Stability and persistence of intergenerational wealth formation: Evidence from Danish wealth records of three generations*

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Abstract

This paper provides novel insights on intergenerational wealth mobility using Danish wealth records. Non-parametric evidence reveals an almost linear relationship between wealth ranks of children and parents with a slope of 1/4, except at the very top of the distribution where the slope is much higher. The wealth relationship is surprisingly stable across subsamples and after controlling for key socioeconomic outcomes. This is consistent with a unidimensional latent factor governing a substantial part of the complicated underlying wealth dynamics and wealth of past generations summarizing almost all relevant information when predicting child wealth. Wealth of grandparents has very strong explanatory power conditional on any level of parental wealth showing that standard two-generation measures severely understate the extent of intergenerational persistence in wealth formation. (JEL classification: D31)

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1 Introduction

A voluminous literature has analyzed how economic well-being is related across generations by studying intergenerational linkages in outcomes such as income, education, and health (see surveys by Solon 1999 and Black and Devereux 2011). Only few studies exist on wealth (e.g., Charles and Hurst 2003) even though variation in wealth across individuals at a given age level may be one of the best proxies for the variation in lifetime economic resources and for the (in)equality of opportunities.[1]

Correlation of wealth across generations may be driven by mechanical correlation in innate abilities across generations and deliberate parental investments in human capital of children as in the standard theory of intergenerational income mobility by Becker and Tomes (1979, 1986), but it may also reflect direct transfers of wealth from the previous generations (inter vivos or through inheritance) and transmissions of savings behavior from parents to children (Stiglitz 1969). Thus, formation of wealth across generations may summarize many different intergenerational channels important for individual well-being. Furthermore, assumptions about intergenerational transmission of wealth at the top of the distribution underlie concerns of Piketty (2014) about self-perpetuating inequality, and intergenerational linkages elsewhere in the distribution may be important for understanding opportunities for entrepreneurship, retirement savings, and financial vulnerability.

In this paper, we provide novel insights on intergenerational wealth mobility using high-quality wealth records from Denmark covering over 1 million child-parents pairs and 100,000 child-parent-grandparent linkages.

First, we look at the basic relationship between wealth of children and wealth of parents. We start with a non-parametric analysis of the relationship between the positions of children and parents in the wealth distribution measured by within-cohort ranks.[2] This evidence reveals an almost linear relationship with the exception of at the very top of the parental wealth distribution (Figure 1). Parents in percentile 10 of the parental wealth distribution have on average children in percentile 40 of the children's wealth distribution, while parents in percentile 90 have children in percentile 60, and within this range moving up one percentile in the parental wealth distribution is

[1] Charles and Hurst (2003) use wealth data from the Panel Study of Income Dynamics (PSID) to estimate the elasticity of child wealth with respect to parental wealth for the United States. They also review a few older studies looking at the intergenerational correlation of wealth. These studies have looked at small non-representative samples with few observations and poor data quality.

[2] The rank measure—also used in the recent study of income mobility in the US by Chetty et al. (2014)—has several advantages compared to other transformations of the data. In particular, it works well with zero and negative observations, which are common in wealth data, in contrast to the logarithmic transformation used to estimate the intergenerational elasticity.

associated with a 1/4 percentile increase in the average position of children. The overall rank-rank slope, which equals the rank correlation coefficient, is also around 0.25. The same linear relationship is evident not just for the mean, but also elsewhere in the distribution (illustrated for quantiles P25 and P75 in Figure 1).

In order to compare with previous work, we also estimate the (age-adjusted) intergenerational wealth elasticity, which in our baseline specification equals 0.27. Charles and Hurst (2003) find an elasticity of 0.37 for the United States using the PSID survey data. The lower estimate for Denmark is not surprising. Denmark has a very homogeneous population and a high degree of redistribution, and comparative studies find that Denmark has a high intergenerational mobility in earnings/income compared to the US and many other countries (Björklund and Jäntti 2009; Chetty et al. 2014). When repeating our analysis for income, we find an almost completely linear rank-rank relationship with a slope around 0.15. Hence, wealth displays less mobility than income. This is in particular the case at the top of the distributions where child wealth is much more strongly related to parental wealth than is the case for income.

Second, we examine the stability of the association between child wealth and parental wealth. Our insight is that stability or lack of it is informative in itself. As described above, wealth formation across generations summarizes many potential intergenerational casual mechanisms, and we show theoretically how an estimate of the intergenerational wealth relationship is related in a complicated way to all of these different mechanisms. Disentangling and identifying the different mechanisms empirically is complicated. Moreover, the association between child wealth and parental wealth is expected a priori to vary across different samples, periods, and age groups and to be rather sensitive to the inclusion of other key economic outcomes, such as income level and education, in the empirical analysis. However, the non-parametric relationship turns out to be very stable, and the rank correlation coefficient estimates from these types of sensitivity analyses all lie in the range 0.20–0.25.[3] In our theoretical framework, we show that this stability of the intergenerational wealth relationship is consistent with a unidimensional latent factor ("ability") being the key driver behind all the underlying causal mechanisms determining the wealth formation across generations, and implying that wealth of parents summarizes all relevant information of parents (a sufficient statistic) needed to predict the wealth of children.

There may be long run forces that reduce or increase the strength of the child-parent wealth

[3] An exception is that the relationship strengthens following death of parents indicating an important role played by bequests.

relationship over time and generations. Recent research has documented substantial changes over the long run in top income shares, in the relative importance of capital and labor income at the top of the income distribution, and in the evolution of inheritance (Atkinson, Piketty, and Saez 2011; Piketty 2011, 2014). When we estimate a non-parametric relationship between parental wealth and grandparental wealth, we find that it is remarkably similar to the relationship between child wealth and parental wealth. Thus, in our data, the formation of wealth across generations is quite stable over time and generations.

Third, we study the persistence of intergenerational wealth formation by exploring the role of grandparental wealth conditional on parental wealth in explaining the wealth variation across children. We find strong non-parametric evidence of a large effect of grandparental wealth at all levels of parental wealth. Children with grandparents in the highest wealth quintile lie on average 9 percentiles higher in the child wealth distribution than children with grandparents in the lowest wealth quintile, and this effect is nearly the same at each percentile level of parental wealth. The effect is much larger than the impact of including additional information about parents in the analysis and is consistent with recent multiple generation studies on education and occupation also finding that standard measures of intergenerational mobility based on two generations underestimate the degree of persistence (Lindahl et al. 2014; Hällsten 2014).[4] It is also consistent with results from studies using an imputation method based on rare surnames to link families across multiple generations (Clark 2014; Clark and Cummins 2014).

Fourth, we focus on the very top of the distribution where our non-parametric evidence indicates a much stronger intergenerational relationship. We show that correlation of wealth ranks at the top in Denmark—one of the most egalitarian countries in the world—is in fact very strong.[5] The odds of ending up in top 1% of the wealth distribution is 16–17 percentage points higher if the parents belong to the top 1% group, which should be compared to the unconditional odds of 1%. This holds across all specifications showing that our conclusion concerning stability also applies when we zoom in on the top part of the distribution. If grandparents are also in the top 1% group

[4] One reason for the empirical results may be that the underlying processes relating wealth across generations have longer memory than just one generation, for example because grandparents have a direct impact on their grandchildren (Solon 2014). Another explanation could be that grandparents have no direct effects but that the coefficient on parental wealth is downward biased because of transitory dynamics or measurement error (Solon 1992), implying that grandparental wealth becomes significant in the regression. Against the last hypothesis, we find that our results are unchanged if we use one, three, five, or seven year averages of wealth in the analysis. Independent of the underlying explanation, the result reveals a much higher persistence in wealth formation across generations than what is obtained from the standard two-generation measures.

[5] The stronger relationship at the top of the wealth distribution compared to the overall average may reconcile why studies based on estate tax returns (Menchik 1979; Wahl 2003; Clark and Cummins 2014) find lower intergenerational wealth mobility than the study by Charles and Hurst (2003) based on a random survey sample of the population.

then the odds of the child getting into the top 1% group increases by another 13 percent. Thus, grandparental wealth also has very strong predictive power in the top part of the distribution.

The remaining part of the paper is organized as follows. Section 2 provides a theoretical framework to understand how the association of wealth between parents and children is related to underlying causal links between generations. Section 3 describes the construction of the data sets and provides summary statistics of key variables. Section 4 describes the results of the empirical analysis. Finally, Section 5 offers concluding remarks and an appendix provides additional details concerning the data and some additional empirical results.

2 A framework for understanding the (in)stability of intergenerational wealth links

We are interested in understanding the relationship between wealth (W)—or some monotone transformation of wealth, such as the natural logarithm or the rank in the overall distribution—of different generations. Let w_g denote the wealth of an individual in generation g after the transformation. In the empirical analysis, we estimate the association between w_g and w_{g-1}, both non-parametrically and, parsimoniously, as a linear regression of w_g on w_{g-1},

$$w_g = \beta_w w_{g-1} + \varepsilon_g, \tag{1}$$

where ε_g is the residual, and β_w is the intergenerational parameter of interest. Here and in what follows, we express all variables in terms of their deviation from the mean in order to eliminate the constant term. Obviously, β_w in Equation (1) is not a structural parameter, and the aim of this section is to obtain a deeper understanding of how estimates of β_w are related to underlying intergenerational causal mechanisms.

2.1 Factors influencing the intergenerational wealth relationship

We start by illustrating in a basic economic model different potential channels that may explain the intergenerational relationship in wealth. In a given year a, an individual of generation g earns income y_g^a, consumes c_g^a, receives bequests and transfers from the previous generation b_g^a, and gives transfers to the next generation q_g^a. It follows then from the budget constraint that the level of wealth of the individual is given by

$$W_g^a = W_g^{a-1}(1 + r_g^a) + y_g^a - c_g^a + b_g^a - q_g^a, \tag{2}$$

where r_g^a is the rate of return on savings for this individual.

Individuals maximize utility subject to the sequence of budget constraints (2) up to a maximum age A. We recognize heterogeneity of individuals and use ξ_g to index preferences and other constraints and uncertainty not otherwise incorporated in the budget constraint. Consequently, the level of wealth of an individual at age a may be expressed in terms of the parameters of the individual problem as

$$W_g^a\left(\{y_g^t\}_{t=0}^A, \{r_g^t\}_{t=0}^A, \{b_g^t\}_{t=0}^A, \{\xi_g^t\}_{t=0}^A\right). \tag{3}$$

In other words, wealth at any given age depends on income over the lifetime, realized rate of return, transfers from parents, preference parameters, and stochastic shocks in the past and, potentially, expected in the future ($t > a$).

The model analogue of β_w in Equation (1) would be $\frac{\Delta w_g}{\Delta w_{g-1}}$, however determining its value requires understanding how parental wealth W_{g-1} affects the determinants of W_g in Equation (3).

Wealth of parents does not enter directly as an argument of child wealth in Equation (3) but may influence or be correlated with the determinants of child's wealth for a number of reasons. By investigating the determinants of wealth in Equation (3), one can identify a number of channels why wealth could co-vary: (*i*) Income (y) of parents and children may be correlated, for example because of a mechanical correlation in innate ability levels or because of deliberate parental investments in child education as in the seminal work of Becker and Tomes (1979). (*ii*) Patience and risk taking behavior (ξ) may be correlated across generations and generate correlation in saving propensities and in average returns on savings (r). (*iii*) Transfers from parents (b) are a function of parents' own characteristics and hence correlated with parental wealth. Thus, a simple insight from this basic model is:

#1: Estimates of the intergenerational wealth parameter β_w in (1) reflect intergenerational linkages flowing through a mix of underlying channels that are responsible for variation in wealth.

2.2 Statistical framework

In order to make progress, we simplify the framework in different ways so that it resembles what has been sometimes dubbed the "mechanical" approach in the intergenerational literature (Goldberger 1989). In doing so, we abstract from strategic bequest/consumption considerations so that b_q is taken as given by an individual. We also abstract from age at which wealth is measured. Studies of intergenerational income mobility have shown that the age at measurement may be important (Haider and Solon 2006), but our empirical results on wealth mobility turn out to be rather insensitive to the age at measurement.

Next, we consider a linearized version of Equation (3),

$$w_g = \mathbf{x}_g \boldsymbol{\beta}, \tag{4}$$

where $\mathbf{x}_g = \left(y_g, r_g, b_g, \xi_g\right)$ is a vector of the different wealth determinants, which we assume follow the law of motion

$$\mathbf{x}_g = \mathbf{x}_{g-1}\boldsymbol{\Xi} + \boldsymbol{\nu}_g, \tag{5}$$

where $\boldsymbol{\Xi}$ is a transition matrix and $\boldsymbol{\nu}_g$ is an error term vector.[6] Note that although wealth does not appear in this equation it does not mean that the relationship between $\mathbf{x}_{g-1}$ and $\mathbf{x}_g$ cannot flow through wealth. For example, a relationship between the incomes of parents and children can be intermediated by parental wealth via investment in education.

Using the relationships (4) and (5), we have $w_g = \mathbf{x}_{g-1}\boldsymbol{\Xi}\boldsymbol{\beta} + \boldsymbol{\nu}_g\boldsymbol{\beta}$ and $w_{g-1} = \mathbf{x}_{g-1}\boldsymbol{\beta}$. This implies that an estimation of our key parameter of interest β_w in Equation (1) corresponds to regressing $\mathbf{Y} = \mathbf{x}_{g-1}\boldsymbol{\Xi}\boldsymbol{\beta} + \boldsymbol{\nu}_g\boldsymbol{\beta}$ on $\mathbf{X} = \mathbf{x}_{g-1}\boldsymbol{\beta}$. Using the standard OLS formula $(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{Y}$ and noting that $\boldsymbol{\nu}_g\boldsymbol{\beta}$ is orthogonal to $\mathbf{x}_{g-1}\boldsymbol{\beta}$, the expectation of β_w is given by

$$\begin{aligned} \mathrm{E}[\beta_w \mid \mathbf{x}_g, \mathbf{x}_{g-1}] &= \left((\mathbf{x}_{g-1}\boldsymbol{\beta})'\mathbf{x}_{g-1}\boldsymbol{\beta}\right)^{-1} \cdot (\mathbf{x}_{g-1}\boldsymbol{\beta})' \cdot (\mathbf{x}_{g-1}\boldsymbol{\Xi}\boldsymbol{\beta}) \\ &= (\boldsymbol{\beta}' \cdot (\mathbf{x}'_{g-1}\mathbf{x}_{g-1}) \cdot \boldsymbol{\beta})^{-1} \cdot \boldsymbol{\beta}' \cdot (\mathbf{x}'_{g-1}\mathbf{x}_{g-1}) \cdot \boldsymbol{\Xi}\boldsymbol{\beta}. \end{aligned} \tag{6}$$

The coefficient β_w is as close as one can get to a "structural" intergenerational correlation of wealth if one insists on summarizing it by a single parameter. Equation (6) shows that it depends on the distribution of characteristics in the parents' population, $\mathbf{x}_{g-1}$, summarized by the population

[6] By assuming that the process is autoregressive of order one, we focus only on the relationship between two generations (children and parents). In the empirical analysis, we consider also the role of grandparents.

covariance matrix $\mathbf{x}'_{g-1}\mathbf{x}_{g-1}$.

In the special case where $\mathbf{x}_{g-1}$ is unidimensional, so that $\boldsymbol{\Xi}$ is a scalar, it is easy to show that $\beta_w = \Xi$, implying that the β_w coefficient reveals the (single) structural parameter. More generally, β_w is specific to the given population, and it does not have a direct causal interpretation. To further illustrate this point, consider the following example

Example 1 *Suppose that elements of x are uncorrelated with each other ($\mathbf{x}'_{g-1}\mathbf{x}_{g-1}$ is diagonal) and $\boldsymbol{\Xi}$ is diagonal. Then, straightforward manipulation of Equation (6) yields*

$$\beta_w = \sum_i \omega_i \Xi_{ii}, \tag{7}$$

where Ξ_{ii} is the (i,i) element of $\boldsymbol{\Xi}$, $\omega_i = \beta_i^2\sigma_{ii}^2/\left(\sum_j \beta_j^2\sigma_{jj}^2\right)$ are weights that sum to one, and σ_{ii}^2 is the (i,i) element of $\mathbf{x}'_{g-1}\mathbf{x}_{g-1}$ (variance of the ith element of $\mathbf{x}_{g-1}$, denoted by x_{g-1i}).

Under these assumptions, β_w is simply a weighted average of the intergenerational correlations of different factors, with weights reflecting both the relevance of a given factor (β_i^2) and the extent of its variation in the population (σ_{ii}^2).

Even when one is willing to assume that $\boldsymbol{\beta}$ and $\boldsymbol{\Xi}$ are structural parameters, they do not translate into a structural interpretation of parameter β_w in the intergenerational wealth relationship (1). Different societies at different points in time may differ with respect to the extent of variation in determinants of wealth—variation in income, tastes, education, bequests, rate of returns may all vary over time with institutions, policies, culture, etc. Each situation will correspond to a different weighted average of Ξ_{ii}s and hence different β_w. Moreover, if we select out a specific subsample of the population, which most likely has characteristics $\mathbf{x}$ differing from the average population, then the estimate of β_w will change even though the intergenerational correlation matrix $\boldsymbol{\Xi}$ is unchanged.

#2: In the general case, estimates of the intergenerational wealth parameter β_w in (1) reflect a weighted average of many intergenerational factors with weights being sample-dependent. We may therefore expect to see different estimates of β_w at different times and places and across different sample choices.

2.3 Controlling for elements of x

Controlling for some element j of $\mathbf{x}_g$ and $\mathbf{x}_{g-1}$ corresponds to shutting down this particular source of variation. To see this, consider Example 1 again. Controlling for $x_{g,j}$ and $x_{g-1,j}$ corresponds to simplifying the formula for β_w in (7) by setting $\sigma^2_{jj} = 0$. In this case, β_w becomes a weighted average of all the other elements in $\boldsymbol{\Xi}$ than element j. Without imposing additional structure, this modified weighted average is expected to be different, and hence we would expect that including various elements of the vector $\mathbf{x}$ in regression specifications would affect the estimate of β_w.

In the general case, one can proceed analogously by first projecting w and all elements of $\mathbf{x}$ other than x_j on x_j. Specifically, suppose that we partition $\mathbf{x}$ into unobservable factors, $\mathbf{x}^U$, and observable factors, $\mathbf{x}^O$. Similarly, let $\boldsymbol{\Xi}_{UU}$ and $\boldsymbol{\Xi}_{UO}$ denote the partitions of the matrix $\boldsymbol{\Xi}$ that determine $\mathbf{x}^U$: $\mathbf{x}^U_g = \mathbf{x}^U_{g-1}\boldsymbol{\Xi}_{UU} + \mathbf{x}^O_{g-1}\boldsymbol{\Xi}_{UO} + \boldsymbol{\nu}^U_g$. Then,

$$\begin{aligned} w_g &= \mathbf{x}_g\boldsymbol{\beta} = \mathbf{x}^U_g\boldsymbol{\beta} + \mathbf{x}^O_g\boldsymbol{\beta} = \mathbf{x}^U_{g-1}\boldsymbol{\Xi}_{UU}\boldsymbol{\beta} + \mathbf{x}^O_{g-1}\boldsymbol{\Xi}_{UO}\boldsymbol{\beta} + \mathbf{x}^O_g\boldsymbol{\beta} + \boldsymbol{\nu}^U_g\boldsymbol{\beta} \\ &= \beta^U_w\mathbf{x}_{g-1}\boldsymbol{\beta} + \mathbf{x}^O_{g-1}\boldsymbol{\beta}^O_{w,g-1} + \mathbf{x}^O_g\boldsymbol{\beta}^O_{w,g} + \zeta^U \\ &= \beta^U_w w_{g-1} + \mathbf{x}^O_{g-1}\boldsymbol{\beta}^O_{w,g-1} + \mathbf{x}^O_g\boldsymbol{\beta}^O_{w,g} + \zeta^U, \end{aligned} \tag{8}$$

where β^U_w is a linear projection of $\mathbf{x}^U_{g-1}\boldsymbol{\Xi}_{UU}\boldsymbol{\beta}$ on $\mathbf{x}_{g-1}\boldsymbol{\beta}$, while partialling out the effect of $\mathbf{x}^O_{g-1}$ and $\mathbf{x}^O_g$ (with $\boldsymbol{\beta}^O_{w,g-1}$ and $\boldsymbol{\beta}^O_{w,g}$ being the resulting coefficients), and ζ^U is an error term comprising of the projection error and $\boldsymbol{\nu}^U_g\boldsymbol{\beta}$. In other words, by controlling for some subset of characteristics of both parents and children (note that controlling for both at the same time is important), we can zoom in on the effect of the remaining characteristics that is orthogonal to the observed ones. Moreover,

#3: In the general case, the estimate of the intergenerational wealth parameter β_w in (1) is expected to change when controlling for key economic outcomes that are important for intergenerational mechanisms (e.g., income and education).

2.4 A unidimensional latent factor model

As discussed above, in general a unique intergenerational wealth coefficient does not exist, because different sources of variation in parental characteristics may translate into different strengths of intergenerational association. However, there is a special case when this is not so. Suppose the variation in all the components of $\mathbf{x}_g$ is driven by a unidimensional latent factor z_g, for example ability, so that $\mathbf{x}_g = z_g\boldsymbol{\Phi}$, where $\boldsymbol{\Phi}$ is a vector of parameters. The latent variable evolves across generations according to $z_g = \phi z_{g-1} + \eta_g$. Then $\mathbf{x}_g = \phi z_{g-1}\boldsymbol{\Phi} + \eta_g\boldsymbol{\Phi}$ and, finally, $\mathbf{x}_g = \phi\mathbf{x}_{g-1} + \eta_g\boldsymbol{\Phi}$. In that case, $\boldsymbol{\Xi} = \phi\mathbf{I}$ in the law of motion (5), where $\mathbf{I}$ is the identity matrix, and $\phi\mathbf{I}$

is a diagonal matrix of ϕs, so that we can verify by (6) that $\mathrm{E}[\beta_w|\mathbf{x}_g, \mathbf{x}_{g-1}] = \phi$. That is, the intergenerational relationship of wealth simply reflects the intergenerational relationship of the latent factor. Moreover, under this simple structure, wealth of parents itself reflects the latent factor and becomes a sufficient statistic to predict the wealth of children.

The case where all underlying intergenerational dynamics are governed by a single latent factor may seem unrealistic. More generally, we may consider a situation where characteristics in $\mathbf{x}_g$ are not perfectly correlated with the latent factor, z_g. We specify

$$\mathbf{x}_g = z_g \boldsymbol{\Phi} + \tilde{\mathbf{x}}_g, \tag{9}$$

where the vector Φ measures the effect of z_g on $\mathbf{x}_g$, and the elements of $\tilde{\mathbf{x}}_g$ are orthogonal to z_g. $\tilde{\mathbf{x}}_g$ may represent a measurement error, or it may be the residual from a projection of $\mathbf{x}_g$ on z_g, so this specification in itself imposes no new restrictions. In addition, though, we assume that $\tilde{\mathbf{x}}_g$ is uncorrelated with z_{g-1}—$\tilde{\mathbf{x}}_g$ may be autocorrelated over time but in a way that is unrelated to the past latent factor.

The latent factor still evolves according to $z_g = \phi z_{g-1} + \eta_g$. In this case, we obtain[7]

$$\begin{aligned} \mathrm{E}[\beta_w|\mathbf{x}_g, \mathbf{x}_{g-1}] \quad = \quad & \phi \\ & -(\boldsymbol{\beta}' \cdot (\mathbf{x}'_{g-1}\mathbf{x}_{g-1}) \cdot \boldsymbol{\beta})^{-1} \cdot \boldsymbol{\beta}' \cdot (\tilde{\mathbf{x}}'_{g-1}\tilde{\mathbf{x}}_{g-1}) \cdot \boldsymbol{\beta}\phi \\ & +(\boldsymbol{\beta}' \cdot (\mathbf{x}'_{g-1}\mathbf{x}_{g-1}) \cdot \boldsymbol{\beta})^{-1} \cdot \boldsymbol{\beta}' \cdot (\tilde{\mathbf{x}}'_{g-1}\tilde{\mathbf{x}}_{g}) \cdot \boldsymbol{\beta}. \end{aligned} \tag{10}$$

The first term reflects the intergenerational correlation of the latent factor. The second term is the standard formula for the attenuation bias, stemming from measurement error as $\mathbf{x}_g$ is no longer perfectly related to the latent factor. The third term is an extra additive intergenerational effect similar to (6), resulting from the potential autocorrelation of $\tilde{\mathbf{x}}$s as represented by $\tilde{\mathbf{x}}'_{g-1}\tilde{\mathbf{x}}_g$. It is present, if the dynamics of the latent factor does not fully capture the dynamics of $\mathbf{x}_g$. Note that (10) collapses to the original specification (6) if we additionally specify the explicit law of motion $\tilde{\mathbf{x}}_g = \tilde{\mathbf{x}}_{g-1}\tilde{\boldsymbol{\Xi}} + \boldsymbol{\epsilon}_g$, and the latent factor process is not present so that $\mathbf{x}_{g-1} = \tilde{\mathbf{x}}_{g-1}$.

The size of terms two and three depend on the distribution of characteristics in the parent population, $\mathbf{x}_{g-1}$ and $\tilde{\mathbf{x}}_{g-1}$, summarized by the population covariance matrices $\mathbf{x}'_{g-1}\mathbf{x}_{g-1}$ and $\tilde{\mathbf{x}}'_{g-1}\tilde{\mathbf{x}}_{g-1}$. Notice that $\tilde{\mathbf{x}}'_{g-1}\tilde{\mathbf{x}}_{g-1}$ is bound to be small if the bulk of the variation in $\mathbf{x}_{g-1}$ is driven by the

[7] The derivation of Equation (10) is shown in Appendix A.1.

latent factor. Therefore, when the latent factor captures the bulk of the variation in $\mathbf{x}_g$ and its autocorrelation, the additional two terms of (10) are small and the latent factor result applies approximately. Thus, we have

#4: When all the underlying intergenerational mechanisms are driven approximately by a unidimensional latent factor, for example ability, the intergenerational wealth parameter β_w in (1) is approximately stable across samples and when controlling for other economic outcomes, and wealth of parents summarizes approximately all relevant information of parents to predict the wealth of children.

2.5 Theoretical conclusions and empirical strategy

The theoretical framework illustrates a number of points concerning the interpretation of empirical estimates of intergenerational wealth mobility (β_w). Estimates of β_w reflects intergenerational linkages flowing through a mix of underlying channels responsible for variation in wealth (#1), and disentangling these different channels is a complicated—if not impossible—task. In the general case, the theory points to fundamental instability in the estimation of β_w; it is sample-dependent (#2) and sensitive to controls for other economic outcomes (#3). However, in the special case where all underlying intergenerational mechanisms are driven by a unidimensional latent factor, the intergenerational wealth parameter β_w is stable across samples and when controlling for other economic outcomes, implying that wealth of parents is a "sufficient statistic" to predict the wealth of children (#4). In Section 4, we provide non-parametric evidence on the formation of wealth across generations and population estimates of β_w, and we then explore the stability of these relationships by looking across various subsamples, periods, and cohorts, and by including key economic outcomes as controls in the regressions. Instability of the wealth relationships would reject the unidimensional latent factor model, while stability would indicate that the latent factor model is a realistic possibility.

3 Data

Our empirical analysis is based on data from several public administrative registers gathered by Statistics Denmark and linked together using personal identification numbers. Every citizen in Denmark is assigned a unique personal identification number at birth and the identification numbers of the mother and the father are registered for all Danes born in 1960 and onwards.[8] This enables us to combine different data sources at the individual level and to link data across generations.

The data on individual wealth and income is based on administrative tax return records. The Danish Tax Agency (SKAT) collects, in addition to information of various income sources, information about the values of asset holdings and liabilities measured at the last day of the year for all Danes, and the bulk of the wealth components are third-party reported.[9] The available pieces of information at Statistics Denmark are the aggregate value of assets and liabilities, respectively, covering the period 1980 to 2011, and from 1997 and onwards it is also possible to obtain complete portfolio information with respect to the value of bonds, stocks, cash in banks, house, mortgage loans, and sum of other loans. Another attractive feature of the wealth data is that the information is not top coded.

The information about the value of financial assets and liabilities at the end of the year is reported to the tax authorities by banks, other financial institutions, and some government institutions, while the cash value of property is assessed by the tax authorities, based on detailed information of the property, and used for taxation of the imputed rent on the property. The third-party reported value of assets includes all deposits, stocks, bonds, value of property, and deposited mortgages. Pension funds are not part of the data, which is also the case in the US study by Charles and Hurst (2003).[10] The third-party reported value of liabilities includes debt in financial institutions, mortgage credit debt, credit and debit card debt, deposited mortgage debt, student debt and debt in The Mortgage Bank (a public institution), debt to financial corporations, debt to the Danish municipalities, and other liabilities such as unpaid taxes and mortgage debt, which are not deposited.

Until 1996, Denmark had a wealth tax, and taxpayers had to self-report car values, boat values, caravan values, title deed of cooperative dwellings, premium bonds, cash deposits, stocks

[8] Registrations of parents exist before 1960 but are incomplete.

[9] The tax authorities use the income information to generate pre-populated tax returns. The information on wealth was originally used to compute the wealth tax, whereas today it is used by the tax agency to cross check if the reported income level is consistent with the change in net-wealth during the year under the assumption of a given estimated consumption level. A recent study by Kleven et al. (2011) reveals, using a large scale randomized tax auditing experiment constructed in collaboration with the Danish tax authorities, only small differences between the third-party reported income items and the corresponding items on the final tax return. This indicates that the third-party reported information of the Danish Tax Agency is of a very high quality.

[10] Pensions represent primarily compulsory saving (the voluntary component is small). The two important parts reflect (1) the value of universal government pension benefit (which would be comparable to the expected value of Social Security payments in the US) and (2) employer contributions that are proportional to wages and determined by bargaining agreements—the closest analogue in the US would be employer contributions to 401(k) or equivalent accounts. Numbers provided by the Danish central bank indicate that pension's share out of total gross wealth averaged 22% over the years 1997-2011.

(both listed and non-listed thereby including privately held companies), and private debt. These components are not included in the computations after 1996. Until 1996 the value of stocks was self-reported, while afterwards it became third-party reported by banks and financial institutions (excluding non-listed stocks). The registration of the company value of self-employed has changed several times, but has stayed unchanged since 1997, where assets and liabilities of the firm were registered separately and included, respectively, in the assets and liabilities of the owner. Another definitional change occurs in 1983. Before 1983 all family wealth of a married couples was assigned to the husband, while the wealth of husbands and wives has been registered separately afterwards.

Ideally we would like to observe wealth, income, etc., of the individual in the middle age and observe the different generations at the same age because of the life-cycle variation in economic outcomes (Haider and Solon 2006). If, for example, parents are around 25 years old when their children are born, and we observe wealth of the child generation in 2011, then we would like to observe wealth of the parents and grandparents in 1986 and 1961, respectively. This goal has to be balanced against data availability (grandparents) and data quality (parents). Our main empirical analyses are based on parental wealth observed in 1997–1999, where the definition of the wealth measure is the same as that used for children in 2009–2011, and grandparental wealth measured in 1983–1985 where wealth of biological grandfathers and grandmothers are more accurately measured than the years before. We take three year averages of wealth of each individual to reduce the importance of transitory components, as often done in the literature on intergenerational income mobility following Solon (1992). In the empirical analysis, we investigate the sensitivity of the results to the age at measurement and to transitory components in the wealth measurement, and conclude that it matters surprisingly little.

The largest change in the definition of wealth occurs around 1997 where the wealth tax was abolished. However, for 1995 and 1996 Statistics Denmark computed assets and liabilities of each individual using both the new definition of wealth (used for children and parents) and the old definition (used for grandparents). In Appendix A.2–A.3, we exploit this overlap to show that the new wealth measure is well approximated by the old way of measuring wealth, and we provide more details on the wealth data.

In the empirical analysis, we consider two types of samples: a child-parents sample (CP) and a child-parents-grandparents (CPG) sample. The CP sample focuses only on child-parents relationships without exploiting information on grandparents. In this sample, we consider all children of age 21–51 in 2011 (ensuring that they are born in 1960 or later), where both parents are alive in 2011, and where both parents are between 21 and 66 years old in 1999. The child-parents-grandparents (CPG) sample is based on the CP sample, but with the additional requirement that at least one grandparent is alive in 1985. To avoid selection problems, we further require that parents are born in 1960 or later, corresponding to a maximum age of 39 in 1999, implying that the personal identifiers of all the grandparents are known.[11]

Table 1 provides summary statistics of the two samples. In the CP sample, we have almost 1.2 million child-parent pairs, and the CPG sample consists of about 100 thousand observations. In both samples, parents are significantly older than their children at the time where wealth levels are observed in the data, and grandparents are older than parents in the CPG sample. Children in the CPG sample are particularly young, but we will present robustness checks to show that the results are not driven by it. As households normally accumulate wealth over the life cycle up to retirement, we should expect to observe the highest wealth for grandparents and higher wealth for parents than for children, which is also the pattern we see in Table 1.

Registered wealth is negative for many individuals. This is, for example, the case for close to half of the child generation. One reason is that we include young persons in their twenties for whom it is optimal to have negative wealth. Another reason is missing components in the wealth measure—mainly pension funds as described above. Finally, it is well-known that Danish households have very high debt-to-income ratios (the liability-income ratio is almost 200 percent for children and over 150 percent for parents in the CP sample) compared to other countries, which has received international attention recently (IMF 2012; European Commission 2012).[12] Our reliance on rank measures allows for incorporating negative wealth and restricting sample to older individuals will serve as important robustness checks.

Table 1 also presents figures for earnings and income, where income includes earnings, self-employment income, and all types of transfers, but excludes capital income.[13] Earnings and income are on average higher for parents than for children, while earnings for grandparents are lower than for parents reflecting that some of the individuals have retired. The table also reports years of education counting completed education. Parents are clearly more educated than grandparents but

[11] The parental age restriction reduces the sample considerably and selects younger children. As a robustness check, we will also consider the unrestricted CPG sample that includes older children. Without the restriction, we obtain nearly the same regression coefficients and a higher statistical precision, but we prefer the restricted sample to avoid sample selection bias.

[12] The difference to the US and other countries may reflect that Denmark has a reasonably high universal public pension benefit level, substantial labor market pension savings by international standards, and an extensive social safety net that reduces the need for precautionary savings.

[13] We exclude capital income in order to avoid a direct relationship from wealth to income in the empirical analysis.

also somewhat more educated than their children in the CPG sample. However, this reflects that some of the younger children are yet to complete their education.

4 Empirical analysis

This section describes the empirical results. First, we present baseline evidence on the relationship between wealth of parents and children—both graphically (displaying non-parametric relationships) and using parametric specifications to obtain population summary statistics. Second, we analyze the sensitivity of these results to various sample definition/selection choices and control variables, thereby following the agenda laid out in Section 2 to explore whether parental wealth proxies for the main characteristics of the parents. Third, we include information of grandparents in the analysis to explore whether the child-parent association is stable across generations and to explore the persistence of wealth formation across generations. Finally, we zoom in on persons in the top 1% of the wealth distribution in order to explore differences between the results for the bulk of the population and those at the very top of the distribution.

4.1 Non-parametric evidence of intergenerational wealth mobility

We first use the child-parents (CP) sample described above to provide non-parametric evidence of the relationship between child wealth and average wealth of the (biological) parents. Most of our analysis is based on the relationship between positions of children and parents in the wealth distribution measured by *within-cohort* ranks. This has several advantages: it accounts for life-cycle changes in wealth, it works well with zero and negative observations that are common in wealth data, and it is a very robust measure (e.g., it is unaffected by all types of monotone transformations of the underlying data). For each child, we compute the rank in the distribution of child wealth for individuals at the same age (with maximum rank normalized to 100), and we do the same for parental wealth based on the average age of the parents.[14] Figure 1 shows a binned scatter plot where child-parents pairs are divided into 100 groups according to the percentile rank of parental wealth and showing for each percentile the mean rank of children. Note that the graph also shows a very small 95 percent confidence interval at each point estimate, reflecting that the child mean rank at each parental wealth percentile is very precisely estimated.

[14] Within an age cohort, ranks are calculated as $\frac{i-0.5}{N} \cdot 100$, where i denotes individuals sorted by wealth, and $i = 1, 2, \ldots, N$. We use these ranks based on the entire distribution throughout the analysis (also when studying different subsamples).

The graph reveals an almost linear relationship with the exception of at the very top and bottom of the parental wealth distribution. Children of parents in percentile 10 are on average in percentile 40, while children of parents in percentile 90 on average are in percentile 60, and within this range moving up one percentile in the parental wealth distribution is associated with a 1/4 percentile increase in the average position of children. The relationship is much stronger at the top of the distribution with a child average rank going from percentile 70 to percentile 75, when going from percentile 99 to percentile 100 in the parental wealth distribution. In Section 4.5, we take a closer look at the upper part of the distribution. The dip down at the bottom of the parental distribution probably reflects that the wealth of the parents in the first percentiles is a bad proxy for their "true type" and ex ante expected wealth. These parents have very large debt and significant negative wealth that may reflect involvement in risky investment decisions that either have gone wrong or have not paid off yet. Consistent with this hypothesis, we find that self-employed are largely overrepresented in the first percentiles.

For comparison, we have done a similar analysis for income (Figure A.1 in the Appendix). This reveals a linear relationship as well between income ranks of parents and children—similar to recent evidence on *income* mobility by Chetty et al. (2014).[15] Moving up one percentile in the parental income distribution is associated with a 1/7 percentile increase in the average position of children almost everywhere in the parental income distribution. Thus, the intergenerational mobility of wealth is considerably lower than the mobility of income.[16]

Figure 1 displays also the 25th percentile and the 75th percentile of the conditional child rank distribution computed for each wealth percentile of parents. For example, for children born to parents in percentile 10, around half of them have a rank between 20 and 60, while 25% of them have a rank below 20 and another 25% have a rank above 60. The child rank levels at the 25th percentile and the 75th percentile increase steadily as we move up in the parental distribution mirroring the development in mean rank level. Again an exception is at the very top of the wealth distribution where the child rank level at the 25th percentile jumps from around 50 to more than 60 when going from percentile 99 to 100 in the parental wealth distribution. Thus, for the top 1% of parents, less than 25% of their children have a rank below 60. Moreover, the graphs shows that

[15] Chetty et al. (2014) also includes evidence about income for Denmark constructed by us for an earlier version of the paper, and using a slightly different sample.

[16] The large increase in the association between parents and children taking place at the top of the wealth distribution is neither observed for income in our sample nor for income in the US in Chetty et al. (2014). For Sweden, Björklund et al. (2012) finds a large association at the top of the distribution when looking at a broad measure of income that includes capital income but not when looking at earnings.

25% of the children have a rank equal to 98% or higher.

4.2 Aggregate measures of wealth mobility

It is useful to have a single measure of the overall degree of wealth mobility, when pursuing the agenda laid out in Section 2, aiming at exploring the stability of the intergenerational wealth formation process. Our preferred measure is the rank correlation coefficient (RCC). Because of the uniform distribution of the rank measure, this may be obtained from a linear regression of child rank on the rank of parents, corresponding to the slope of the OLS fitted line in Figure 1. The result of this regression, reported in Panel A of Table 2, is a baseline estimate of 0.24, which is very precisely estimated because of the large sample size with 1.2 million child-parents observations. Thus, on average a one percentile increase in the position of parents in the wealth distribution is associated with a 1/4 percentile increase in the average position of children, in line with the conclusion above that the slope in Figure 1 is 1/4 almost everywhere with the exception of at the tails of the parental distribution.

For comparison, Panel B of Table 2 also reports the elasticity of child wealth with respect to parental wealth, corresponding to estimating an ordinary least squares regression after using a natural logarithmic transformation of the data (i.e., for those with positive wealth). Studies on intergenerational income mobility normally report the intergenerational elasticity, and this is also done by Charles and Hurst (2003) in their study of intergenerational wealth mobility. Column 1 of Table 2 reports the estimated elasticity without age adjustment, while column 2 reports the age-adjusted elasticity obtained by including age dummies of both children and parents in the regression. We obtain a child-parents age-adjusted elasticity of 0.27, implying that children born to parents with a wealth level that is 1 percent above the mean of the parental generation can expect to obtain a wealth level that is 0.27 percent above the mean of the child generation. Charles and Hurst (2003) find an age-adjusted elasticity of 0.37 for the United States using the PSID survey data. The lower estimate for Denmark is not surprising. Denmark has a very homogeneous population and a high degree of redistribution, and comparative studies find that Denmark has a high intergenerational mobility in earnings/income compared to the US and many other countries (Björklund and Jäntti 2009; Chetty et al. 2014).

When applying the log transformation, we are throwing away all child-parents pairs where either the child or the parents have zero or negative net wealth. Most of the empirical literature analyzing intergenerational relationships look at economic outcomes that do not attain negative values by definition, for example earnings. This is, however, not the case for net wealth, which may well be negative and where standard life cycle theory predicts negative values for young persons who have increasing earnings profiles.[17]

The rank transformation of the data allows for non-positive wealth observations and avoids therefore the potential selection problem occurring, for example, when using the log transformation. This is also the case for the inverse hyperbolic sine transformation (IHS), $w = \log(W + \sqrt{W^2+1})$, which is interesting because it behaves as $\pm\log(|W|)$ everywhere with the exception of in the neighborhood of zero. It therefore provides (approximately) an intergenerational wealth (or debt) elasticity for both positive and negative values. Panel C of Table 1 shows that the elasticity estimate in this case becomes around 0.2, both with and without age adjustment, which is considerably lower than the estimate obtained when applying the log transformation, and revealing that it may create severe selection bias to remove observations with negative wealth.[18]

4.3 Stability of the intergenerational wealth relationship

In Section 4.1 we established the remarkable stability of the child-parents rank-rank slope at around 1/4 almost everywhere in the wealth distribution. In this section, we examine the stability of the intergenerational wealth relationship in a number of other ways.

Life-cycle variation may be important when measuring intergenerational mobility in economic outcomes (Haider and Solon 2006). Note also that, using the sample of those with positive wealth, there is a large difference in the estimate of the elasticity of child wealth with respect to parental wealth depending on whether age dummy controls are included in the regression or not (Panel B of Table 2, columns 1 vs. 2). On the other hand, the elasticity based on the IHS transformed data does not change much when including age controls (Panel C), indicating that the importance of age controls for the log transformation may be a result of sample selection. The RCC estimate is also insensitive to the inclusion of age controls (Panel A). The within-cohort rank measure accounts for differences in wealth across individuals due to each individual being observed at different points in time on a life-cycle wealth profile, but the strength of the intergenerational relationship may still vary with age. In order to explore whether this is the case, we first split the sample into five age groups of equal size and repeat the analysis in Figure 1 for each age group. Figure 2 shows the

[17] The lack of information of pension wealth is another reason for registering negative household wealth in our case and in Charles and Hurst (2003).

[18] A concern may be that outliers or observations with zero or close to zero wealth may be very important for these estimates. We have run sensitivity analyses, which reveal no effects on the estimates of removing observations in the tail of the distribution and around zero wealth.

results for all age groups at the same time. The relationships for the four child age groups 26–31, 32–36, 37–42 and 43+ lie very close to each other at each parental percentile and the RCC estimates are all within the small range 0.21–0.25. The profile for the youngest group, where children are in the age interval 21–25, is more steep with an RCC equal to 0.27. This is not dramatically different from the overall average of 0.24 and may reflect that parents have a somewhat larger role to play in early adulthood than later in life, for example because of wealth transfers during education.

The RCC is also rather insensitive to variation in parental age with estimates lying in the narrow range 0.23–0.26 when we divide the sample into five equally sized subsamples based on parental age and compute the RCC for each subsample (results not reported).

The conclusion that the intergenerational wealth relationship is rather insensitive to the age of children and parents at the time of measurement is further confirmed by Table 2 where columns 3–6 report split sample results according to child age and parental age, also for the log transformation and the IHS transformation. In the last column of Table 2, we look at the variation in the age of parents within child-parents pairs by exploiting the time dimension in our data instead of only looking across child-parents pairs, thereby changing the age of both children and parents. When we re-run the baseline analysis using the wealth observations of parents 12 years later in life—the period 2009–2011 instead of 1997–1999—we obtain a non-parametric diagram nearly identical to Figure 1 (not reported) and, as shown in column 7 of Table 2, the RCC is only a little higher than the baseline estimate.

Attenuation bias created by measurement error and transitory components in the economic outcomes has been a major concern in the intergenerational income mobility literature since the influential contribution of Solon (1992), and it is common to take averages over some years as we have done to reduce the potential bias. In our case, the results are very similar whether we use wealth observed for just a single year or use three-year averages, five-year averages, or seven-year averages of wealth. The non-parametric diagrams, which are shown in Figure 3, Panels A-D, are close to identical, and the RCC estimates lie in the narrow interval from 0.23 to 0.25. This conclusion is in line with results for income mobility based on administrative data by Chetty et al. (2014).

There may be many underlying mechanisms behind the intergenerational correlation in wealth as described in Section 2. For example, income may be related across generations because of inheritability of innate ability levels, and the wealth levels of children and parents may simply serve as proxies for the income levels because of a positive correlation between wealth and income for given savings rates. If this is the only source of the intergenerational relationship in wealth, then the relationship would disappear in the regression when we control for income levels of both children and parents, see Equation (8) in Section 2.3. It may also be that parents with high wealth invest more in the human capital formation of their children as they do in the seminal theory of income mobility by Becker and Tomes (1979). This would raise the income and wealth of their children and would generate a positive correlation between child wealth and parental wealth working through child income. If this channel is stronger than other sources of intergenerational correlation in wealth, then our estimate of the intergenerational wealth coefficient should fall when we introduce income as an additional regressor. Column 2 of Table 3 reports the result from such a regression, where we include the within-cohort rank of income in the regression. The coefficient on the (rank) wealth of parents is basically unchanged from Table 2 (repeated in column 1 of Table 3 for convenience), and the coefficients on the income levels of parents and children are small.

In Figure 4, we have repeated the non-parametric diagram for five equally sized income group subsamples of children (Panel A) and parents (Panel B), respectively. It shows tiny effects of income after controlling for wealth of parents. The slopes in Panel A are in the range 0.23–0.27 and in Panel B in the range 0.22–0.25. Moreover, the (vertical) variation within each wealth percentile is very small. For example, going from the bottom quintile to the top quintile in the parental income distribution only increases the wealth rank of children, conditional on wealth of parents, by 2 on average. In comparison, it is worth noting that, conditional on parental income quintiles, going from percentile 10 to 90 in the parental wealth distribution increases the wealth rank of children by 19 on average. We obtain the same conclusions if we restrict income to earnings alone (results not reported). These results suggest that the mechanisms behind the intergenerational wealth relationship running through income are well captured by parental wealth, in line with the latent factor model in Section 2, where parental wealth is a sufficient statistic to predict child wealth.

An intergenerational relationship in education is documented in many studies (see survey by Black and Devereux 2011). Beyond the direct effect of education on income and wealth, education may also be related to preference parameters, such as impatience and risk attitudes that also govern saving propensities and portfolio choices important for wealth accumulation. However, our results reveal small effects of accounting for education in the analysis. Figure 5 repeats our non-parametric rank-rank diagram, grouping on child education (Panel A) and parental education (Panel B). Groups of education are created to approximately represent quintiles in the distribution of graduated children and parents, respectively. In Panel A, slopes are similar for all five groups and lie in the range of 0.20–0.25. The group with the least education is slightly lower than the rest—a fact mostly driven by children in their 20s that have yet to graduate. Going from least to most child education only spans a vertical distance in child average wealth rank of 5, conditional on parental wealth rank. In Panel B, we see only a small effect on child wealth ranks, conditional on parental wealth rank, of having a very long education compared to the other education groups, which is reflected in an average vertical distance in the graph between highest and lowest of less than 3 child wealth rank points. Slopes lie in the narrow interval of 0.22–0.25. Finally, the overall estimate of the RCC after controlling for years-of-schooling dummies for both parents and children is nearly the same as the baseline estimate (see columns 1 and 3 of Table 3).

The non-parametric diagram in Figure 1 is almost identical if we split the sample by child gender or by marital status of the child (reported in Figure A.2 in the Appendix). In column 4 of Table 3, we include these variables as well as dummy variables for number of siblings. This implies that we only exploit the variation within families of a given size to estimate the relationship and thereby control for intergenerational mechanisms related to family size, for example that parents with many children may devote less financial resources per child to educational investments and make smaller wealth transfers per child. Also in this case, the coefficient on parental wealth rank stays almost the same. We obtain the same conclusion of stability when including regional dummies for children and parents, as shown in column 5 of Table 3. Finally, in column 6, we include all the control variables at the same time–counting child and parental variables this amounts to a total of 35 years-of-schooling dummies, 18 social demographics dummies, 196 regional dummies, and 72 age dummies. The coefficient on parental wealth is only slightly smaller than the baseline estimate of the RCC. The coefficients on income are still small but also rather sensitive to the inclusion of the other control variables.

An important difference between intergenerational mobility in income and in wealth is that the latter may be influenced by direct transfers of wealth. So far, we have only considered children whose parents both are alive, as also done by Charles and Hurst (2003). In Table 4, we report estimates of the RCC for samples where parents die between 1999 (time of parental wealth recording) and 2011 (time of child wealth recording). This gives an indication of the role of bequest. Column 1 repeats our baseline estimate, while columns 2 and 3 report the results from samples where one parent dies and where two parents die, respectively. It shows that the RCC estimate is considerably higher for these samples, in particular for the (small) sample where both parents die. Columns 4 and 5 enable us to compare samples where only one parent is alive in 1999 and where this parent is alive or dead in 2011. This comparison also indicates the existence of bequests that increase the intergenerational correlation of wealth between children and parents.[19]

4.4 Wealth across three generations

In this section, we use the child-parents-grandparents (CPG) sample, which enables us to analyze wealth across three generations. The children and parents are younger in the CPG subsample than in the full CP sample. For comparison, we therefore start by reconstructing our baseline rank-rank diagram. This is done in Panel A of Figure 6, which is very similar to Figure 1, and with an overall rank-rank slope as well as age-adjusted RCC of 0.22 (Table 5, column 1), which is only slightly smaller than the baseline estimate from the CP sample (0.23). This is also consistent with the full sample evidence in Figure 2, showing that the parent-child wealth rank relationship is almost invariant to child's age, even when children are in their 20s.

It is interesting to know whether the relationship between child wealth and parental wealth is stable over time/generations. There may be long run forces that reduce or increase the strength of the relationship, and recent research has documented substantial changes over the long run in top income shares, in the relative importance of capital and labor income at the top of the income distribution, and in the evolution of inheritance (Atkinson, Piketty, and Saez 2011; Piketty 2011, 2014). In Panel B of Figure 6, we display the relationship between wealth of parents and wealth of grandparents in the data. Panels A and B are remarkably similar and so are the RCC estimates reported in columns 1 and 2 of Table 5. Thus, in our data, the formation of wealth across generations is quite stable over time and generations.

Next, we explore the degree of persistence in wealth formation across generations by analyzing whether grandparental wealth has any explanatory power beyond parental wealth. We start in Table 5 by looking separately at the relationship between children and grandparents, which gives an RCC estimate of 0.16. Thus, moving up one percentile in the grandparental wealth distribution is associated with children moving up 0.16 percentiles in the wealth distribution of children, which is 3/4 of the baseline child-parents estimate. Column 4 reports the results from including both parental wealth and grandparental wealth in the estimation. When compared to the univariate

[19] Charles and Hurst (2003) look also at asset ownership of parents and children in order to investigate the role of intergenerational correlation in portfolio compositions. We do not include financial composition dummies in the above regressions, because such dummies for the child would be constructed directly from the variables entering in the wealth outcome variable. Including financial composition dummies for parents have only small effects on the parental wealth rank coefficient. Including self-employment dummies for both child and parents have basically no effect.

relationships (columns 1 and 3), we see that the coefficients on parents and grandparents are only a little smaller, suggesting that grandparental wealth adds to the prediction of child wealth mostly information that is orthogonal to that contained in parental wealth. If we move up 10 percentiles in the grandparental wealth distribution then this regression predicts a more than one percentile increase in the position of children, conditional on parental wealth staying at the same level. This effect of grandparents is reasonably stable along the different percentiles of parents. Figure 7 shows our baseline rank-rank diagram when we split the sample into five groups according to the wealth quintiles of grandparents. The vertical distance between children of grandparents in the first quintile and children of grandparents in the fifth quintile is approximately 9 percentiles at each percentile level of parental wealth. This implies that children having grandparents in quintile 5 instead of quintile 1 on average lie 9 percentiles higher in the child wealth distribution for a given level of parental wealth.

In column 5 of Table 5, we add the same controls as we did in the last column of Table 3 together with dummy variables for number of cousins and for number of living grandparents in 2011.[20] The inclusion of these controls reduces the coefficients on wealth of parents and on wealth of grandparents only a little.

As mentioned before, children included in our CPG sample are particularly young: almost all of them are in their 20s. In order to test the importance of having such a young sample, we replicate our results using the unrestricted CPG sample that eliminates the restriction that parents have to be born in 1960 or after. This change increases the sample size almost fivefold, with a quarter of the children in the sample now in their 30s or 40s. The drawback of lifting this restriction is that we no longer are guaranteed to know personal identifiers of all of the grandparents. In Table A.1, we replicate the key specifications from Table 5 using this unrestricted sample and find very little changes in the results. We also split the sample at age of 33 (as in Table 2; 33 is the median child's age in the full sample) and find comparable results, with the coefficient for grandparents falling somewhat but remaining large and statistically significant. Finally, Figure A.3 shows estimates of parental and grandparental effects using varying lower bounds for child's age and confirming that the grandparental effect is very strong regardless of which age group is used, with only a little bit of sensitivity due to inclusion of the very youngest individuals. We conclude that our baseline results

[20] If grandparents transfer money to grandchildren, then the effect of many cousins would be less money received on average per grandchild. By including dummy variables for number of cousins, we are only exploiting the variation within families of same size (measured by the number of cousins). We include dummy variables for number of living grandparents in 2011, because grandparents may die after we have observed their wealth in 1983-85, implying that parents and children may inherit their wealth.

are not driven by having a young sample.

The strong explanatory power of grandparental wealth conditional on parental wealth shows that the degree of persistence in wealth formation across generations is much higher than what is captured by the standard intergenerational measures based on the relationship between two generations. Note also that the stability of the coefficients of parents and grandparents is in line with wealth of previous generations being a sufficient statistic, approximately summing up all relevant information needed to make the best prediction of child wealth.

Grandparental wealth may enter significantly in the regressions because the underlying stochastic processes relating wealth across generations have more memory than just one generation, for example because grandparents have a direct impact on their grandchildren as in the theory of Solon (2014). An alternative explanation is that grandparental wealth does not matter in itself but becomes significant because of measurement problems related to information about parents, creating attenuation bias in the estimate of the child-parents relationship. As described in the previous section, our estimates are robust to averaging wealth over time and hence are unlikely to suffer from attenuation bias coming from temporary variation in wealth or noise in the measurement. However, we cannot exclude the possibility that wealth of the parents (together with other observables) does not fully capture all the relevant aspects of "social status" inherited from the grandparents that are influencing wealth of the children. In this case, a two-stage least squares estimation using wealth of grandparents as an instrument for wealth of parents might allow for identifying the underlying persistence in "social status" transferred from the previous generation. The strong assumption for this to provide a consistent estimator is, of course, that grandparents do not have any direct influence on the wealth of children. Table A.2 in the Appendix shows the results from 2SLS estimations along these lines. This gives a child-parents coefficient in the range 0.65–0.80, which is around three times as high as the ordinary least squares estimates described in Sections 4.2–4.3.

The conclusion from this part of the analysis, independently of whether grandparents matter directly for the wealth of children or whether the child-parents coefficient should be tripled, is that the wealth formation process across generations is much more persistent than what is captured by a standard intergenerational measure based on only two generations of data. This conclusions is in line with other recent studies of multiple generations, described in the Introduction.

4.5 Top one percent relationship

Our non-parametric evidence in Figure 1 indicates that the relationship between the wealth rank of parents and the rank of a child is very stable (linear) within the wealth distribution, with the exception of at the very top of the distribution. When going from percentile 99 to percentile 100 in the parental wealth distribution, the average rank of the children increases from percentile 70 to 75, which should be compared to the overall slope of 1/4. This large difference between the top and the average may reconcile why previous studies in the U.S. that were based on estate tax returns (Menchik 1980; Wahl 2003; Clark and Cummins 2014) have found an intergenerational relationship in wealth that is much stronger than the study by Charles and Hurst (2003) based on a representative survey sample of the population.

The intergenerational relationship of wealth is much stronger than the intergenerational relationship of income at the top of the distributions. In the CP sample, among parents in the top 1% of the wealth distribution, 18 percent of their children are also in the top 1% group (corresponding to 18 times the random odds of 1%), while for parents in the top 1% of the income distribution less than 5 percent of their children are also in the top 1% of the income distribution.

The strong relationship at the top of the distribution raises the question whether the channels of intergenerational transmission of wealth are different here, and it may be that the finding of stability of the intergenerational wealth relationship in Section 4.3 does not apply when we focus on the very top of the distribution. In Table 6, we replicate the analysis for the very top. We operationalize it by regressing a dummy variable that indicates whether the child is in the top 1% group or not on a dummy indicator for the parent being in the top 1% (and similarly for income). The first column shows that children with top 1% parents have a 16.6 percent higher chance of being in the top 1% group compared to children of parents not in the top 1% group. For the specifications with controls in the other columns, the estimates all lie in the narrow range of 16–17 percent. Thus, our results indicate also in this case a remarkable stability to the inclusion of income controls, schooling dummies, social demographics, and regional information.

The main conclusion from Section 4.4 is that grandparental status is very important conditional on parental status, revealing a much higher degree of persistence in wealth formation across generations than what is reflected in two-generation measures. This conclusion is only reinforced at the top part of the distribution. If both parents and grandparents are in the top 1% group then the odds of the children ending up in the top 1% group nearly doubles compared to the case where we only condition on parents being in the top 1% group. Thus, in the CPG sample, children with both parents and grandparents in the top 1% have a chance of 26 percent of ending up in the top 1% group themselves compared to 13 percent if we only condition on parents being in the top 1%.

5 Concluding remarks

This paper contributes to the literature on intergenerational mobility with novel evidence on wealth formation across generations, a context in which evidence has been scarce. The empirical analysis is based on population-wide wealth data for three generations, which allows us to explore the stability and persistence of the intergenerational wealth relationship in a way not possible with the small samples often available for this type of research. Our non-parametric evidence reveals an almost linear relationship between wealth ranks of children and parents with a slope of 1/4, except at the very top of the distribution where the slope is much higher. This relationship between wealth of children and wealth of parents turns out to be surprisingly stable across age, time, generations, income classes, levels of education, and with little explanatory power left for other parental characteristics. While a theoretically possible explanation is that the strength of the intergenerational correlation flowing through various channels happens to be about the same by accident, a more appealing case seems to be that a unidimensional latent factor approximately drives the various intergenerational channels operating through these economic outcomes, in which case parental wealth summarizes the relevant information of parents needed to predict the wealth of children. In general, our empirical evidence is consistent with this view but does not, of course, prove that a unidimensional latent factor is governing all the underlying dynamics.

Including information of grandparental wealth in the empirical analysis shows that standard two-generation measures severely underestimate the degree of persistence in the wealth formation process across generations, in line with other recent multiple generation studies (see the Introduction). Our large sample size allows us to document a systematic large effect of grandparental wealth, conditional on parental wealth, at all levels of parental wealth. Grandparental wealth has much more predictive power than any non-wealth information on parents, reinforcing the finding that ancestors' characteristics other than wealth have little explanatory power.

This paper provides evidence from Denmark—a country that is very egalitarian with very equal distributions of income and wealth. Our results indicate that wealth mobility is higher in Denmark than in the US, in line with similar findings for income mobility by Chetty et al. (2014). In strong contrast to the substantial overall mobility in wealth, we find a very low intergenerational mobility at the top of the wealth distribution. Thus, simple summary measures of mobility for the full populations may provide a misleading picture of what happens at the extremes of the distribution.

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Table 1: Summary statistics

	Child-Parent (CP) sample		Child-Parent-Grandparent (CPG) sample		
	Children 2009-2011	Parents 1997-1999	Children 2009-2011	Parents 1997-1999	Grandparents 1983-1985
Age	33.9	48.6	23.4	35.0	47.1
	(8.2)	(7.7)	(2.3)	(2.2)	(5.1)
Share men	0.51		0.51		
	(0.50)		(0.50)		
Share married	0.61		0.34		
	(0.49)		(0.47)		
Number of siblings	2.6		2.7		
	(0.9)		(0.9)		
Number of cousins			6.3		
			(2.6)		
Years of education[a]	12.9	12.1	11.0	12.1	8.9
	(2.4)	(2.8)	(1.7)	(2.2)	(2.3)
Earnings	256,173	287,404	128,966	280,438	247,120
	(208,212)	(175,066)	(103,573)	(136,481)	(134,212)
Income[b]	321,521	364,423	171,306	339,185	370,646
	(220,614)	(287,814)	(91,834)	(113,403)	(163,515)
Share self-employed[c]	0.04	0.08	0.01	0.06	0.10
	(0.19)	(0.19)	(0.10)	(0.17)	(0.16)
Share owning stocks	0.22	0.26	0.15	0.13	0.07
	(0.41)	(0.36)	(0.36)	(0.28)	(0.14)
Share owning property[d]	0.47	0.59	0.11	0.58	0.43
	(0.50)	(0.34)	(0.31)	(0.41)	(0.42)
Share owning bonds[e]	0.06	0.06	0.03	0.01	0.11
	(0.23)	(0.19)	(0.16)	(0.08)	(0.29)
Share with bank deposits	0.97	0.90	0.96	0.89	0.33
	(0.18)	(0.22)	(0.19)	(0.24)	(0.29)
Value of assets	626,275	909,696	93,936	574,491	822,172
	(1,724,771)	(2,247,272)	(351,900)	(865,855)	(1,087,937)
Share with bank debt[d]	0.79	0.73	0.70	0.89	0.55
	(0.41)	(0.35)	(0.46)	(0.25)	(0.43)
Share with mortgage debt[d]	0.45	0.56	0.11	0.58	0.36
	(0.50)	(0.36)	(0.31)	(0.41)	(0.41)
Value of liabilities	604,255	585,576	128,573	595,642	547,038
	(1,311,986)	(1,059,941)	(326,488)	(691,913)	(814,819)
Net wealth	22,019	324,120	-34,636	-21,151	275,134
	(1,060,814)	(1,817,095)	(213,777)	(527,319)	(682,810)
Percentiles of wealth					
20th	-231,674	-90,179	-91,207	-185,177	-10,950
40th	-69,005	45,130	-24,733	-87,575	108,117
60th	7,964	253,803	3,685	-15,577	269,548
80th	147,060	585,157	28,039	119,754	496,151
Observations	1,195,716	1,195,716	100,425	100,425	100,425

Notes: The table reports mean values and standard deviations (in parentheses) of the variables. Age, education, and ownership variables are as of 2011 for children, 1998 for parents, and 1983 for grandparents. Wealth, income, and earnings variables are averaged over the years 2009-2011 for children, 1997-1999 for parents, and 1983-1985 for grandparents. Parental values are given as the average of that of the biological father and mother. Likewise, for grandparents we use the average of all grandparents. All monetary variables are measured in DKK (1 USD is approximately 5.5 DKK) and deflated with nominal GDP to 2010-prices.

Child-Parent (CP) sample: Children are born in 1960 or later and are thus aged 21-51 in 2011, both parents are alive in 2011 and aged 21-66 in 1999, and children are neither immigrants nor descendants of immigrants.

Child-Parents-Grandparents (CPG) sample: Children and parents are born in 1960 or later, and both parents are alive in 2011. Thus, parents are aged 21-39 in 1999, and children are aged 21-36 in 2011. Children are neither immigrants nor descendants of immigrants, and have at least one grandparent alive in 1985.

Both samples are restricted to child-parents pairs with child and parental income exceeding 1,000 DKK. Imposing this restriction reduces the CP sample by 6,444 child-parent pairs and the CPG sample by 262 child-parent-grandparent triples.

a) Measures years of completed education. The variable is based on 2010 data for children.

b) Income includes earnings, self-employment income, and all types of transfers. Income is exclusive of capital income for children and parents but not for grandparents. Note that grandparental income is not used in the ensuing empirical analyses.

c) Self-employed dummy for children is based on 2010 data.

d) Property ownership dummy, mortgage debt dummy, and bank debt dummy for grandparents is based on 1987 data. Sample sizes for these numbers are slightly lowered by death of grandparents occurring between 1983 and 1987. This issue is innocuous to our analyses as the variable is not included in the analyses.

e) Bond ownership dummy for grandparents is based on 1995 data. The sample size for this number is slightly lowered by death of grandparents occurring between 1983 and 1995. This issue is innocuous to our analyses as the variable is not included in the analyses.

Table 2: OLS estimates of the child-parent wealth relationship with rank, log, and IHS transformation of the data

	Baseline no age controls	Baseline age controls	Child age ≤ 33	Child age > 33	Parental age < 50	Parental age ≥ 50	Parental wealth 2009-2011
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A. Rank transformation							
Parental wealth	0.242	0.234	0.235	0.232	0.225	0.243	0.260
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	1,195,716	1,195,716	583,451	612,265	580,560	615,156	1,193,993
Adj. R^2	0.058	0.070	0.079	0.062	0.073	0.065	0.082
B. Log transformation							
Parental wealth	0.377	0.266	0.281	0.254	0.262	0.268	0.270
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
Observations	397,410	397,410	158,992	238,418	148,220	249,190	443,187
Adj. R^2	0.085	0.267	0.166	0.065	0.180	0.106	0.277
C. IHS transformation							
Parental wealth	0.209	0.191	0.186	0.195	0.178	0.206	0.211
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	1,195,716	1,195,716	583,451	612,265	580,560	615,156	1,193,993
Adj. R^2	0.042	0.103	0.148	0.059	0.147	0.056	0.105

Notes: This table shows estimates from OLS regressions of child wealth (in some transformation) on parental wealth (transformed), using the CP sample described in Table 1. The dependent variable is the rank, log, and IHS transformation of the average 2009-2011 wealth of children. In all columns except (7), parental wealth is the average of 1997-1999 wealth.
Columns (2)-(7) include child and parental age dummies. Parental age is the rounded mean age of the parents. Robust standard errors are reported in parentheses.
In panel A, wealth variables are transformed into within-cohort wealth ranks as rank = $100 \cdot (i - 0.5)/N$, $i = 1, 2, ..., N$. I.e., for each child, we compute the rank in the distribution of child wealth for individuals at the same age (with maximum rank normalized to 100). We do the same for parents based on their average age. In Panel B, wealth is transformed using the natural logarithm. In Panel C, we use the inverse hyperbolic sine transformation (IHS) given by $w = \log(W + \text{sqrt}(W^2+1))$.

Table 3: Sensitivity to inclusion of other factors

	Baseline	Income	Education	Demographics	Region	All
	(1)	(2)	(3)	(4)	(5)	(6)
Parental wealth	0.234	0.231	0.225	0.230	0.231	0.219
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Parental income		0.014				-0.004
		(0.001)				(0.001)
Child income		0.007				0.013
		(0.001)				(0.001)
Years-of-schooling dummies[a]			X			X
Social demographics dummies[b]				X		X
Municipality dummies[c]					X	X
Child and par. age dummies	X	X	X	X	X	X
Observations	1,195,716	1,195,716	1,195,716	1,195,716	1,195,716	1,195,716
R-squared	0.070	0.070	0.075	0.074	0.081	0.091
Adj. R-squared	0.070	0.070	0.075	0.074	0.081	0.090

Notes: This table shows estimates from OLS regressions of child wealth rank on parental wealth rank and other covariates, using the CP sample described in Table 1. All wealth and income variables are ranked within child and parental age cohorts, respectively. Parental age is the rounded mean age of the parents. Robust standard errors are reported in parentheses.

a) Years-of-schooling dummies for both child and parent are included. Years of schooling is recorded as of 2010.

b) Social demographics include number-of-siblings dummies, child gender dummies, and child marital status dummies.

c) Municipality dummies include dummies for child and parental municipality of residence as of 2011. Parental municipality is determined as a random draw between the residence of the father and the mother if they do not live together. There are 98 municipalities in Denmark.

Table 4: Sensitivity of child-parents wealth rank correlations to number of living parents

	Two living parents in 1999 and 2011	Two living parents in 1999, one in 2011	Two living parents in 1999, zero in 2011	One living parent in 1999 and 2011	One living parent in 1999, zero in 2011
	(1)	(2)	(3)	(4)	(5)
Parental wealth	0.234	0.261	0.390	0.197	0.288
	(0.001)	(0.002)	(0.008)	(0.002)	(0.006)
Child and par. age dummies	X	X	X	X	X
Observations	1,195,716	208,798	17,804	133,930	26,062
R-squared	0.069	0.069	0.130	0.055	0.097
Adj. R-squared	0.069	0.069	0.126	0.055	0.095

Notes: Dependent variable is child wealth. Wealth variables are ranked within child and parental age cohorts, respectively. Parental age is the rounded mean age of the parents. All regressions are run on an extended version of the CP sample including data from children with parents dying before we observe child wealth. Robust standard errors are reported in parentheses.

Table 5: Child-parent and child-parent-grandparent wealth rank correlations

	Child wealth	Parental wealth		Child wealth	
	(1)	(2)	(3)	(4)	(5)
Parental wealth	0.215			0.191	0.176
	(0.003)			(0.003)	(0.003)
Grandparental wealth		0.205	0.162	0.116	0.081
		(0.003)	(0.003)	(0.003)	(0.003)
Parental income					0.038
					(0.003)
Child income					-0.060
					(0.003)
Years-of-schooling dummies[a]					X
Social demographics dummies[b]					X
Municipality dummies[c]					X
Number of cousins dummies					X
Child age dummies	X		X	X	X
Parental age dummies	X	X		X	X
Grandparental age dummies		X	X	X	X
Observations	100,425	100,425	100,425	100,425	100,425
R-squared	0.075	0.047	0.048	0.091	0.152
Adj. R-squared	0.075	0.046	0.047	0.090	0.149

Notes: This table shows OLS estimates of intergenerational rank correlations of wealth across three generations, using the CPG sample described in Table 1. All wealth and income variables are ranked within child, parental, and grandparental age cohorts, respectively. Parental and grandparental age is the rounded mean age of the parents and grandparents, respectively. Robust standard errors are reported in parentheses.

a) Years-of-schooling dummies for both child and parent are included. Years of schooling is recorded as of 2010.

b) Social demographics include number-of-siblings dummies, child gender dummies, and child marital status dummies.

c) Municipality dummies include dummies for child and parental municipality of residence as of 2011. Parental municipality is determined as a random draw between the residence of the father and the mother if they do not live together. There are 98 municipalities in Denmark.

Table 6: Intergenerational top one correlation and sensitivity to main controls

	Child wealth					
	(1)	(2)	(3)	(4)	(5)	(6)
Parental wealth	0.166	0.160	0.166	0.166	0.164	0.159
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Child income		0.075				0.071
		(0.003)				(0.003)
Parental income		0.024				0.022
		(0.002)				(0.002)
Years-of-schooling dummies[a]			X			X
Social demographics dummies[b]				X		X
Municipality dummies[c]					X	X
Child and par. age dummies	X	X	X	X	X	X
Observations	1,195,716	1,195,716	1,195,716	1,195,716	1,195,716	1,195,716
R-squared	0.030	0.036	0.031	0.032	0.032	0.040
Adj. R-squared	0.030	0.036	0.031	0.031	0.031	0.039

Notes: This table shows estimates from linear probability models regressing a dummy variable, indicating whether or not a child is in the top 1 percent of the wealth distribution of his or her cohort, on a number of covariates. All wealth and income variables are dummies indicating whether the person is in the top one percent of the distribution based on cohort-specific ranks. Parental age is the rounded mean age of the parents. All regressions are on the CP sample described in Table 1. Robust standard errors are reported in parentheses.

a) Years-of-schooling dummies for both child and parent are included. Years of schooling is recorded as of 2010.

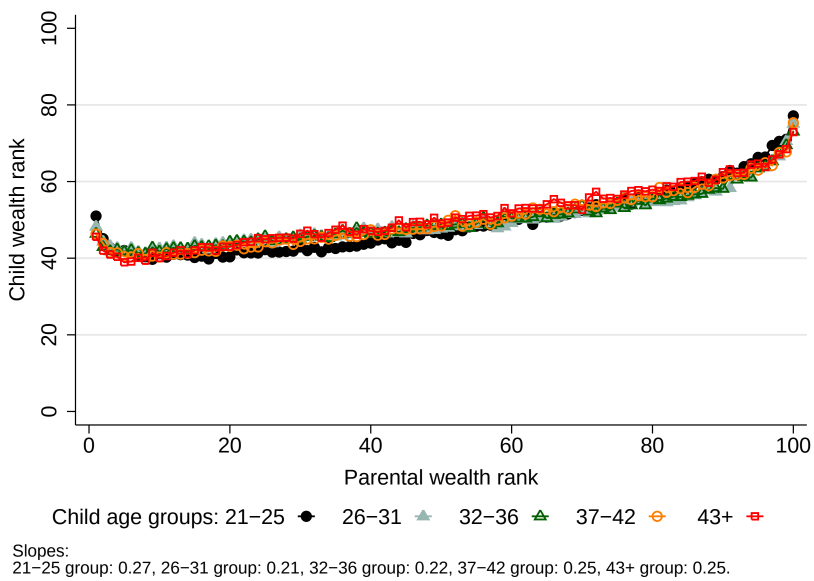
b) Social demographics include number-of-siblings dummies, child gender dummies, and child marital status dummies.

c) Municipality dummies include dummies for child and parental municipality of residence as of 2011. Parental municipality is determined as a random draw between the residence of the father and the mother if they do not live together. There are 98 municipalities in Denmark.

Figure 1: Mean child wealth rank vs. parental wealth rank

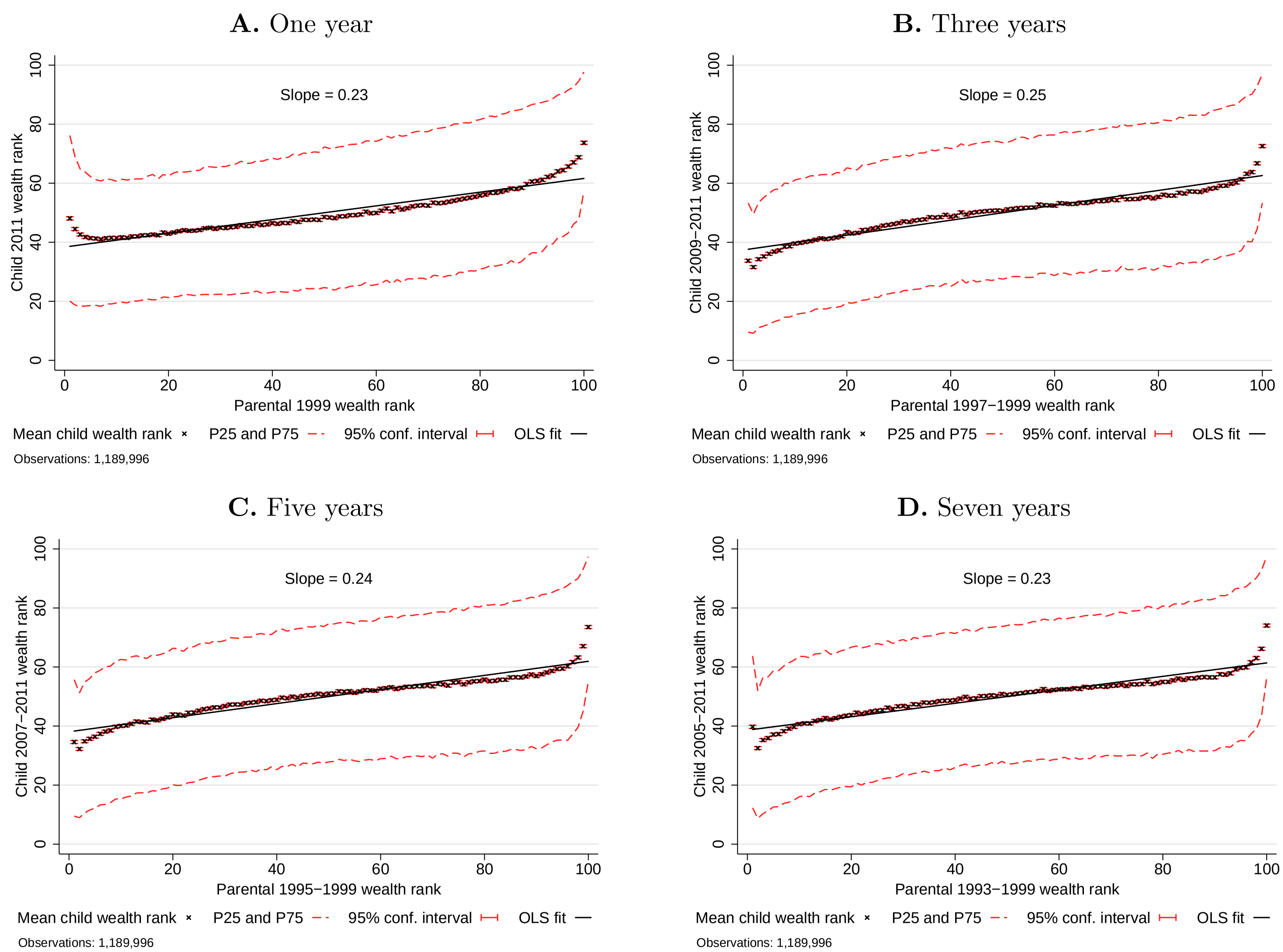
Notes: This figure presents a non-parametric binned scatter plot of child-parent pairs divided into percentiles according to parental wealth ranks and showing for each percentile the mean rank of children. Wealth ranks (with maximum value normalized to 100) are calculated within each cohort of children and parents, respectively, using the average age of parents (rounded to nearest integer value) to establish parental cohorts. Child wealth is individual wealth averaged over the years 2009-2011, and parental wealth is the average of father's and mother's wealth averaged over the years 1997-1999. The figure is based on the CP sample, c.f. description in Table 1, and the OLS slope reported in the figure is estimated using microdata, not binned data.

Figure 2: Child-parent wealth rank relationship by child age groups



Notes: This figure presents a non-parametric binned scatter plot of the child-parent wealth rank relationship similar to Figure 1, but stratified on child age groups. Age groups are selected in order that groups are of approximately equal size, using the CP sample. See the notes for Figure 1 for an explanation of how wealth ranks are generated. The OLS slopes reported under the figure are estimated using microdata.

Figure 3: Child-parent wealth rank relationship: The importance of number of years used in wealth averages

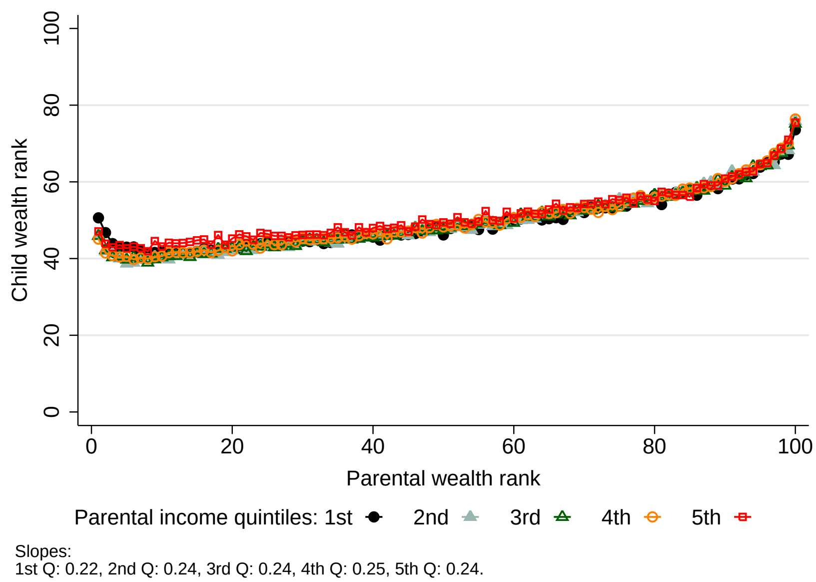


Notes: This figure investigates the importance of attenuation bias in the child-parent wealth rank relationship when using the mean of 1, 3, 5, or 7 years of wealth data to generate wealth ranks. In Panel A, we use one year of wealth to generate ranks; in Panel B, we use three years; in Panel C, we use five years; in Panel D, we use seven years. All figures are made from the same sample. Starting from the CP sample, we drop child-parent pairs in which the child or the parents have missing observations in any of the seven years necessary to generate all four figures. This implies a loss of 5,720 observations compared to the CP sample. OLS slopes reported in the figures are estimated using microdata.

Figure 4: Stability of the child-parent wealth rank relationship with respect to income

A. Rank relationship by child income quintiles

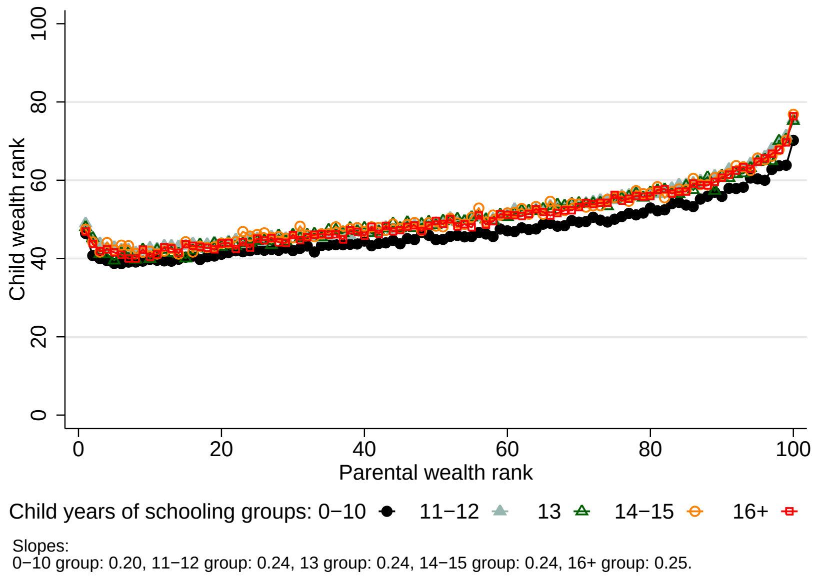
B. Rank relationship by parental income quintiles



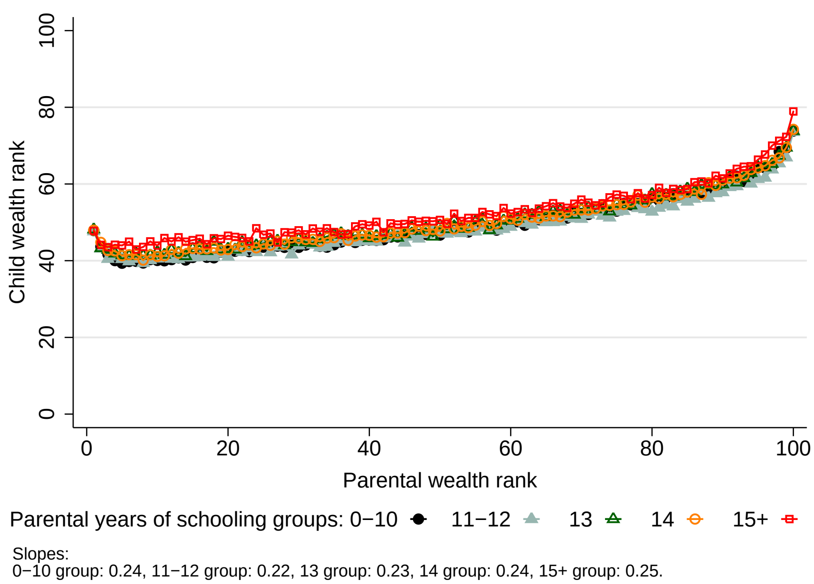
Notes: This figure presents a non-parametric binned scatter plot of the child-parent wealth rank relationship (similar to Figure 1) by child income quintiles (Panel A) and parental income quintiles (Panel B), respectively, using the CP sample. See the notes for Figure 1 for an explanation of how wealth ranks are generated. Income quintiles are determined using the same ranking procedure as that generating wealth ranks, i.e., incomes are ranked within each age cohort for children and for parents, respectively, where we use the average age of the mother and father (rounded to nearest integer value) for parental cohorts. The OLS slopes reported under the figures are estimated using microdata.

Figure 5: Stability of the child-parent wealth rank relationship with respect to parental and child education level

A. Rank relationship by child years of schooling



B. Rank relationship by parental years of schooling



Notes: This figure presents a non-parametric binned scatter plot of the child-parent wealth rank relationship (similar to Figure 1) by child years of schooling (Panel A) and parental years of schooling (Panel B), using the CP sample. Education groups are created to approximately represent quintiles in the distribution of graduated children and parents, respectively. See the notes for Figure 1 for an explanation of how wealth ranks are generated. The OLS slopes reported under the figures are estimated using microdata.

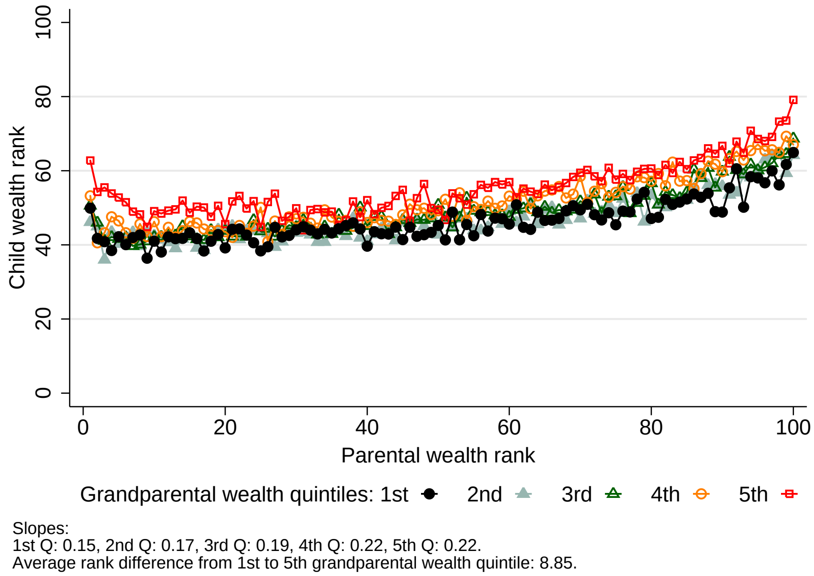
Figure 6: Stability over time/across generations of the intergenerational wealth rank relationship

A. Children vs. parents

B. Parents vs. grandparents

Notes: The figures are based on the CPG sample (cf. notes for Table 1) and present non-parametric binned scatter plots of the child-parent wealth rank relationship (Panel A) and of the parents-grandparents wealth rank relationship (Panel B). Wealth ranks are generated as explaned in Figure 1, ranking children within child age cohorts, parents within parental age cohorts, and grandparents within grandparental age cohorts. For parents and grandparents, respectively, we determine the age on which to base the ranking procedure as the average age of the mother and father or of the grandparents, in both cases rounding to nearest integer value. The procedure and variables are explained in greater detail in the notes for Figure 1. Grandparental wealth is the average of all grandparents alive averaged over the years 1983-1985. The OLS slopes reported in the figures are estimated using microdata.

Figure 7: Stability of the child-parent wealth rank relationshup with respect to grandparental wealth



Notes: This figure is based on the CPG sample (cf. notes for Table 1) and presents a non-parametric binned scatter plot of the child-parent wealth rank relationship by quintiles of grandparental wealth. Wealth ranks are generated as explaned in Figure 5, ranking wealth of each generation within age cohorts. The OLS slopes reported in the figures are estimated using microdata.

A Appendix (not for publication)

A.1 Derivation of Equation (10)

We start with modified law of motion (9) in Section 2.4, $\mathbf{x}_g = z_g\mathbf{\Phi} + \tilde{\mathbf{x}}_g$. The latent factor evolves according to

$$z_g = \phi z_{g-1} + \eta_g \tag{A.1}$$

with intergenerational coefficient ϕ, and where η_g is an iid error term.

In order to derive $\mathrm{E}[\beta_w|\mathbf{x}_g, \mathbf{x}_{g-1}]$, note that $w_{g-1} = \mathbf{x}_{g-1}\boldsymbol{\beta}$ from (4). Using (4), (9), and (A.1), we may find an expression for w_g given by

$$\begin{aligned}
w_g &= \mathbf{x}_g\boldsymbol{\beta} = z_g\mathbf{\Phi}\boldsymbol{\beta} + \tilde{\mathbf{x}}_g\boldsymbol{\beta} \\
&= \phi z_{g-1}\mathbf{\Phi}\boldsymbol{\beta} + \tilde{\mathbf{x}}_g\boldsymbol{\beta} + \eta_g\mathbf{\Phi}\boldsymbol{\beta} \\
&= \phi\mathbf{x}_{g-1}\boldsymbol{\beta} - \phi\tilde{\mathbf{x}}_{g-1}\boldsymbol{\beta} + \tilde{\mathbf{x}}_g\boldsymbol{\beta} + \eta_g\mathbf{\Phi}\boldsymbol{\beta}.
\end{aligned}$$

Using the standard OLS formula from regressing $w_g = \phi\mathbf{x}_{g-1}\boldsymbol{\beta} - \phi\tilde{\mathbf{x}}_{g-1}\boldsymbol{\beta} + \tilde{\mathbf{x}}_g\boldsymbol{\beta} + \eta_g\mathbf{\Phi}\boldsymbol{\beta}$ on $w_{g-1} = \mathbf{x}_{g-1}\boldsymbol{\beta}$, and noting that η_g is uncorrelated with $\boldsymbol{\beta}\mathbf{x}_{g-1}$, we get

$$\begin{aligned}
E[\beta_w|\mathbf{x}_g, \mathbf{x}_{g-1}] &= (\boldsymbol{\beta}' \cdot (\mathbf{x}'_{g-1}\mathbf{x}_{g-1}) \cdot \boldsymbol{\beta})^{-1} \cdot \boldsymbol{\beta}' \cdot \mathbf{x}'_{g-1} \times \\
&\qquad [\phi\mathbf{x}_{g-1}\boldsymbol{\beta} - \phi\tilde{\mathbf{x}}_{g-1}\boldsymbol{\beta} + \tilde{\mathbf{x}}_g\boldsymbol{\beta}] \\
&= \phi \qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad \text{(A.2)} \\
&\quad - (\boldsymbol{\beta}' \cdot (\mathbf{x}'_{g-1}\mathbf{x}_{g-1}) \cdot \boldsymbol{\beta})^{-1} \cdot \boldsymbol{\beta}' \cdot (\mathbf{x}'_{g-1}\tilde{\mathbf{x}}_{g-1}) \cdot \boldsymbol{\beta\phi} \\
&\quad + (\boldsymbol{\beta}' \cdot (\mathbf{x}'_{g-1}\mathbf{x}_{g-1}) \cdot \boldsymbol{\beta})^{-1} \cdot \boldsymbol{\beta}' \cdot (\mathbf{x}'_{g-1}\tilde{\mathbf{x}}_g) \cdot \boldsymbol{\beta}.
\end{aligned}$$

We can rewrite the second and third terms by using (9) and noting our assumptions that z_{g-1} is uncorrelated with $\tilde{\mathbf{x}}_{g-1}$ and $\tilde{\mathbf{x}}_{\mathbf{g}}$

$$\mathbf{x}'_{g-1}\tilde{\mathbf{x}}_{g-1} \cdot \boldsymbol{\beta\phi} = (z_{g-1}\mathbf{\Phi} + \tilde{\mathbf{x}}_{g-1})'\,\tilde{\mathbf{x}}_{g-1} \cdot \boldsymbol{\beta\phi} = \tilde{\mathbf{x}}'_{g-1}\tilde{\mathbf{x}}_{g-1} \cdot \boldsymbol{\beta\phi},$$

and

$$\mathbf{x}'_{g-1}\tilde{\mathbf{x}}_g \cdot \boldsymbol{\beta} = (z_{g-1}\mathbf{\Phi} + \tilde{\mathbf{x}}_{g-1})'\,\tilde{\mathbf{x}}_g \cdot \boldsymbol{\beta} = \tilde{\mathbf{x}}'_{g-1}\tilde{\mathbf{x}}_g \cdot \boldsymbol{\beta}.$$

In this way we can rewrite (A.2) to get

$$
\begin{aligned}
E[\beta_w|\mathbf{x}_g, \mathbf{x}_{g-1}] = \phi& \\
&- (\boldsymbol{\beta}' \cdot (\mathbf{x}'_{g-1}\mathbf{x}_{g-1}) \cdot \boldsymbol{\beta})^{-1} \cdot \boldsymbol{\beta}' \cdot (\tilde{\mathbf{x}}'_{g-1}\tilde{\mathbf{x}}_{g-1}) \cdot \boldsymbol{\beta}\boldsymbol{\phi} \\
&+ (\boldsymbol{\beta}' \cdot (\mathbf{x}'_{g-1}\mathbf{x}_{g-1}) \cdot \boldsymbol{\beta})^{-1} \cdot \boldsymbol{\beta}' \cdot (\tilde{\mathbf{x}}'_{g-1}\tilde{\mathbf{x}}_{g}) \cdot \boldsymbol{\beta},
\end{aligned}
$$

which is the expression (10) in Section 2.4.

A.2 More details on the wealth data

The wealth data records are subject to a few data breaks due to changing classifications of certain assets and liabilities, changes in reporting requirements, changes in tax treatment, etc. Table A.3 provides an overview of all data breaks in the underlying components of assets and liabilities. Although we do not construct the aggregate measures of assets and liabilities but instead rely on those compiled by Statistics Denmark, the table is still informative regarding the stability of the definition of wealth in the period. On the larger lines, subcomponents are generally third-party reported since 1997, whereas they relied in part on third-party reports and self-reporting prior to 1997.

The treatment of company values for self-employed has undergone a number of changes since the 1980s. In the period 1981 to 1985, firm assets such as buildings and operating fixture, equipment, machines, and cars are included. In 1981, buildings and operating fixture, equipment, machines, cars, etc. are registered at 80 percent of the cash value or the balance sheet book value. It is calculated as 75 percent of the cash value in 1982, 70 percent of the cash value in 1983–1988, and 60 percent of the cash value in 1988–1996. In the period 1986 to 1996, the equity of the firm is computed separately and included in the assets of a self-employed. In addition to the above assets, the computation of firm equity also includes financial assets of the firm, inventory, etc., and company debt is subtracted. From 1997 only firm assets are included in the assets of the owner while firm liabilities are included in the liabilities of the owner.

A.3 Analyzing the impact of the 1997 change in the definition of wealth

The definition of wealth was changed as of 1997, where the wealth tax was abolished as described in Section 3. However, for 1995 and 1996 Statistics Denmark computed assets and liabilities of each individual using both the new definition of wealth (used for children and parents) and the old definition (used for grandparents). In Table A.4 and Figures A.4 and A.5 we exploit this overlap to show that the new wealth measure is well approximated by the old way of measuring wealth.

In Table A.4 we run OLS regressions of the new definition of wealth (rank transformed) measured in 1995 on the old definition of wealth (rank transformed) measured also in 1995. Columns 1 and 2 run regressions for grandparental and parental wealth, respectively, in the CPG sample, and column 3 runs the regression for parental wealth in the CP sample.[21] In all three cases, the slope coefficient is fairly close to unity, supporting our claim that the new definition approximates well the old definition.

Figure A.4 presents scatter plots of the new definition plotted against the old definition of wealth in 1995 for the same three cases as mentioned above. Axes are confined to wealth levels of no more than ±1 million DKK (in 2010-prices) for readability. Again we find that observations tend to be concentrated around the 45 degree line through origo.

In Figure A.5 we show histograms of the deviations of the new definition of wealth in 1995 from the old definition. The histograms confine the primary axis to discrepancies of less than ±1 million DKK (in 2010-prices) for readability. The distribution of discrepancies for all three cases are symmetric around zero and do not show any tendency for the new definition to systematically over- or underpredict old definition wealth.

[21] Notice that the CP and CPG sample sizes are slightly lower than those reported in Table 1. This is due to observations with missing values in 1995, e.g., due to temporary emigration or, in the case of grandparents, death.

Table A.1: Three-generation wealth rank regressions using the unrestricted CPG sample

				Split sample by child age	
				≤ 33	> 33
	(1)	(2)	(3)	(4)	(5)
Parental wealth	0.233	0.208	0.196	0.196	0.190
	(0.001)	(0.001)	(0.001)	(0.002)	(0.004)
Grandparental wealth		0.091	0.074	0.078	0.046
		(0.001)	(0.001)	(0.002)	(0.004)
Parental income			0.020	0.024	-0.020
			(0.002)	(0.002)	(0.005)
Child income			-0.050	-0.062	0.065
			(0.002)	(0.002)	(0.005)
Years-of-schooling dummies[a]			X	X	X
Social demographics dummies[b]			X	X	X
Municipality dummies[c]			X	X	X
Number of cousins dummies			X	X	X
Child age dummies	X	X	X	X	X
Parental age dummies	X	X	X	X	X
Grandparental age dummies		X	X	X	X
Observations	471,118	471,118	471,118	406,926	64,192
R-squared	0.080	0.089	0.125	0.138	0.075
Adj. R-squared	0.079	0.089	0.124	0.137	0.070

Notes: This table shows OLS estimates of intergenerational rank correlations of wealth across three generations, using the CPG sample described in Table 1, but without the restriction that parents are born in 1960 or later. Columns 4 and 5 show a split sample by child age (as of 2011). All wealth and income variables are ranked within child, parental, and grandparental age cohorts, respectively. Parental and grandparental age is the rounded mean age of the parents and grandparents, respectively. Robust standard errors are reported in parentheses.

a) Years-of-schooling dummies for both child and parent are included. Years of schooling is recorded as of 2010.

b) Social demographics include number-of-siblings dummies, child gender dummies, and child marital status dummies.

c) Municipality dummies include dummies for child and parental municipality of residence as of 2011. Parental municipality is determined as a random draw between the residence of the father and the mother if they do not live together.

Table A.2: Child-parent wealth rank correlations using grandparental wealth as an instrument

	(1)		(2)	
	1st stage	2nd stage	1st stage	2nd stage
Grandparental wealth	0.193		0.181	
	(0.003)		(0.003)	
Parental wealth		0.810		0.633
		(0.018)		(0.018)
Parental income			-0.027	0.050
			(0.004)	(0.004)
Child income			-0.012	-0.054
			(0.003)	(0.004)
Years-of-schooling dummies[a]			X	X
Social demographics dummies[b]			X	X
Municipality dummies[c]			X	X
Number of cousins dummies			X	X
Grandparental age	X		X	
Child and parental age dummies	X	X	X	X
Observations	100,425	100,425	100,425	100,425
F-test (1st stage)	1299.201		1058.983	
F-test p.-val. (1st stage)	0.000		0.000	
Partial R-sq (1st stage)	0.040		0.033	
R-sq (1st stage)	0.051		0.075	
Adj. R-sq (1st stage)	0.051		0.072	

Notes: This table shows estimates from 1st and 2nd stages of instrumental variable regressions of the child-parent wealth rank relationship, using grandparental wealth rank (and a 2nd order polynomial in grandparental age) as instruments for parental wealth rank. All regressions are on the CPG sample described in Table 1. Wealth and income variables are ranked within child, parental, and grandparental age cohorts, respectively. Parental and grandparental age is the rounded mean age of the parents and grandparents, respectively. Robust standard errors are reported in parentheses.

a) Years-of-schooling dummies for both child and parent are included. Years of schooling is recorded as of 2010.

b) Social demographics include number-of-siblings dummies, child gender dummies, and child marital status dummies.

c) Municipality dummies include dummies for child and parental municipality of residence as of 2011. Parental municipality is determined as a random draw between the residence of the father and the mother if they do not live together.

Table A.3: Wealth Data Documentation

	80	81	82	83	84	85	86	87	88	89	90	91	92	93	94	95	96	97	98	99	00	01	02	03	04	05	06	07	08	09	10	11	Variables
Assets																																	(*=ends with akt)
Bank deposits					*a*								*b*	*c*				*d*															INDESTPI/ BANK*
Bonds					*a*								*e*					*f*				*g*											KURSOBL/ INDESTPI/ OBL*
Deeds					*a*								*h*	*e*				*d*															KURSPANT/ INDESTPI/ PANT*
Stocks					*a*										*i*			*d*				*g*											KURS*
Value of property				*j*	*a*													*k*															KOEJD/ KOEJD_NY05
Liabilities																																	(*=ends with GALD, GAELD or GÆLD)
Bank debt					*a,l*		*m*	*n*			*n*	*n*		*n*	*o*			*d*															GÆLDIO/ BANK*/ PRI*/ BANK*
Mortgage debt					*a,o*													*d*															PRI*/ OBL*
Deed debt					*a,o*			*p*					*q*	*r*				*d*															PRI*/ PANT*/ BANK*/ PANT*

Color coding:

- Combined 3rd party reporting and self reporting
- 3rd party reports
- Variable overlap
- Variable shift

Data breaks

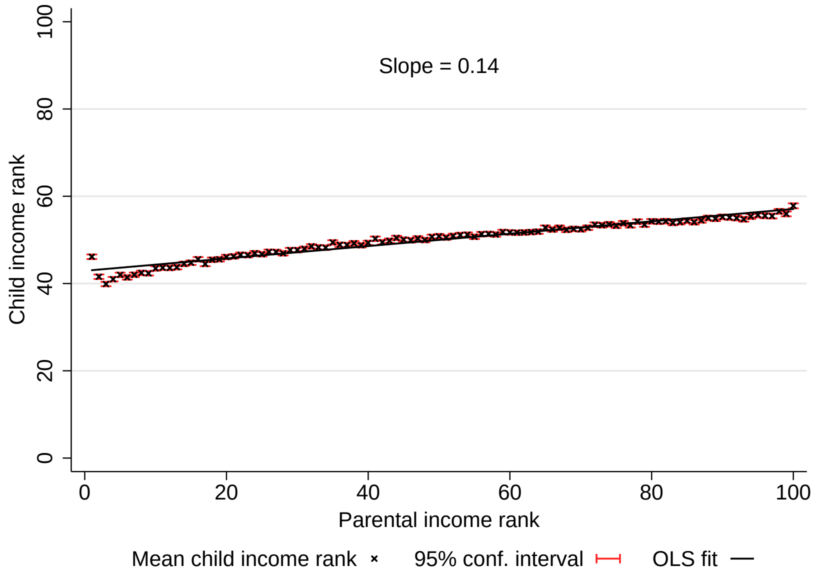
a During 1984-1986, not incl. people with special income; Income from stocks and bonds, self-employed, or income from other countries. From 1987 and onwards everyone is included.
b Including market value of bonds.
c Including deeds in deposits.
d Wealth tax is abolished. Only 3rd party info. from financial institutions and banks is available.
e Included in the aggregate variable indestpi. No seperate registration.
f Wealth tax is abolished. Only 3rd party info. from financial institutions and banks is available. Only incl. bonds in deposits.
g From 2001 the part of a mutual fond placed in bonds is moved from KURSAKT to OBLAKT.
h Only incl. deeds in deposits.
i Excl. unlisted stocks from 1994-1996.
j Value of property is for 500,000 people only registered in the aggregate asset variable, QAKTIVF.
k KOEJD only includes residential property, KOEJD_NY05 also includes business property and undeveloped land.
l Included in the aggregate variable GÆLDIO, which includes all other debt (including debt to foreign countries) than mortgage debt. No separate registration.
m Independent registration of debt to financial institutions. Deeds issued by financial institutions is included.
n During 1987-1993 debt in own business is not included in BANKGAELD. From 1990 and onwards including debt in The Mortgage Bank, pension funds, insurance and financial companies, credit and debit card debt. From 1991 including student debt in financial institutions. From 1993 including debt in deposited deeds (PANTGALD). The variable does not exist in 1994, bank debt is only registrered as part of the aggregate variable PRIGÆLD.
o No separate registration. Variable included in the aggregate variable PRIGÆLD.
p During 1987-1993 deed debt in own business is not included in PANTGALD.
q From 1992 excluding debt in deeds, which are not deposited.
r Debt in deposited deeds is included in the variable BANKGAELD and later PRIGÆLD. No separate registration.

Table A.4: Wealth data break 1995, new definition regressed on old definition

	CPG sample		CP sample
	Grandparental wealth	Parental wealth	Parental wealth
	(1)	(2)	(3)
Grandparental wealth	0.938		
	(0.001)		
Parental wealth		0.870	0.876
		(0.002)	(0.000)
Constant	3.100	6.511	6.225
	(0.077)	(0.090)	(0.026)
Observations	68,218	100,332	1,194,701
R-squared	0.880	0.757	0.767
Adj. R^2	0.880	0.757	0.767

Notes: This table exploits the overlap in 1995 of the new and old definitions of wealth as recorded by Statistics Denmark. The table shows regressions of the new definition of wealth on the old definition of wealth (both transformed into within-cohort ranks) and a constant term. Regressions in column 1-2 are run on the CPG sample described in Table 1. The regression in column 3 is run on the CP sample.
The difference in sample size compared to Table 1 is due to missing values of 1995 wealth. Robust standard errors are reported in parentheses.

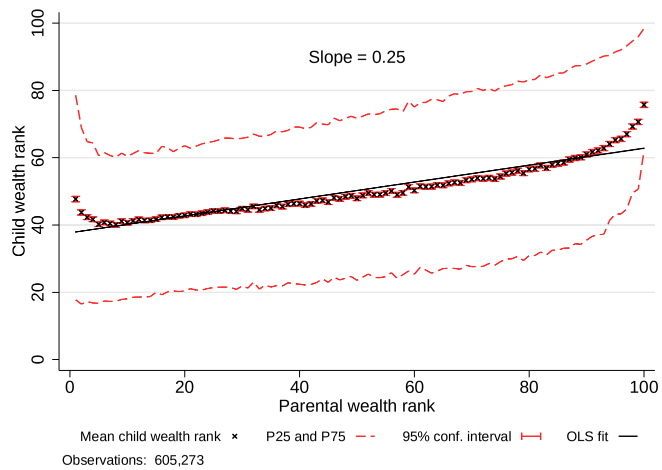
Figure A.1: Child-parent income rank relationship



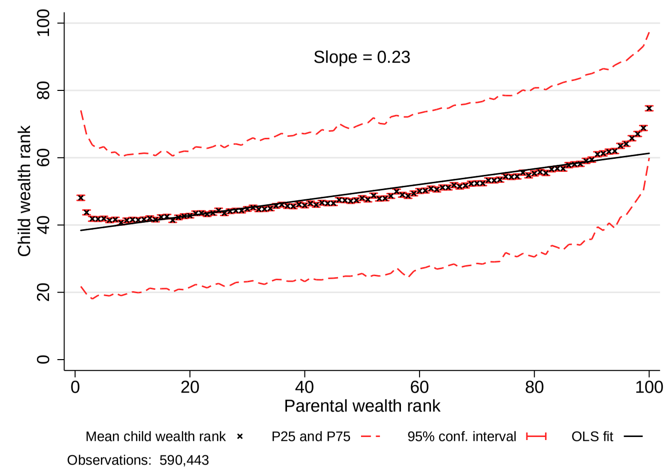
Notes: This figure presents a non-parametric binned scatter plot of child-parent pairs divided into percentiles according to parental income ranks and showing for each percentile the mean income rank of children. Income ranks are generated using the same procedure as used in generating wealth ranks. I.e., ranks are calculated within age cohorts. Child income is individual income averaged over the years 2009-2011, and parental income is the average of father's and mother's income averaged over the years 1997-1999. Income contains earnings, pensions, public transfers, foreign income, and income from closely held companies, but not capital income. The figure is based on the CP sample, c.f. description in Table 1, and the OLS slope reported in the figure is estimated using microdata.

Figure A.2: Child-parent wealth rank relationship by child gender and by child marital status

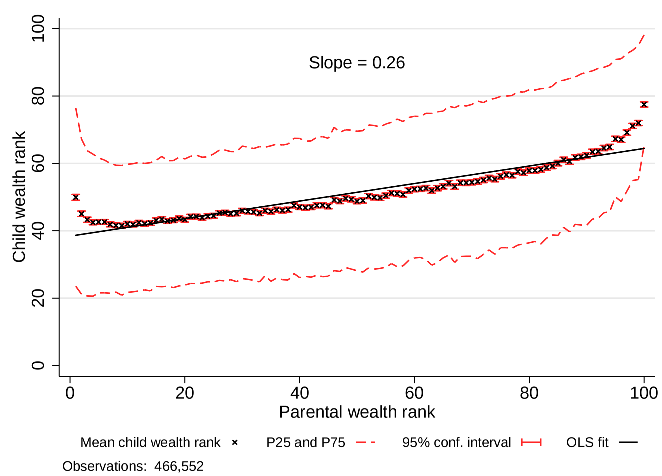
A. Men



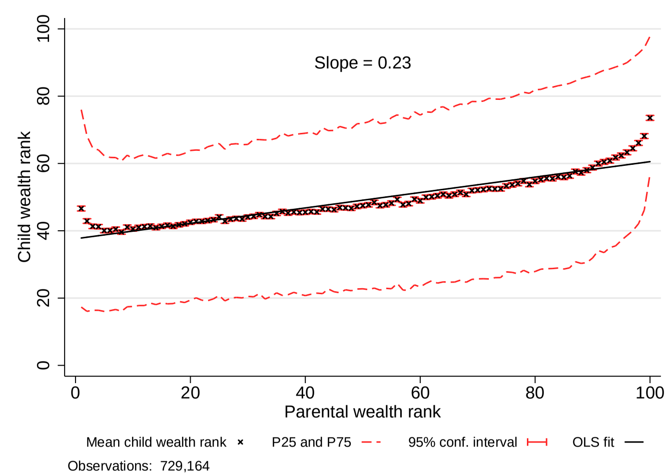
B. Women



C. Married

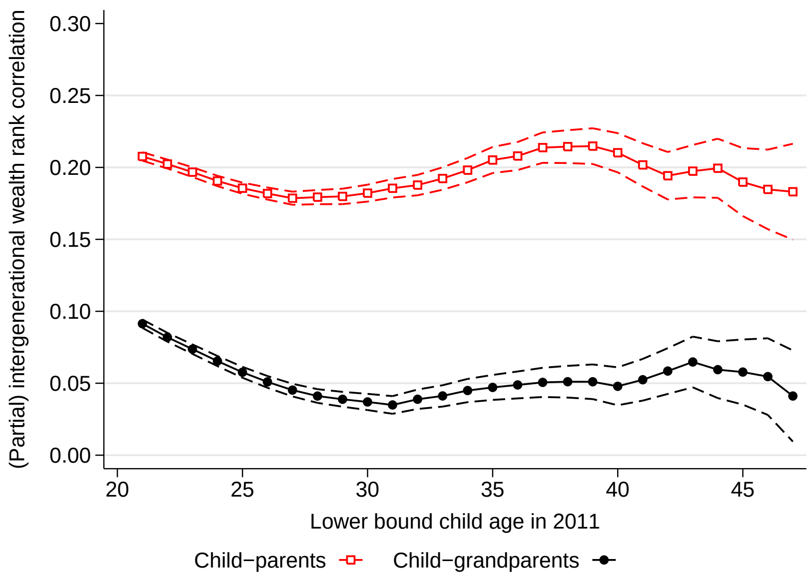


D. Unmarried



Notes: These figures present non-parametric binned scatter plots of the child-parent wealth rank relationship (similar to Figure 1), using the CP sample. Panels A and B show the result of splitting the sample by child gender, and Panels C and D show the result of splitting the sample by child marital status. See the notes for Figure 1 for an explanation of how wealth ranks are generated. Ranks are generated prior to sample splitting. The OLS slopes reported under the figures are estimated using microdata.

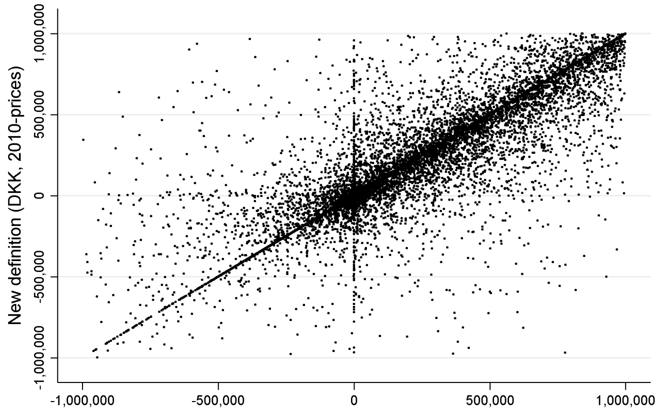
Figure A.3: The importance of lower bound child age in the unrestricted CPG sample



Notes: This figure shows estimates of partial intergenerational wealth rank correlation between children and their parents and between children and their grandparents, using the unrestricted CPG sample, and for varying lower bounds of child age. The unrestricted CPG sample differs from the CPG sample in that we do not demand parents be born in 1960 or later. As a consequence, we will not know all personal identifiers to grandparents in the sample. The sample size is 471,118 at lower bound child age of 21—almost a fivefold increase compared to the CPG sample. The estimates depicted in the graph derive from an OLS regression of child wealth rank regressed on parental wealth rank, grandparental wealth rank, and child, parental, and grandparental age dummies. Dashed lines are 95 percent confidence bounds.

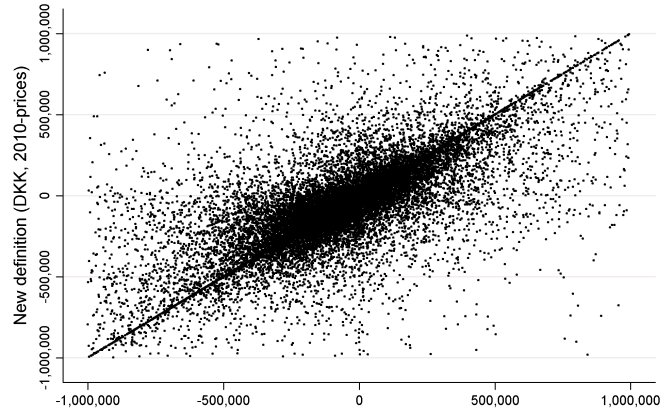
Figure A.4: Analysis of the wealth data break in 1995

A. Grandparents, CPG sample



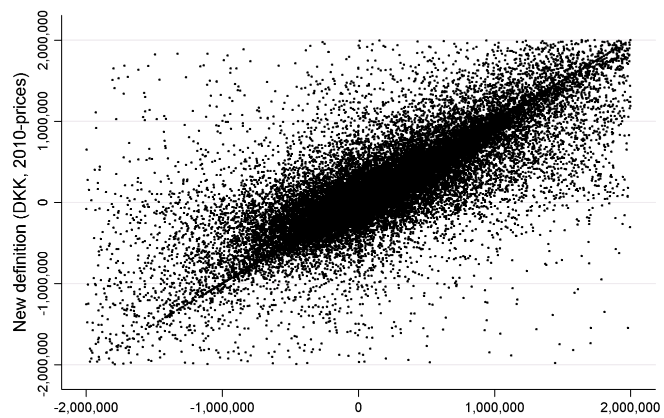
Notes: Depicted sample is the CPG sample described in Table 1, less observations with missing values of 1995-wealth. Only showing observations within +/- 1 million DKK. Sample size: 68,218.

B. Parents, CPG sample



Notes: Depicted sample is the CPG sample described in Table 1, less observations with missing values of 1995-wealth. Only showing observations within +/- 1 million DKK. Sample size: 100,332.

C. Parents, CP sample

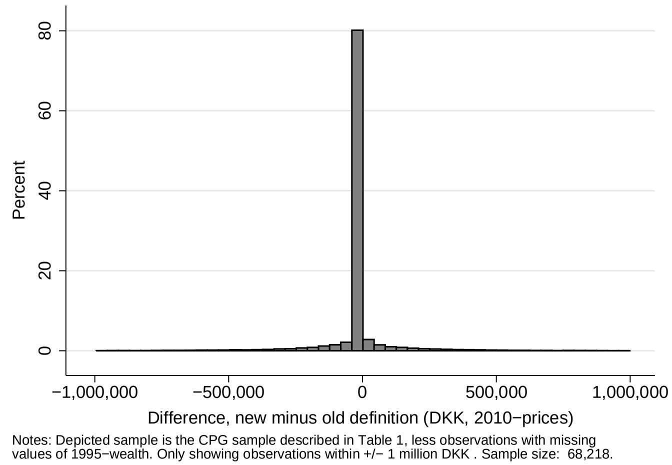


Notes: Depicted sample is the CP sample described in Table 1, less observations with missing values of 1995-wealth. Only showing 10% of observations within +/- 2 million DKK. Sample size: 1,194,701.

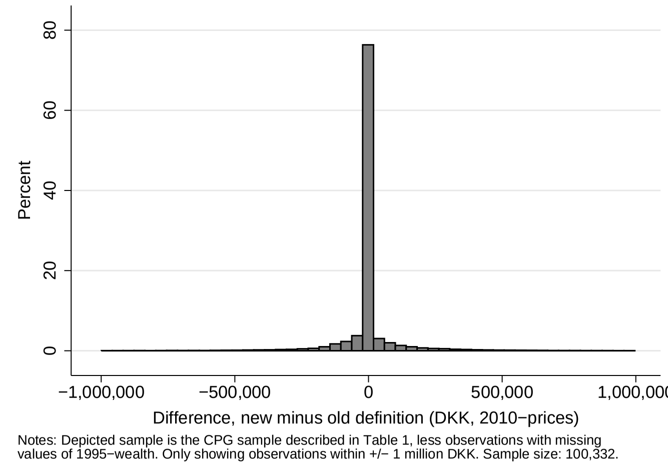
Notes: Scatter plots of individual wealth as recorded by the new definition plotted against wealth as recorded by the old definition. Panels A and B show the plot for grandparents and parents, respectively, in the CPG sample. Panel C shows the plot for parents in the CP sample. Sample sizes differ compared to those in Table 1 due to missing observations in 1995, e.g. grandparents dying before 1995, and as we only show observations not exceeding 1 million DKK (in 2010-prices).

Figure A.5: Analysis of the wealth data break in 1995

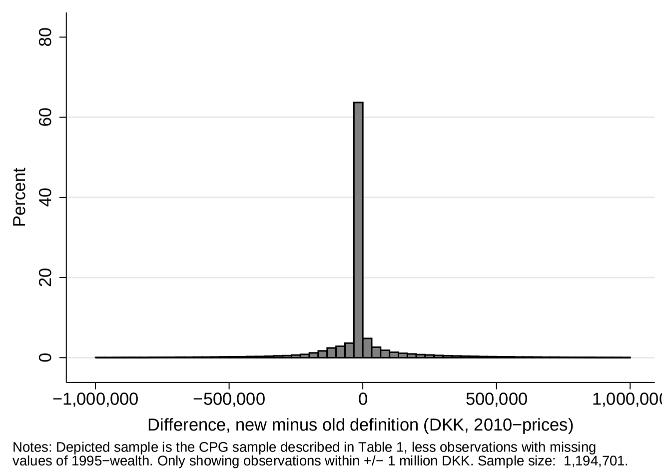
A. Grandparents, CPG sample



B. Parents, CPG sample



C. Parents, CP sample



Notes: Histograms of the difference in wealth as measured by the new and old definitions in 1995. Panels A and B show the histograms for grandparents and parents, respectively, in the CPG sample. Panel C shows the plot for parents in the CP sample. Sample sizes differ compared to those in Table 1 due to missing observations in 1995, e.g., grandparents dying before 1995.