval $[x - k; x + k]$ of the conditioning variable.

Table A.5: Estimates of $\widehat{\beta}^{LF}_{siblings}$ across the wealth distribution of generation t_{-2}

Pct	$k=5$		$k=7.5$		$k=10$		Pct	$k=5$		$k=7.5$		$k=10$	
	β	S.E.	β	S.E.	β	S.E.	β	S.E.	β	S.E.	β	S.E.	
1	0.319	(0.009)	0.314	(0.007)	0.311	(0.007)	51	0.271	(0.007)	0.275	(0.005)	0.277	(0.005)
2	0.319	(0.008)	0.313	(0.007)	0.315	(0.006)	52	0.271	(0.007)	0.274	(0.006)	0.277	(0.005)
3	0.313	(0.008)	0.311	(0.007)	0.314	(0.006)	53	0.272	(0.007)	0.274	(0.006)	0.275	(0.005)
4	0.31	(0.007)	0.314	(0.006)	0.319	(0.006)	54	0.271	(0.007)	0.276	(0.006)	0.277	(0.005)
5	0.311	(0.007)	0.314	(0.006)	0.319	(0.006)	55	0.276	(0.007)	0.276	(0.006)	0.275	(0.005)
6	0.304	(0.007)	0.316	(0.006)	0.319	(0.005)	56	0.28	(0.007)	0.275	(0.006)	0.276	(0.005)
7	0.305	(0.007)	0.319	(0.006)	0.322	(0.005)	57	0.279	(0.007)	0.277	(0.006)	0.278	(0.005)
8	0.302	(0.007)	0.319	(0.006)	0.319	(0.005)	58	0.276	(0.007)	0.278	(0.006)	0.28	(0.005)
9	0.311	(0.007)	0.313	(0.006)	0.32	(0.005)	59	0.28	(0.007)	0.281	(0.006)	0.278	(0.005)
10	0.313	(0.007)	0.314	(0.006)	0.32	(0.005)	60	0.279	(0.007)	0.28	(0.006)	0.278	(0.005)
11	0.311	(0.007)	0.312	(0.006)	0.316	(0.005)	61	0.282	(0.007)	0.28	(0.006)	0.278	(0.005)
12	0.314	(0.007)	0.313	(0.006)	0.313	(0.005)	62	0.286	(0.007)	0.281	(0.006)	0.277	(0.005)
13	0.311	(0.007)	0.311	(0.006)	0.312	(0.005)	63	0.286	(0.007)	0.283	(0.006)	0.277	(0.005)
14	0.315	(0.007)	0.309	(0.006)	0.312	(0.005)	64	0.284	(0.007)	0.278	(0.006)	0.278	(0.005)
15	0.313	(0.007)	0.31	(0.006)	0.312	(0.005)	65	0.281	(0.007)	0.278	(0.006)	0.277	(0.005)
16	0.318	(0.007)	0.312	(0.006)	0.308	(0.005)	66	0.276	(0.007)	0.277	(0.006)	0.278	(0.005)
17	0.312	(0.007)	0.311	(0.006)	0.306	(0.005)	67	0.276	(0.007)	0.279	(0.006)	0.278	(0.005)
18	0.313	(0.007)	0.311	(0.006)	0.306	(0.005)	68	0.279	(0.007)	0.277	(0.006)	0.276	(0.005)
19	0.307	(0.007)	0.307	(0.006)	0.306	(0.005)	69	0.276	(0.007)	0.275	(0.006)	0.277	(0.005)
20	0.305	(0.007)	0.306	(0.006)	0.304	(0.005)	70	0.276	(0.007)	0.276	(0.006)	0.276	(0.005)
21	0.299	(0.007)	0.303	(0.006)	0.305	(0.005)	71	0.274	(0.007)	0.275	(0.006)	0.273	(0.005)
22	0.293	(0.007)	0.298	(0.006)	0.303	(0.005)	72	0.27	(0.007)	0.274	(0.006)	0.273	(0.005)
23	0.295	(0.007)	0.295	(0.006)	0.301	(0.005)	73	0.265	(0.007)	0.273	(0.006)	0.275	(0.005)
24	0.293	(0.007)	0.295	(0.006)	0.298	(0.005)	74	0.269	(0.007)	0.271	(0.006)	0.273	(0.005)
25	0.292	(0.007)	0.293	(0.006)	0.296	(0.005)	75	0.271	(0.007)	0.268	(0.006)	0.272	(0.005)
26	0.291	(0.007)	0.292	(0.006)	0.295	(0.005)	76	0.271	(0.007)	0.269	(0.006)	0.272	(0.005)
27	0.29	(0.007)	0.292	(0.006)	0.295	(0.005)	77	0.27	(0.007)	0.269	(0.006)	0.271	(0.005)
28	0.287	(0.007)	0.29	(0.006)	0.295	(0.005)	78	0.272	(0.007)	0.269	(0.006)	0.27	(0.005)
29	0.287	(0.007)	0.293	(0.006)	0.294	(0.005)	79	0.269	(0.007)	0.273	(0.005)	0.272	(0.005)
30	0.284	(0.007)	0.292	(0.006)	0.291	(0.005)	80	0.267	(0.007)	0.272	(0.006)	0.272	(0.005)
31	0.29	(0.007)	0.292	(0.006)	0.29	(0.005)	81	0.27	(0.007)	0.273	(0.005)	0.273	(0.005)
32	0.295	(0.007)	0.289	(0.006)	0.288	(0.005)	82	0.271	(0.007)	0.275	(0.005)	0.272	(0.005)
33	0.293	(0.007)	0.286	(0.006)	0.288	(0.005)	83	0.273	(0.007)	0.272	(0.005)	0.272	(0.005)
34	0.293	(0.007)	0.288	(0.006)	0.286	(0.005)	84	0.273	(0.007)	0.269	(0.005)	0.272	(0.005)
35	0.286	(0.007)	0.287	(0.005)	0.287	(0.005)	85	0.271	(0.007)	0.268	(0.005)	0.271	(0.005)
36	0.289	(0.007)	0.285	(0.005)	0.286	(0.005)	86	0.275	(0.007)	0.271	(0.005)	0.271	(0.005)
37	0.285	(0.007)	0.286	(0.005)	0.286	(0.005)	87	0.272	(0.007)	0.271	(0.005)	0.272	(0.005)
38	0.289	(0.007)	0.287	(0.005)	0.285	(0.005)	88	0.269	(0.007)	0.27	(0.005)	0.272	(0.005)
39	0.284	(0.007)	0.284	(0.005)	0.284	(0.005)	89	0.272	(0.007)	0.27	(0.005)	0.272	(0.005)
40	0.29	(0.007)	0.282	(0.005)	0.282	(0.005)	90	0.273	(0.006)	0.274	(0.005)	0.274	(0.005)
41	0.282	(0.007)	0.285	(0.005)	0.281	(0.005)	91	0.269	(0.006)	0.272	(0.005)	0.276	(0.005)
42	0.277	(0.007)	0.281	(0.005)	0.28	(0.005)	92	0.271	(0.006)	0.274	(0.005)	0.275	(0.005)
43	0.276	(0.007)	0.278	(0.005)	0.282	(0.005)	93	0.271	(0.006)	0.276	(0.005)	0.274	(0.005)
44	0.275	(0.007)	0.274	(0.005)	0.279	(0.005)	94	0.269	(0.006)	0.274	(0.006)	0.275	(0.005)
45	0.277	(0.007)	0.276	(0.005)	0.279	(0.005)	95	0.271	(0.006)	0.275	(0.006)	0.276	(0.005)
46	0.273	(0.007)	0.273	(0.005)	0.276	(0.005)	96	0.274	(0.007)	0.275	(0.006)	0.274	(0.005)
47	0.274	(0.007)	0.272	(0.005)	0.274	(0.005)	97	0.278	(0.007)	0.272	(0.006)	0.274	(0.006)
48	0.274	(0.007)	0.273	(0.005)	0.274	(0.005)	98	0.279	(0.008)	0.275	(0.007)	0.275	(0.006)
49	0.274	(0.007)	0.275	(0.005)	0.273	(0.005)	99	0.277	(0.008)	0.276	(0.007)	0.273	(0.006)
50	0.269	(0.007)	0.275	(0.005)	0.276	(0.005)	100	0.279	(0.009)	0.279	(0.007)	0.271	(0.006)

Note: Point estimates and standard errors as reported in Figure 8a ($k = 7.5$) and its robustness ($k = 5$ and $k = 10$), where k defines the interval $[x - k; x + k]$ of the conditioning variable.

Table A.6: Estimates of $\widehat{\beta}^{LF}_{cousins}$ across the wealth distribution of generation t_{-2}

Pct	$k=5$		$k=7.5$		$k=10$		Pct	$k=5$		$k=7.5$		$k=10$	
	β	S.E.	β	S.E.	β	S.E.	β	S.E.	β	S.E.	β	S.E.	
1	0.156	(0.008)	0.143	(0.006)	0.141	(0.006)	51	0.099	(0.006)	0.091	(0.005)	0.095	(0.004)
2	0.151	(0.007)	0.141	(0.006)	0.14	(0.006)	52	0.095	(0.006)	0.094	(0.005)	0.097	(0.004)
3	0.143	(0.007)	0.14	(0.006)	0.136	(0.005)	53	0.091	(0.006)	0.096	(0.005)	0.094	(0.004)
4	0.142	(0.006)	0.139	(0.006)	0.137	(0.005)	54	0.095	(0.006)	0.098	(0.005)	0.094	(0.004)
5	0.14	(0.006)	0.139	(0.005)	0.135	(0.005)	55	0.097	(0.006)	0.097	(0.005)	0.094	(0.004)
6	0.135	(0.006)	0.138	(0.005)	0.134	(0.005)	56	0.1	(0.006)	0.098	(0.005)	0.093	(0.004)
7	0.127	(0.006)	0.137	(0.005)	0.134	(0.005)	57	0.1	(0.006)	0.095	(0.005)	0.094	(0.004)
8	0.124	(0.006)	0.13	(0.005)	0.134	(0.005)	58	0.096	(0.006)	0.092	(0.005)	0.091	(0.004)
9	0.127	(0.006)	0.126	(0.005)	0.134	(0.004)	59	0.094	(0.006)	0.093	(0.005)	0.09	(0.004)
10	0.12	(0.006)	0.123	(0.005)	0.132	(0.004)	60	0.094	(0.006)	0.091	(0.005)	0.09	(0.004)
11	0.11	(0.006)	0.126	(0.005)	0.127	(0.004)	61	0.087	(0.006)	0.088	(0.005)	0.091	(0.004)
12	0.108	(0.006)	0.121	(0.005)	0.121	(0.004)	62	0.091	(0.006)	0.087	(0.005)	0.09	(0.004)
13	0.108	(0.006)	0.115	(0.005)	0.12	(0.004)	63	0.091	(0.006)	0.087	(0.005)	0.086	(0.004)
14	0.106	(0.006)	0.107	(0.005)	0.12	(0.004)	64	0.085	(0.006)	0.089	(0.005)	0.085	(0.004)
15	0.103	(0.006)	0.106	(0.005)	0.117	(0.004)	65	0.082	(0.006)	0.091	(0.005)	0.084	(0.004)
16	0.102	(0.006)	0.108	(0.005)	0.111	(0.004)	66	0.082	(0.006)	0.085	(0.005)	0.079	(0.004)
17	0.101	(0.006)	0.104	(0.005)	0.108	(0.004)	67	0.078	(0.006)	0.082	(0.005)	0.082	(0.004)
18	0.101	(0.006)	0.103	(0.005)	0.105	(0.004)	68	0.077	(0.006)	0.077	(0.005)	0.083	(0.004)
19	0.098	(0.006)	0.105	(0.005)	0.104	(0.004)	69	0.076	(0.006)	0.073	(0.005)	0.082	(0.004)
20	0.102	(0.006)	0.101	(0.005)	0.104	(0.004)	70	0.072	(0.006)	0.073	(0.005)	0.083	(0.004)
21	0.103	(0.006)	0.101	(0.005)	0.105	(0.004)	71	0.072	(0.006)	0.073	(0.005)	0.081	(0.004)
22	0.102	(0.006)	0.1	(0.005)	0.105	(0.004)	72	0.072	(0.006)	0.079	(0.005)	0.078	(0.004)
23	0.094	(0.006)	0.103	(0.005)	0.104	(0.004)	73	0.074	(0.006)	0.083	(0.005)	0.082	(0.004)
24	0.096	(0.006)	0.101	(0.005)	0.103	(0.004)	74	0.079	(0.006)	0.081	(0.005)	0.088	(0.004)
25	0.101	(0.006)	0.101	(0.005)	0.102	(0.004)	75	0.084	(0.006)	0.081	(0.005)	0.089	(0.004)
26	0.102	(0.006)	0.1	(0.005)	0.108	(0.004)	76	0.082	(0.006)	0.092	(0.005)	0.094	(0.004)
27	0.103	(0.006)	0.1	(0.005)	0.109	(0.004)	77	0.078	(0.006)	0.093	(0.005)	0.094	(0.004)
28	0.1	(0.006)	0.111	(0.005)	0.107	(0.004)	78	0.086	(0.006)	0.095	(0.005)	0.096	(0.004)
29	0.101	(0.006)	0.11	(0.005)	0.105	(0.004)	79	0.099	(0.006)	0.095	(0.005)	0.098	(0.004)
30	0.1	(0.006)	0.11	(0.005)	0.105	(0.004)	80	0.105	(0.006)	0.097	(0.005)	0.096	(0.004)
31	0.112	(0.006)	0.106	(0.005)	0.104	(0.004)	81	0.114	(0.006)	0.101	(0.005)	0.097	(0.004)
32	0.113	(0.006)	0.106	(0.005)	0.103	(0.004)	82	0.111	(0.006)	0.101	(0.005)	0.097	(0.004)
33	0.117	(0.006)	0.102	(0.005)	0.105	(0.004)	83	0.114	(0.006)	0.105	(0.005)	0.1	(0.004)
34	0.112	(0.006)	0.102	(0.005)	0.104	(0.004)	84	0.113	(0.006)	0.109	(0.005)	0.099	(0.004)
35	0.107	(0.006)	0.103	(0.005)	0.103	(0.004)	85	0.106	(0.006)	0.108	(0.005)	0.099	(0.004)
36	0.104	(0.006)	0.107	(0.005)	0.101	(0.004)	86	0.108	(0.006)	0.107	(0.005)	0.101	(0.004)
37	0.101	(0.006)	0.104	(0.005)	0.1	(0.004)	87	0.111	(0.006)	0.103	(0.005)	0.098	(0.004)
38	0.108	(0.006)	0.102	(0.005)	0.103	(0.004)	88	0.111	(0.006)	0.098	(0.005)	0.099	(0.004)
39	0.103	(0.006)	0.101	(0.005)	0.101	(0.004)	89	0.096	(0.006)	0.099	(0.005)	0.096	(0.004)
40	0.102	(0.006)	0.102	(0.005)	0.1	(0.004)	90	0.092	(0.006)	0.097	(0.005)	0.096	(0.004)
41	0.086	(0.006)	0.101	(0.005)	0.099	(0.004)	91	0.087	(0.006)	0.087	(0.005)	0.094	(0.004)
42	0.084	(0.006)	0.098	(0.005)	0.099	(0.004)	92	0.083	(0.006)	0.086	(0.005)	0.096	(0.004)
43	0.086	(0.006)	0.091	(0.005)	0.101	(0.004)	93	0.082	(0.006)	0.086	(0.005)	0.095	(0.004)
44	0.088	(0.006)	0.088	(0.005)	0.099	(0.004)	94	0.077	(0.006)	0.084	(0.005)	0.088	(0.004)
45	0.09	(0.006)	0.089	(0.005)	0.098	(0.004)	95	0.082	(0.006)	0.082	(0.005)	0.089	(0.005)
46	0.092	(0.006)	0.091	(0.005)	0.093	(0.004)	96	0.076	(0.006)	0.082	(0.005)	0.083	(0.005)
47	0.094	(0.006)	0.092	(0.005)	0.088	(0.004)	97	0.074	(0.006)	0.081	(0.005)	0.083	(0.005)
48	0.092	(0.006)	0.095	(0.005)	0.089	(0.004)	98	0.069	(0.007)	0.081	(0.006)	0.082	(0.005)
49	0.094	(0.006)	0.093	(0.005)	0.092	(0.004)	99	0.072	(0.007)	0.076	(0.006)	0.079	(0.005)
50	0.093	(0.006)	0.091	(0.005)	0.093	(0.004)	100	0.078	(0.008)	0.071	(0.007)	0.082	(0.006)

Note: Point estimates and standard errors as reported in Figure 8b ($k = 7.5$) and its robustness ($k = 5$ and $k = 10$), where k defines the interval $[x - k; x + k]$ of the conditioning variable.

Table A.7: Estimates of λ^{LF} across the wealth distribution of generation t_{-2}

Pct	$k=5$		$k=7.5$		$k=10$		Pct	$k=5$		$k=7.5$		$k=10$	
	β	S.E.	β	S.E.	β	S.E.		β	S.E.	β	S.E.	β	S.E.
1	0.699	(0.031)	0.675	(0.025)	0.674	(0.024)	51	0.606	(0.028)	0.576	(0.019)	0.587	(0.018)
2	0.687	(0.029)	0.672	(0.025)	0.667	(0.023)	52	0.592	(0.026)	0.586	(0.021)	0.592	(0.019)
3	0.677	(0.026)	0.671	(0.024)	0.658	(0.023)	53	0.579	(0.025)	0.592	(0.019)	0.585	(0.02)
4	0.677	(0.025)	0.666	(0.024)	0.655	(0.022)	54	0.592	(0.024)	0.596	(0.021)	0.581	(0.017)
5	0.669	(0.026)	0.665	(0.021)	0.651	(0.021)	55	0.594	(0.025)	0.594	(0.021)	0.584	(0.021)
6	0.666	(0.028)	0.66	(0.023)	0.649	(0.02)	56	0.597	(0.027)	0.597	(0.017)	0.58	(0.021)
7	0.646	(0.024)	0.654	(0.019)	0.646	(0.019)	57	0.599	(0.023)	0.586	(0.021)	0.581	(0.019)
8	0.64	(0.026)	0.64	(0.023)	0.647	(0.02)	58	0.591	(0.025)	0.576	(0.018)	0.57	(0.018)
9	0.638	(0.026)	0.636	(0.019)	0.647	(0.019)	59	0.578	(0.024)	0.575	(0.024)	0.569	(0.018)
10	0.618	(0.029)	0.627	(0.021)	0.643	(0.018)	60	0.582	(0.021)	0.57	(0.02)	0.568	(0.02)
11	0.596	(0.023)	0.635	(0.023)	0.632	(0.019)	61	0.557	(0.025)	0.561	(0.023)	0.572	(0.02)
12	0.586	(0.023)	0.621	(0.025)	0.622	(0.021)	62	0.565	(0.028)	0.558	(0.022)	0.568	(0.016)
13	0.59	(0.025)	0.609	(0.022)	0.622	(0.016)	63	0.563	(0.025)	0.556	(0.02)	0.558	(0.019)
14	0.581	(0.026)	0.588	(0.019)	0.619	(0.017)	64	0.546	(0.029)	0.565	(0.02)	0.554	(0.019)
15	0.572	(0.025)	0.586	(0.018)	0.612	(0.02)	65	0.541	(0.026)	0.573	(0.023)	0.549	(0.02)
16	0.567	(0.021)	0.587	(0.019)	0.6	(0.015)	66	0.544	(0.028)	0.553	(0.022)	0.534	(0.018)
17	0.568	(0.024)	0.579	(0.018)	0.595	(0.018)	67	0.531	(0.028)	0.541	(0.022)	0.544	(0.019)
18	0.569	(0.024)	0.575	(0.021)	0.585	(0.017)	68	0.526	(0.026)	0.526	(0.022)	0.548	(0.019)
19	0.565	(0.025)	0.585	(0.019)	0.582	(0.018)	69	0.526	(0.026)	0.514	(0.024)	0.544	(0.02)
20	0.577	(0.027)	0.576	(0.02)	0.586	(0.017)	70	0.513	(0.03)	0.515	(0.024)	0.548	(0.019)
21	0.586	(0.025)	0.576	(0.019)	0.586	(0.019)	71	0.511	(0.027)	0.516	(0.026)	0.546	(0.018)
22	0.589	(0.024)	0.579	(0.02)	0.589	(0.018)	72	0.517	(0.03)	0.537	(0.022)	0.535	(0.02)
23	0.565	(0.024)	0.591	(0.021)	0.586	(0.017)	73	0.528	(0.029)	0.55	(0.025)	0.547	(0.021)
24	0.571	(0.025)	0.585	(0.021)	0.587	(0.019)	74	0.542	(0.028)	0.547	(0.026)	0.567	(0.024)
25	0.588	(0.025)	0.588	(0.022)	0.587	(0.015)	75	0.557	(0.027)	0.549	(0.022)	0.574	(0.025)
26	0.592	(0.026)	0.586	(0.021)	0.604	(0.019)	76	0.552	(0.028)	0.585	(0.03)	0.589	(0.023)
27	0.596	(0.023)	0.585	(0.021)	0.607	(0.018)	77	0.535	(0.027)	0.587	(0.032)	0.588	(0.027)
28	0.591	(0.024)	0.617	(0.024)	0.603	(0.019)	78	0.563	(0.026)	0.596	(0.031)	0.596	(0.026)
29	0.594	(0.024)	0.612	(0.027)	0.597	(0.021)	79	0.605	(0.044)	0.589	(0.028)	0.599	(0.024)
30	0.593	(0.025)	0.615	(0.02)	0.6	(0.018)	80	0.627	(0.037)	0.597	(0.032)	0.594	(0.027)
31	0.621	(0.028)	0.603	(0.02)	0.598	(0.016)	81	0.65	(0.04)	0.609	(0.031)	0.597	(0.025)
32	0.618	(0.029)	0.605	(0.027)	0.597	(0.019)	82	0.64	(0.034)	0.605	(0.031)	0.598	(0.025)
33	0.633	(0.03)	0.598	(0.024)	0.603	(0.02)	83	0.645	(0.038)	0.621	(0.031)	0.608	(0.025)
34	0.617	(0.029)	0.595	(0.024)	0.602	(0.023)	84	0.642	(0.037)	0.635	(0.029)	0.604	(0.028)
35	0.612	(0.023)	0.599	(0.022)	0.598	(0.02)	85	0.624	(0.045)	0.633	(0.028)	0.605	(0.022)
36	0.599	(0.036)	0.612	(0.023)	0.595	(0.02)	86	0.626	(0.043)	0.629	(0.033)	0.612	(0.022)
37	0.596	(0.034)	0.602	(0.025)	0.59	(0.019)	87	0.64	(0.039)	0.616	(0.033)	0.601	(0.026)
38	0.612	(0.032)	0.595	(0.024)	0.602	(0.021)	88	0.642	(0.043)	0.601	(0.034)	0.602	(0.024)
39	0.603	(0.029)	0.595	(0.024)	0.596	(0.022)	89	0.593	(0.022)	0.605	(0.031)	0.594	(0.024)
40	0.593	(0.035)	0.6	(0.024)	0.596	(0.018)	90	0.582	(0.025)	0.596	(0.029)	0.593	(0.025)
41	0.552	(0.028)	0.595	(0.024)	0.594	(0.019)	91	0.567	(0.03)	0.564	(0.019)	0.585	(0.027)
42	0.55	(0.026)	0.592	(0.029)	0.595	(0.025)	92	0.555	(0.022)	0.561	(0.02)	0.591	(0.031)
43	0.56	(0.021)	0.574	(0.022)	0.598	(0.02)	93	0.551	(0.027)	0.56	(0.02)	0.59	(0.029)
44	0.565	(0.024)	0.568	(0.018)	0.594	(0.024)	94	0.534	(0.028)	0.554	(0.021)	0.565	(0.021)
45	0.571	(0.025)	0.567	(0.019)	0.592	(0.023)	95	0.551	(0.027)	0.547	(0.027)	0.566	(0.024)
46	0.581	(0.024)	0.576	(0.021)	0.579	(0.018)	96	0.527	(0.029)	0.547	(0.026)	0.55	(0.022)
47	0.584	(0.024)	0.582	(0.022)	0.568	(0.019)	97	0.515	(0.028)	0.547	(0.029)	0.551	(0.022)
48	0.579	(0.023)	0.588	(0.019)	0.569	(0.018)	98	0.497	(0.033)	0.543	(0.028)	0.546	(0.026)
49	0.586	(0.026)	0.582	(0.02)	0.579	(0.018)	99	0.508	(0.037)	0.524	(0.028)	0.54	(0.023)
50	0.589	(0.026)	0.575	(0.02)	0.581	(0.016)	100	0.529	(0.043)	0.504	(0.032)	0.551	(0.028)

Note: Point estimates and standard errors as reported in Figure 9 ($k = 7.5$) and its robustness ($k = 5$ and $k = 10$), where k defines the interval $[x - k; x + k]$ of the conditioning variable.

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