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Multigenerational Mobility in the US, the UK, and Germany

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Abstract

Using harmonized household survey data, we analyse long run social mobility in the US, the UK, and Germany and test recent theories of multigenerational persistence of socio-economic status. In this country comparison setting we find evidence against Gregory Clark's "universal law of social mobility". In general, our results show that the long run persistence of socio-economic status tends to vary with the institutional context. Our findings on the existence of a direct and independent effect of grandparents' social status on grandchildren's status are mixed.

Keywords: Dynastic Inequality, Intergenerational Mobility, Multigenerational Persistence, Three generations, Grandparental Effect.

JEL Classification: D63, I24, J62

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1 Introduction

In many developed countries, the levels of income concentration experienced by current generations are as high as those experienced by their ancestors at the beginning of the 20th century (Piketty, 2014). Although trends of cross sectional inequality are informative in themselves, they neglect the movement of families within the income distribution - as well as their opportunities to improve their socio-economic status - over the course of time. Indeed, theories of justice suggest to focus on both dimensions of inequality: the static dimension, i.e. the income distribution at a given point in time, and the dynamic dimension (Rawls, 1971). The latter can be evaluated analysing the persistence of inequality between generations, or rather its antonym: social intergenerational mobility.

Recently, the relevance of the intergenerational dimension for distributional analyses has gained increasing attention by researchers and policy makers. A growing number of studies evaluates social intergenerational mobility measuring the degree of association between parents' and children's outcomes (e.g. income, earnings, occupation, or educational attainment). However, while this procedure seems to be suitable as a broad measure for equality of opportunity in a society (Chetty et al., 2014b; Corak, 2013), it is still not clear whether it leads to erroneous conclusions about the persistence of inequality in the long run. For instance, empirical studies show that long run mobility tends to be overestimated if it is extrapolated from the canonical two-generational mobility framework (e.g. Lindahl et al., 2015). Generally, the existing evidence is still mixed and refers to single countries. Researchers drew contrasting conclusions about, first, the long run persistence of socio-economic status, and, second, the existence of a direct effect that grandparents exert on the economic outcomes of their grandchildren. Therefore, it is of scientific importance and political relevance to add further evidence and to empirically verify different facets of intergenerational mobility over multiple generations. One of the main contributions of this study is to provide a comprehensive analysis on the subject in a common framework using harmonized data for three countries with different welfare regimes, the US, the UK, and Germany.

From a normative perspective, the analysis of long run intergenerational persistence of social status is crucial for a social planner who strives to *level the playing field*. Inasmuch, as the degree of intergenerational mobility of today's adults reflects the distribution of opportunities of yesterday's children, the analysis of mobility over three consecutive generations mirrors the circumstances faced by parents investing in their children's human capital. Hereby, since the vast recent literature on multigenerational persistence mainly focuses on single countries, it is valuable to evaluate the role played by the historical and institutional context. In this work, we therefore analyse the long run transmission of social status in three countries with very different institutional characteristics and historical backgrounds, providing comparable and consistent estimates of intergenerational mobility over three generations.

We perform the analysis with data from nationally representative household surveys that allow us to link individuals to their parents' and grandparents', and to reconstruct the educational history of families over three consecutive generations. The surveys are highly comparable and enable us to perform a harmonized cross-country analysis, testing recent theories of multigenerational persistence like Gregory Clark's provocative hypothesis of a "universal law of social mobility" (Clark, 2014). Furthermore, we test for the existence of a direct and independent effect that grandparents exert on their grandchildren, i.e. the part of the association between outcomes which is not mediated by parents. Additionally, to the best of our knowledge, we are the first to empirically account for ethnic capital – i.e the quality of the ethnic environment in which parents make their investments (Borjas, 1992) – within a multigenerational set-up.

Our main findings are the following: We find the strongest association between grandparents' and grandchildren's educational attainment in Germany and substantially lower associations in the UK. The US lies in between. Furthermore, we provide evidence against Clark's hypothesis of a fairly low and constant rate of social mobility over time and space. Although we cannot reject all implications of Clark's hypothetical construct, we do reject his strongest conclusion that the long run persistence of social status is independent of the specific historical and institutional context. In particular, we even find cross-country differences in the effect of direct interaction between grandparents and grandchildren.

The remainder of this paper is organized as follows: In Section 2 we review the literature on multigenerational mobility and introduce some of the most influential theories of long run persistence. Section 3 describes the data. Section 4 presents descriptive evidence on intergenerational mobility over two and three generations in the US, the UK, and Germany: First, assessing multigenerational mobility as equalizer of dynastic inequality in 4.1; Then, accounting for short-run and long-run mobility trends in 4.2; Last, applying non-parametric approaches in 4.3. Our test results on the theories of multigenerational persistence are presented and discussed in Section 5. Section 6 concludes.

2 Conceptual Framework and Literature Review

A widely accepted approach to measure intergenerational persistence of socio-economic status is to estimate the following linear regression model:

$$y_{it} = \alpha + \beta_{-m} \cdot y_{it-m} + \varepsilon_{it}, \tag{1}$$

where y_{it} is an outcome indicator of the socio-economic status of individual i belonging to generation t, and y_{it-m} of her ancestors' outcomes that date back m generations. The slope coefficient β_{-m} describes how much of the outcome advantage or disadvantage is transmitted within families over m generations on average. Thus, it can be interpreted as the persistence of inequality between families over the course of time.

Such analysis is usually performed on two subsequent generations, i.e. on parents and children. Since parents are arguably the most influential source for the formation of human capital, the association between parents' and children's outcomes is certainly of primary interest. Furthermore, although the channels of transmission are still not fully investigated, it generally seems plausible to assume a direct effect of parents on their children. Indeed, seminal theoretical contributions in economics on the intergenerational transmission of inequality build on a mainly two generational set up (Becker and Tomes, 1979, 1986; Loury, 1981; Solon, 1992). In addition, in many available data sets it is possible and less complicated to link parents and children, in contrast to higher ordered ancestors.

If the aim is to predict or extrapolate long run mobility patterns, the straightforward method that follows from the regression based procedure presented in equation (1) relies on a restrictive assumption, namely that the process is autoregressive of order one, and implies that

$$\beta_{-m} \approx (\beta_{-1})^m \quad \forall m \epsilon \mathbb{N}^+.$$

The finding of a directly estimated coefficient which is higher than the extrapolation would suggest ($\beta_{-m} > (\beta_{-1})^m$) was defined as "iterated regression fallacy". Stuhler (2014), who introduced the term, proves and extensively discusses the drawbacks of the iteration based extrapolation procedure for the analysis of multigenerational mobility (see also Braun and Stuhler, 2016).

The topic came up recently because of an increasing interest in the long run persistence of economic inequality. A new wave of studies by economists and sociologists emerged that analyses intergenerational mobility over three or more generations with different methodologies. While older studies mostly did not reject the hypothesis that the underlying process of intergenerational transmission of socio-economic status is of Markovian nature – i.e. that the socio-economic status of grandparents and older ancestors is totally mediated by the status of parents – recent studies basically reject this hypothesis and agree that the iterated extrapolation underestimates the long run persistence of economic inequality. For instance, earlier empirical works on multigenerational mobility did not find any significant association between grandparents' and grandchildren's outcomes, when controlling for parental outcomes (Behrman and Taubman, 1985; Peters, 1992; Ridge, 1974; Warren and Hauser, 1997).[1] This first line of research was, however, more focused on testing the implication of a negative grandparental coefficient as theorized by Becker and Tomes (1979) or finding a direct causal effect of grandparents.

In contrast, recent studies test the iteration procedure against direct or grouped observational data over three or more generations. One of the first empirical studies to show that an extrapolation by iteration might not fully capture the actual degree of intergenerational persistence is Lindahl et al. (2015) using longitudinal data from the Swedish Malmö study. Other recent studies mainly support these findings measuring intergenerational associations over three, four, or even more generations.[2]

[1]One exemption is Hodge (1966) who rejects the hypothesis of a first-order Markov chain in the transmission of occupations. For a review of earlier literature on multigenerational mobility, see also Warren and Hauser (1997).

[2]Recent studies evaluate the intergenerational persistence of distinct outcomes over three or more generations, such as earnings (Lindahl et al., 2015; Lucas and Kerr, 2013), wealth (Adermon et al., 2015), occupation (Chan and Boliver, 2013; Hertel and Groh-Samberg, 2014; Knigge, 2016), education (Braun and Stuhler, 2016; Celhay and Gallegos, 2015; Kroeger and Thompson, 2016), cognitive abilities (Hällsten, 2014), longevity (Piraino et al., 2014), and mental health (Johnston et al., 2013). Studies that measure the transmission over more than four generations mostly do not rely on direct family

Two prominent approaches try to explain this divergence between the predicted and the actual degree of intergenerational persistence. The first argues in favour of a so-called *latent factor* that determines the transmission of socio-economic status (Clark, 2014; Clark and Cummins, 2015). The second states that there is a direct and causal effect that grandparents exert on their grandchildren (Mare, 2011, among others).

A commonly adopted way to evaluate the statistical association between grandparents and grandchildren, abstracting from the mediating role of parents, is to estimate a regression which includes both the socio-economic status of parents and grandparents:

$$y_{it} = a + b_{-1} \cdot y_{it-1} + b_{-2} \cdot y_{it-2} + \vartheta_{it}. \tag{2}$$

Hereby, a positive significant coefficient of grandparents is often interpreted in the sense that an independent effect of grandparents persists over and above the effect of parents. However, as Braun and Stuhler (2016), Solon (2014), and Stuhler (2014) point out, the observation of a significant coefficient for grandparental outcomes does not automatically signalize a causal relationship. A direct causal effect of grandparents is a possible explanation, but omitted variable bias could explain a positive grandparental coefficient as well. Omitted variables could be, for instance, the education or occupational status of the other parent. *Ethnic capital*, understood as the quality of the ethnic environment in which parents make their investments, might be another factor of interest, which has been found to play an important role for the intergenerational transmission of human capital (Borjas, 1992). Indeed, the *latent factor model* argues that b_{-2} is positive and significantly larger than zero when estimating equation (2), because the variable included to measure the socio-economic status of grandparents captures an unobserved part of parents' socio-economic status which is fundamental for the intergenerational transmission mechanism; i.e. any kind of endowment, like abilities, preferences, or cultural heritage (see Clark and Cummins, 2015).

2.1 *The latent factor model*

Braun and Stuhler (2016) formalize the association between the observable outcome y_{it} and the unobservable endowment e_{it} following the *latent factor model* as

$$y_{it} = \rho e_{it} + u_{it} \tag{3}$$

$$e_{it} = \lambda e_{it-1} + v_{it} \tag{4}$$

linkages, but instead use the informative content of surnames (Barone and Mocetti, 2015; Clark and Cummins, 2015; Collado et al., 2013). Olivetti et al. (2016) estimate intergenerational mobility over three generations using first names. The only studies, apart from the present work, to analyse multigenerational mobility in a framework including more than one country are Clark (2014) and Hertel and Groh-Samberg (2014). For recent exhaustive overviews, see Pfeffer (2014); Solon (2014).

in a one-parent one-offspring family setting, assuming that both error terms u_{it} and v_{it} are uncorrelated with other variables and past values. The parameter λ can be interpreted as a "heritability" coefficient and captures the degree of unobservable endowments passed on from generation $t-1$ to generation t. The parameter ρ is called "transferability" coefficient and measures the scope of inherited endowments that can be converted into the observed outcome. If the variances of y_{it} and e_{it} are normalized to one, the observed correlation in outcome y between generation t and generation $t-m$ comes up to

$$\beta_{-m} = \rho^2 \lambda^m. \tag{5}$$

Therefore, multigenerational persistence is higher if both the degree of inheritability λ and transferability ρ is higher. As Braun and Stuhler (2016) show, estimating equation (1) for children's on parents' status and grandparents' status separately, using direct individual observations which can be linked over three generations (instead of grouped observations over surname groups as in Clark and Cummins, 2015), λ and ρ can be identified as

$$\frac{\beta_{-2}}{\beta_{-1}} = \frac{\rho^2 \lambda^2}{\rho^2 \lambda} = \lambda, \tag{6}$$

$$\sqrt{\frac{(\beta_{-1})^2}{\beta_{-2}}} = \rho. \tag{7}$$

Since constant variances are assumed, the regression coefficients equal the correlation coefficients. Adopting this specification, Braun and Stuhler (2016) test the hypothesis made by Clark (2014) on the heritability coefficient λ, and on the existence of a "universal law" of multigenerational persistence, i.e. the true rate of intergenerational persistence is almost the same in every country and time period. Using their own estimated correlations for Germany and the estimates in Lindahl et al. (2015) for Sweden, they find evidence against a constant heritability coefficient. Besides, their estimates for λ are significantly lower than the value suggested by Clark (0.75).[3]

2.2 *The grandparental effect model*

Another branch of research tries to explain the excess persistence arguing that differences in status inequality across generations are not exclusively transmitted from parents to children. Grandparents might exert a direct and independent effect on their grandchildren, too, for example by investing in their grandchildren's human capital and by shaping their preferences while living in the same multigenerational household (e.g. Mare, 2011; Pfeffer, 2014). Other sorts of direct effects of grandparents could lie in the genetic transmission of certain traits, the strength of family networks or reputation, and the

[3]Further evidence against such a high heritability coefficient is provided in a recent study by Nybom and Vosters (2016) within a two-generational set up. Including multiple proxy measures of parental background into a single estimate of status persistence, the authors find no evidence of bias in prior estimates of social intergenerational mobility in Sweden.

role of inheritances.[4] All these are possible explanations of a positive significant grandparental coefficient in equation (2) which go beyond technical issues like measurement error and omitted variable bias as discussed above.[5] So, to test for a direct effect of grandparents, abstracting from merely technical reasons driving the statistical relationship, requires an extension of the baseline model displayed in equation (2).

A common approach is to include additional variables to control for other socio-economic characteristics of the parents. For instance, information on the outcomes of both fathers and mothers are included in the regression instead of taking only the highest or the mean of the two. This way, unobserved characteristics that might explain the underlying transmission of status are covered more properly and a positive significant grandparental coefficient is a closer indicator of a direct relationship. However, the grandparental coefficient could still be biased upward due to the omission of other characteristics. *Ethnic capital* is an important feature that has been found to largely explain the different patterns of intergenerational transmission from parents to children between blacks and whites or natives and immigrants (e.g. Borjas, 1992). A similar relationship might also exist in a three-generational framework and is, thus, of particular importance. Our data allows to analyse this aspect controlling for migration background and race of individuals.

Another approach is to use information on direct contact between grandparents and grandchildren – or on a higher likelihood of contact between them – and compare the regression coefficients of individuals with and without direct contact to their grandparents. This method allows to account for intergenerational effects from grandparents to grandchildren generated by direct contact abstracting from those direct links that should be the same for individuals with and without a direct contact to their grandparents, which includes the genetic transmission of traits or the role of family networks. When information on exposure or coresidence are directly available, the analysis is straightforward. For example, Zeng and Xie (2014) show for rural China that the effect of grandparental education on school dropout is significantly stronger for coresident grandparents than for those who are not living in the same household as their grandchildren. However, when this information is not available, a common procedure is to use information on the year of death of the grandparents and check if the grandparent died before the grandchild was born, which is the identification strategy adopted also in the present study. Braun and Stuhler (2016) apply this strategy, too, and find no significant difference between the regression coefficients of grandparents who died before their grandchildren were born and grandparents who were still alive.[6]

[4] A discussion of the ways in which grandparents can affect their grandchildren can be found e.g. in Kroeger and Thompson (2016) and Solon (2014).

[5] For an overview of factors that might explain the excess persistence see, among others, Solon (2014). A recent theoretical examination of multigenerational persistence based on *careers* can be found in Zylberberg (2016).

[6] Since Braun and Stuhler (2016) find a significant correlation between year of death and the education of grandparents, they present further applications using World War II as an exogenous source of variation in the time of death. All tests on this behalf confirm their main results.

2.3 *Universal law of social mobility and the role of institutions*

A remarkable difference between the *latent factor model* and the *grandparental effect model* is related to their implications about the role of institutions to affect intergenerational mobility and the persistence of inequality. While the former argues that social policy interventions can only change short run patterns of social mobility, without having any effect on the long run effects of dynasties, the latter stresses the importance of the environment. Mare (2011) argues, for example, that the effect of grandparents on their grandchildren might vary between and within countries, and depend on the historical and institutional context. Indeed, recent empirical findings for different countries seem to confirm this theory. For instance, while Zeng and Xie (2014)'s findings point at the existence of a direct effect of coresident grandparents on their grandchildren in rural China, the application of LaFave and Thomas (2014) to Indonesia shows no effect of grandparental resources on grandchildren's human capital.

To investigate the importance of the institutional context and to test the hypothesis of a "universal law" of social intergenerational mobility, we propose a novel approach. First, we analyse time trends in the intergenerational persistence of human capital over two and three generations for different cohorts. Then, we pool the samples of the three countries and allow for country-specific intercepts. Technically, this procedure should reduce the omitted variable bias deriving from differences in institutions and enable to evaluate whether a common behaviour exists between societies in the transmission of inequality over two and three generations, while abstracting from characteristics which should be equally transmitted from grandparents and parents to children across countries. In addition, as mentioned above, our data allows us to control for migration or ethnic background. Thus, we are able to model potential between-group differences in intercepts (see Solon, 2014).

3 Data

Our analysis is based on three very similar and nationally representative longitudinal household surveys: i) the *German Socio-Economic Panel* (SOEP) for Germany, ii) the *Panel Study of Income Dynamics* (PSID) for the US, and iii) the *British Household Panel Survey* (BHPS) for the UK which we extend by information from the follow up survey *Understanding Society* (UKHLS). Using these surveys has several advantages for our analysis: First, the data sets are highly comparable and they are designed upon similar schemes. Indeed, SOEP, PSID and BHPS/UKHLS are part of the Cross-National Equivalent File (CNEF) where different data sets are harmonized for cross-national comparisons (see Frick et al., 2007). Second, socio-economic conditions of respondents and their family members are carefully reported over time, even when children leave their initial household. Third, the three data sets entail retrospective questions on parental characteristics. These information allow us to reconstruct the educational history of families over three consecutive generations. Since important structural differences affected individuals living in East and West Germany before and after reunification we restrict our German sample to families residing in West Germany before reunification.

Table 1: *Descriptive statistics*

	Germany				USA				UK			
	Year of Birth	Education	s.d.	N	Year of Birth	Education	s.d.	N	Year of Birth	Education	s.d.	N
Children	1972	12.56	2.609	3210	1970	13.95	2.258	6303	1975	12.87	2.724	1532
Fathers	1942	11.53	2.445	2893	1942	12.88	3.226	5589	1946	10.84	4.066	1413
Mothers	1945	10.68	2.057	3135	1944	12.86	2.563	6268	1948	10.21	3.965	1516
GF-F	1917	10.71	3.450	2672	1927	11.06	3.962	5539	1920	9.74	3.922	964
GM-F	1913	9.08	3.133	2677	1925	11.64	3.355	5319	1917	8.14	3.651	960
GF-M	1913	10.73	3.305	2913	1924	11.01	4.005	6202	1918	9.72	4.008	1374
GM-M	1910	9.24	2.980	2948	1923	11.50	3.473	6068	1914	8.29	3.797	1368

Notes: Means, standard deviations, and number of observations. Education measured in completed years of education. GF/GM-F/M: Grandfather/Grandmother-Father's/Mother's side.

Source: Own estimations based on SOEP (Germany), PSID (USA), and BHPS/UKHLS (UK).

The main challenge is to find a measure for human capital and socio-economic status that is comparable across countries and generations. An ideal measure would account for generation-specific differences due to educational institutions as well as country- and time-specific differences in the capability to generate income in the labour market. We approximate these concepts with a widely accepted measure for the human capital stock of an individual: completed years of education. Completed years of education includes the regular years of schooling needed to obtain the indicated educational degree (measured in ISCED levels) and accounts for vocational training and tertiary education as well as for the occupation (measured in ISCO levels). Detailed information on the data and the exact codification of completed years of education for children, parents, and grandparents can be found in the Supplemental Material.

For a matter of fact, due to the structure of the educational system, in the UK it might be less appropriate to adopt a continuous measure like years of education when measuring intergenerational mobility (Dearden et al., 1997). We address this issue measuring mobility also by correlation coefficients and by adopting an outcome variable that indicates the relative standing of individuals and their ancestors. To obtain this measure, which is conceptually even closer to the notion of human capital and comparable across countries and time periods, we perform a linear transformation of the relevant outcome variables for grandparents, parents, and children. The transformation yields the standard score (Z-Score) of educational achievements by cohorts:

$$z_{ijT} = \frac{y_{ijT} - \bar{y}_{jT}}{\sigma_{jT}}. \tag{8}$$

Here, $\bar{y}_{jT}$ and σ_{jT} are the mean and standard deviation of completed years of education of all individuals from generation $T \epsilon \{t, t-1, t-2\}$ in cohort j. The cohort refers to the cohort of the children's generation. This measurement gives the relative standing (in standard deviations) of an individual, his parents, and grandparents with respect to their reference groups, i.e. people competing with them in the labour market.

The main strength of this approach is the higher comparability between countries and time periods, accounting especially for the expansion of educational attainment in the second half of the 20th century that took place in all three countries under examination.[7] The Z-Score is adopted to built quantiles of children's, parents', and grandparents' relative educational position that are used to display transition matrices and mobility curves. As further robustness check, we also run the complete analysis using the Z-Score of educational attainment instead of the completed years of education. As usually done in the literature, we will refer to the parents' and grandparents' education (educational position) as the completed years of education (the Z-Score) of the parent and grandparent with the

[7] Standardizing the outcome variables by adopting Z-Scores yields regression estimates which are similar to the correlation coefficients (reported below the tables) with one important difference: The correlation coefficient is standardized by the variances of the entire sample, while our transformation compares individuals with their respective cohort. Furthermore, applying the transformation on the outcome variables instead of the estimated parameter allows us to test the coefficient of grandparents against zero, controlling for parents, within a simple regression.

highest educational attainment (educational position) within the family (Black and Devereux, 2011). In further analyses we also disentangle this measurement and analyse the education (educational position) of fathers, mothers, and all four grandparents, separately.

We draw the same sample in each survey. For our analysis, we need families that participated in the respective survey for at least two generations and where the first participating generation (parents; generation *t-1*) has available retrospective information on their father's or mother's educational attainments and occupation. We integrate this information to a measure for grandparents' education (generation *t-2*) and associate it to adult children (generation *t*) with available information on educational attainment. Our samples consist of individuals born between 1960 and 1985 with available information on the educational attainment of at least one of their parents as well as grandparents. In addition, individuals have to be at least 28 years old at the time of their last interview. The age restriction helps us to reduce bias due to uncompleted educational biographies and is justified empirically by observing patterns in our data: the mean of completed years of education is stable from the age of 28 onwards.

Table 1 shows the weighted means and standard deviation of completed years of education observed in our samples over three generations. In all three countries, educational attainment has substantially increased over generations. The US sample shows the highest averages, while educational attainments are lower and rather similar in Germany and in the UK. These patterns match with the ones found in other data sets on cross-national educational achievements.[8]

4 Descriptive Evidence on Multigenerational Mobility

4.1 *Dynastic inequality*

First, we look at changes in the distribution of educational attainment over time. For this purpose, we measure the degree of inequality in the distribution of completed years of education for each generation and the degree of inequality in the distribution of family means across generations. The resulting analysis is close to the one proposed by Shorrocks (1978b) and mirrors the concept of dynastic inequality (Jäntti and Jenkins, 2015). Table 2 shows short and long-run (dynastic) inequality for each country, as well as two indices to account for multigenerational mobility as an equalizer of long term inequality. Three different inequality measures are applied that share the characteristic of strong Lorenz-dominance, but differ in their sensitivity towards changes along the distribution: i) Gini coefficient, which reacts stronger to changes at the middle of the distribution; i) Theil index, which is sensitive to changes at the lower middle of the distribution; and iii) Coefficient of Variation (CV), which is more sensitive to changes at the top of the distribution. The two computed mobility measures are the ones proposed by Shorrocks (1978a) and Fields (2010). The first relates dynastic

[8] A comparison of mean years of schooling observed in the Barro-Lee data on educational attainment as well as an analysis of selectivity issues regarding the analysed sample are included in the Supplemental Material.

Table 2: *Multigenerational mobility as an equalizer of dynastic inequality*

(a) Germany

	t	*t-1*	*t-2*	*Family Mean*	*M(S)*	*M(F)*
Gini	0.117	0.107	0.136	0.101	0.719	0.256
s.e.	*0.0011*	*0.0015*	*0.0033*	*0.0016*	*0.0033*	*0.0144*
Theil	0.022	0.020	0.047	0.017	0.811	0.642
s.e.	*0.0004*	*0.0005*	*0.0033*	*0.0005*	*0.0090*	*0.0134*
CV	0.209	0.204	0.276	0.182	0.736	0.339
s.e.	*0.0020*	*0.0023*	*0.0062*	*0.0029*	*0.0052*	*0.0113*

(b) USA

	t	*t-1*	*t-2*	*Family Mean*	*M(S)*	*M(F)*
Gini	0.089	0.100	0.144	0.090	0.711	0.376
s.e.	*0.0011*	*0.0013*	*0.0024*	*0.0012*	*0.0075*	*0.0069*
Theil	0.012	0.018	0.046	0.014	0.769	0.693
s.e.	*0.0003*	*0.0006*	*0.0013*	*0.0005*	*0.0160*	*0.0076*
CV	0.166	0.187	0.276	0.162	0.722	0.412
s.e.	*0.0035*	*0.0027*	*0.0038*	*0.0022*	*0.0087*	*0.0067*

(c) UK

	t	*t-1*	*t-2*	*Family Mean*	*M(S)*	*M(F)*
Gini	0.100	0.153	0.208	0.113	0.754	0.454
s.e.	*0.0029*	*0.0036*	*0.0032*	*0.0020*	*0.0163*	*0.0130*
Theil	0.024	0.049	0.073	0.021	0.854	0.707
s.e.	*0.0017*	*0.0020*	*0.0027*	*0.0010*	*0.0147*	*0.0154*
CV	0.202	0.291	0.375	0.201	0.768	0.463
s.e.	*0.0054*	*0.0054*	*0.0052*	*0.0042*	*0.0114*	*0.0125*

Notes: Gini, Theil and Coefficient of Variation. *t, t-1, t-2* are the generation of children, parents and grandparents, respectively. *Family mean* is the mean of completed years of education over three generations. *M(S)* is the mobility index proposed by Shorrocks: $M(S) = 1 - \frac{I(\sum_{T=t-2}^{t} y_T)}{\sum_{T=t-2}^{t} w_T I(y_T)}$ with $w_T = \bar{y_T}/\bar{y_F}$. *M(F)* is the mobility index proposed by Fields: $M(F) = 1 - \frac{I(\sum_{T=t-2}^{t} y_T)}{I(y_{t-2})}$. $I()$ denotes the inequality index, y_T is the outcome in generation T, and $\bar{y_F}$ the family mean. The closer the value is to one, the greater is mobility in both indeces. Bootstrapped s.e. with 100 replications.
Source: Own estimations based on SOEP (Germany), PSID (USA), and BHPS/UKHLS (UK).

inequality to the weighted inequality in all generations, the second evaluates mobility as equalizer of long term outcomes relative to the initial shape of the distribution.

In all countries, we find decreasing inequality in completed years of education from the grandparents' to the children's generation. The UK shows relatively high inequality of educational attainments in the grandparents' and parents' generation, but also the highest degree of mobility. Inequality in children's completed years of education tends to be the largest in Germany. The US tend to be the country with the lowest educational inequality. The evaluation of differences in mobility between Germany and the US depends on the applied measure. Measuring mobility relative to the initial level of inequality – i.e. in the grandparents generation – Germany is less mobile to a larger extent than measuring it with respect to the overall distribution.

It is expedient to compare short-run inequality with dynastic inequality. It has been argued that whenever dynastic inequality is less than inequality in any given generation there was some equalizing mobility between generations (Jäntti and Jenkins, 2015). In our analysis, Germany is the only country with dynastic inequality being lower than cross-sectional inequality in every generation and for all measures. In the US, inequality in the children's generation is lower than dynastic inequality if measured by the Gini and Theil index. In the UK, inequality in generation t is lower than dynastic inequality measured by the Gini index, but higher or equally large for the other two measures. In conclusion, mobility acts as an equalizer of dynastic inequality in all three countries, especially in Germany, although the impacts on the distribution are of distinct magnitude.

4.2 *Multigenerational mobility trends*

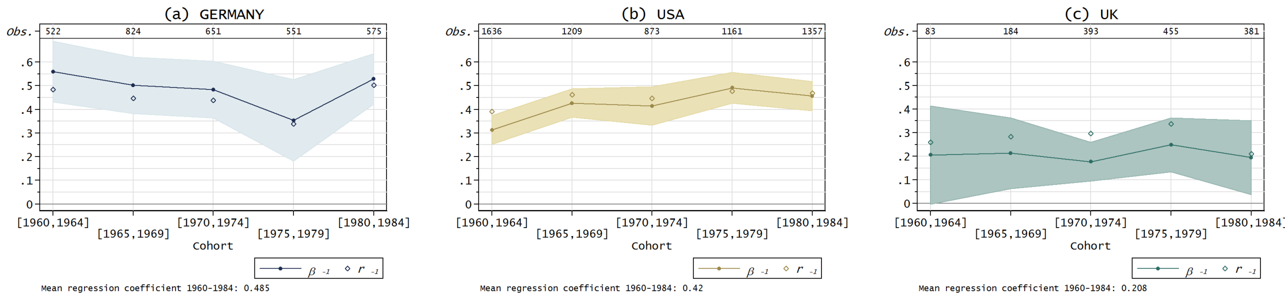
In this part, we show trends of multigenerational mobility. Figure 1 depicts two indicators which measure the degree of intergenerational mobility over two and three generations experienced by different cohorts: i) The regression coefficient, β_{-m}, obtained by regressing children's education on parents' $(m = 1)$ or grandparents' $(m = 2)$ education, measured in completed years of education; ii) The correlation coefficient, r_{-m}, which accounts for changes in the distribution of educational attainments $(r_{-m} = (\sigma_{-m}/\sigma_0)\beta_{-m})$.[9]

Mobility patterns generally differ between countries. Panel A shows the two generation case, i.e. parents and children. Educational mobility is the lowest in Germany with an average regression coefficient of 0.49, and is higher in the US and the UK where coefficients are 0.42 and 0.21, respectively. The development of mobility rates is, however, different between the US and the UK. Older cohorts show a relatively high degree of mobility in both countries, but mobility decreased in the US by far more for younger cohorts than in the the UK where it remained almost unchanged. Correlation coefficients show similar patterns within countries. A major difference is that correlation coefficients tend to be smaller than regression coefficients in Germany while they tend to be higher in the US and

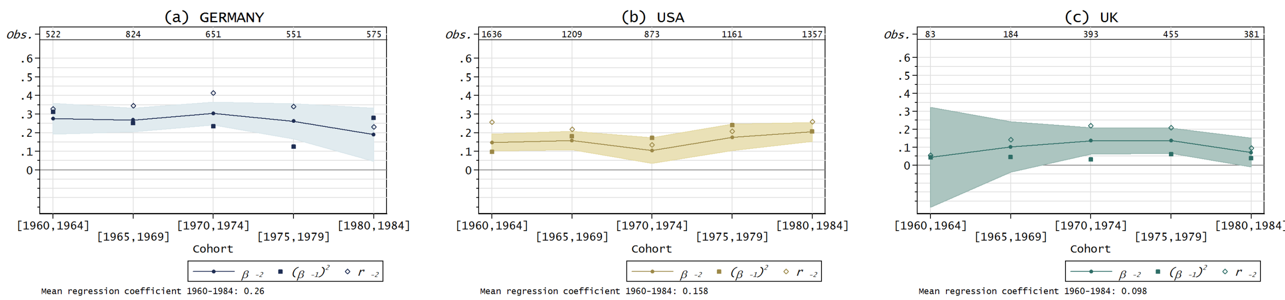
[9] σ_0 is the standard deviation of educational attainment in the children's generation.

Figure 1: *Multigenerational Mobility Trends – Regression (β) and correlation (r) coefficients*

Panel A – Two Generations; Parents' on children's education



Panel B – Three Generations; Grandparents' on grandchildren's education



Source: Own estimations based on SOEP (Germany), PSID (USA), and BHPS/UKHLS (UK).

the UK. This relates to changes in the variance of educational attainment over time.[10]

Panel B shows intergenerational mobility over three generations, i.e. grandparents and grandchildren. Although coefficients are substantially smaller and somewhat more stable within countries, the ranking between countries is basically unchanged. On average, ten years of grandparental education are associated to an increase in grandchildren's education of about three years in Germany, one and a half years in the US and less than one year in the UK.

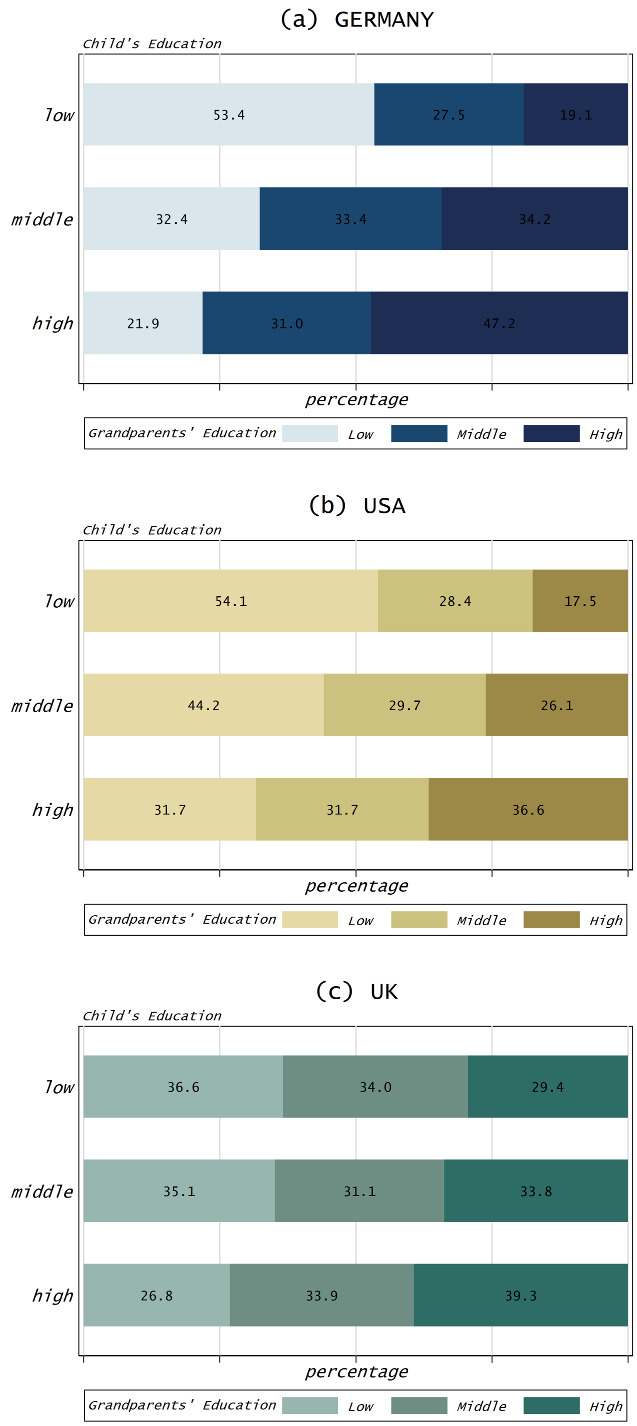
4.3 *Transition matrices & mobility curves*

Deeper insights into intergenerational mobility can be derived from non-parametric approaches. These give further insights on how structural mobility – e.g. because of educational expansion – affects intergenerational mobility in each country and in which parts of the distribution mobility takes place.

First, we construct mobility matrices which show the percentage of children with low, middle, and high educational attainment for each class of grandparents' educational position; depicted in Figure 2. Educational position is based on the Z-Scores of educational attainment by cohorts as explained in Section 3. The three quantiles – low, middle, and high – display the position within the respective distribution of the cohort's educational attainment. The highest upward mobility from the bottom to

[10]The relatively low number of observations in our UK sample makes the analysis less reliable than in the two other countries.

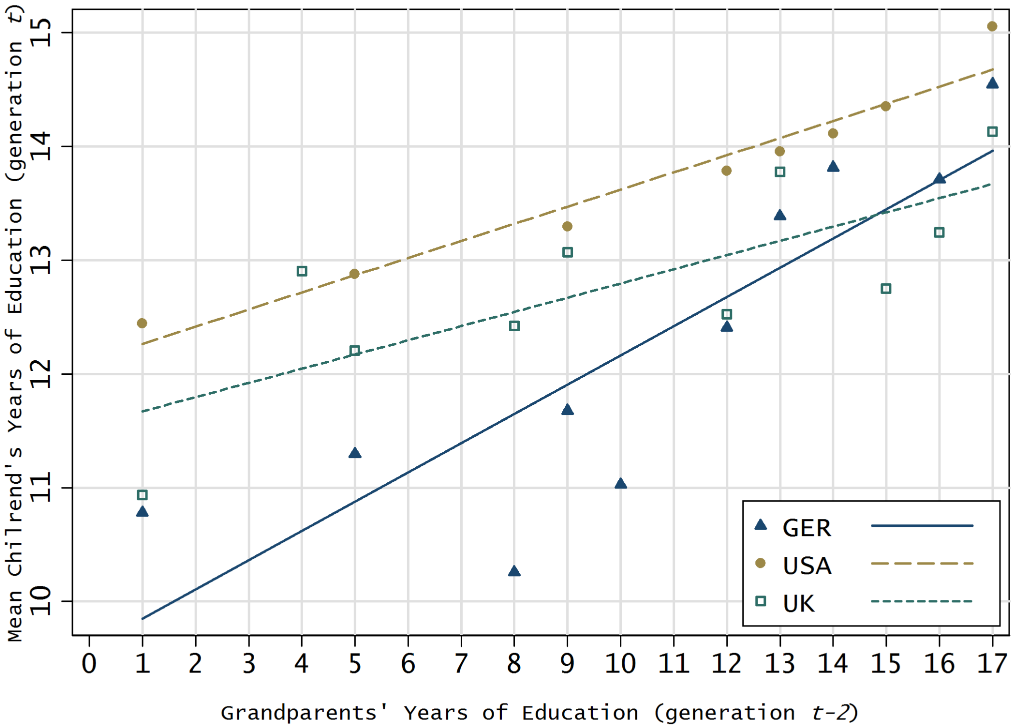
Figure 2: *Transition matrices by quantiles of the Z-Score of educational attainment*

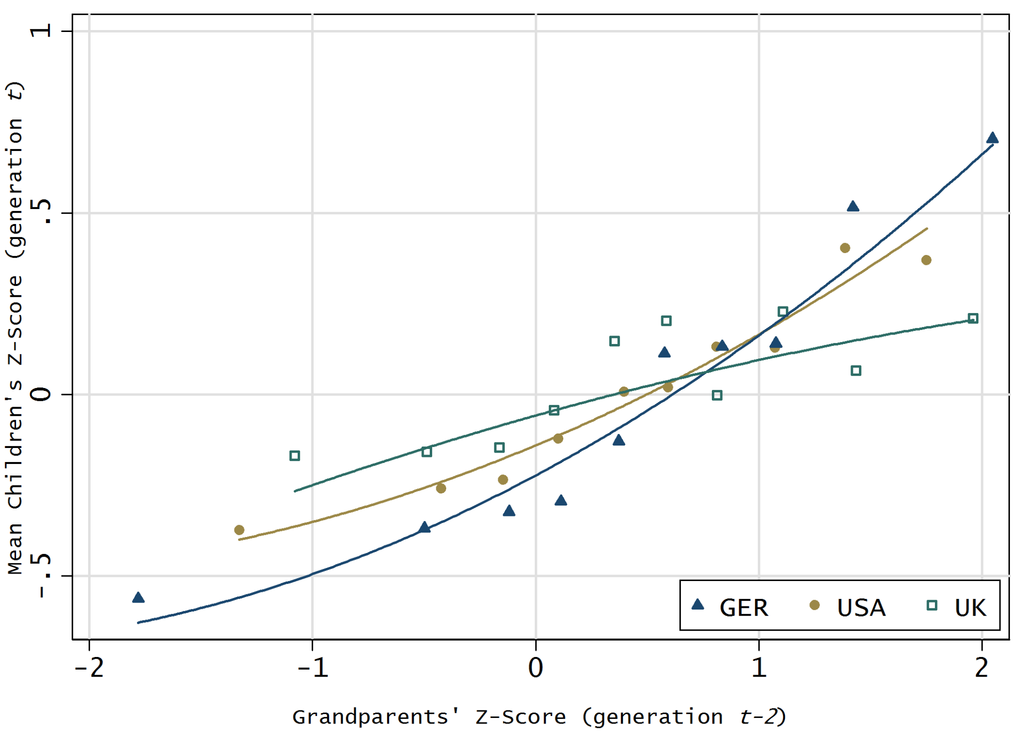


Source: Own estimations based on SOEP (Germany), PSID (USA), and BHPS/UKHLS (UK).

Figure 3: *Mobility curves – Mean education of grandchildren by grandparents' education*

(a) *Completed years of education - Linear fit*





(b) *Educational position (Z-Score) - Quadratic fit*

Source: Own estimations based on SOEP (Germany), PSID (USA), and BHPS/UKHLS (UK).

the top of the distribution is observed in the US, the lowest in Germany; 31.7 and 21.9 % of children with high education have grandparents with low education, respectively. Interestingly, both countries show a similar persistence at the bottom of the distribution. For instance, in our samples for Germany and the US about 53 and 54 percent of children with low educational position have grandparents in the bottom part of the distribution. In contrast, only 37 percent of the individuals in our UK sample show this pattern. Furthermore, Germany shows the highest persistence at the top of the distribution with 47 percent, while in the US and the UK it is about 37 and 39 percent, respectively.

Second, we compute *mobility curves* over three generations.[11] Figure 3 displays the average years of education and educational position of grandchildren for each level of grandparents' education and educational position. Hereby, the former accounts for absolute changes while relative changes within the distribution are registered in the second. This method has the advantage to show how absolute mobility differs over the distribution of grandparents' status. We find differences between countries – especially between Germany and the US – to be marked in the lower part of the distribution. For instance, the average education of grandchildren in the bottom part of the grandparents' distribution is substantially lower in Germany. In contrast, in the upper part of the distribution differences are smaller. Our sample for the UK shows a much flatter curve signalizing higher mobility within the distribution. Generally, differences between countries are less pronounced measuring social status by educational positions rather than years of education. For instance, for lower than average educational attainment of grandparents the mean educational position of the children is lower than the mean of their reference group in all three countries.

5 Testing Theories of Multigenerational Persistence

5.1 *Iterated regression fallacy*

Table 3 shows our estimates of equation (1) where we separately regress children's education on parents' and grandparents' education, and equation (2) where we regress children's education on both parents' and grandparents' education. As commonly done in the literature, we only consider the education of the parent and grandparent with the highest educational level within the family (Black and Devereux, 2011).[12] Intergenerational correlation coefficients are reported below the tables. The outcome variable is completed years of education.

The regression coefficients of parents' education in column (1) and grandparents' education in column (2) confirm the patterns observed before; the UK shows the highest degree of intergenerational mobility, Germany the lowest. In the regression analysis including both, parents and grandparents education, in column (3), the grandparental coefficient is positive in each application, but only

[11] Mobility curves are usually applied to measure the mean income rank of children for each rank of their parents (see e.g. Bratberg et al., 2016). See also Chetty et al. (2014a).

[12] Estimates for Grandfather-Father-Son and Grandmother-Mother-Daughter lineages are included in the Appendix (Tables A5-A8) and discussed below.

Table 3: *Regression analysis - Outcome: Completed years of education*

(a) Germany

	(1)	(2)	(3)
Parents (β_{-1})	0.484***		0.413***
	(0.0295)		(0.0394)
Grandparents (β_{-2})		0.258***	0.101***
		(0.0243)	(0.0297)
Observations	3210	3210	3210

Correlation coefficients: r_{-1} = 0.451 , r_{-2} = 0.327
Test $(\beta_{-1})^2 = \beta_{-2}$: F = 0.8984, Prob > F = 0.3433 ; $(\beta_{-1})^2$ = 0.235

(b) USA

	(1)	(2)	(3)
Parents (β_{-1})	0.400***		0.386***
	(0.0169)		(0.0195)
Grandparents (β_{-2})		0.167***	0.021
		(0.0137)	(0.0150)
Observations	6303	6303	6303

Correlation coefficients: r_{-1} = 0.453 , r_{-2} = 0.254
Test $(\beta_{-1})^2 = \beta_{-2}$: F = 0.2221, Prob > F = 0.6375 ; $(\beta_{-1})^2$ = 0.160

(c) UK

	(1)	(2)	(3)
Parents (β_{-1})	0.208***		0.189***
	(0.0284)		(0.0288)
Grandparents (β_{-2})		0.111***	0.047**
		(0.0210)	(0.0197)
Observations	1532	1532	1532

Correlation coefficients: r_{-1} = 0.279 , r_{-2} = 0.163
Test $(\beta_{-1})^2 = \beta_{-2}$: F = 10.4645, Prob > F = 0.0012 ; $(\beta_{-1})^2$ = 0.043

Notes: Tables show regressions of children's educational outcomes on the outcomes of the parent or grandparent with highest education within the family. Cluster adjusted s.e. at family level in parenthesis. Statistical significance level * 0.1 ** 0.05 *** 0.01.
Source: Own estimations based on SOEP (Germany), PSID (USA), and BHPS/UKHLS (UK).

significantly different from zero for Germany and the UK. According to these first results, we cannot reject the hypothesis for the US that the intergenerational transmission of human capital follows an AR(1) process, while we reject it for Germany and the UK.

Next, we test if the directly estimated coefficients of grandparents are equal to the ones predicted by the iterative regression procedure, i.e. squaring the coefficient of parents ($H_0 : \beta_{-2} = \beta_{-1}^2$). The tests are reported below the Tables. Although the estimated grandparental coefficients in columns (2) are always greater than the squared parental coefficient, we cannot reject the hypothesis that they are equal for Germany and the US. Performing the same analysis for each cohort separately, we find that the squared parental coefficient neither systematically over nor under predicts the directly estimated grandparental coefficient (see Panel B of Figure 1).

As further robustness check, we perform the same analysis adopting the Z-Score of educational attainment measured in comparison to individuals of the same cohort. The observed patterns are the same and results do not change qualitatively applying either measurement.[13] An insightful finding is that applying the Z-Score of educational attainment changes the country ranking between Germany and the US regarding the association between parents' and children's outcomes. Interestingly, our results as well as previous studies on educational mobility found the US to be more mobile than Germany (e.g. Chevalier et al., 2009; OECD, 2015), while studies on income mobility over two generations mostly found the opposite or, at least, no significant differences between the two countries (e.g. Couch and Dunn, 1997; Schnitzlein, 2015). Thus, we interpret our finding in the sense that the Z-Score yields a better approximation of social status which, indeed, was our primary goal when applying this transformation.

So far, our cross-country results are mixed and show that the validity of the iterated regression procedure to extrapolate long-run mobility estimates varies by countries. The evidence for the US suggests that there is no direct effect of grandparents on grandchildren. However, such a clear statement cannot be done for Germany and the UK at this point of the analysis.

5.2 *Latent Factor Model*

Table 4 entails the parameter estimates to test the hypotheses of Clark's latent factor model described in Section 2.1. Using the correlation coefficients between children and parents, and children and grandparents, we calculate the heritability coefficient λ and the transferability coefficient ρ as in equation (6) and (7). Figure 4 sums up the estimated coefficients for each country.

In our application, λ varies between 0.560 and 0.726 and ρ between 0.692 and 0.899.[14] Clark's hypothesis that λ is larger than the correlation in observed outcomes is confirmed. However, since

[13] Tables A1-A4 show the main results with this alternative outcome variable, all other estimations applying the Z-Score can be found in the Supplemental Material.

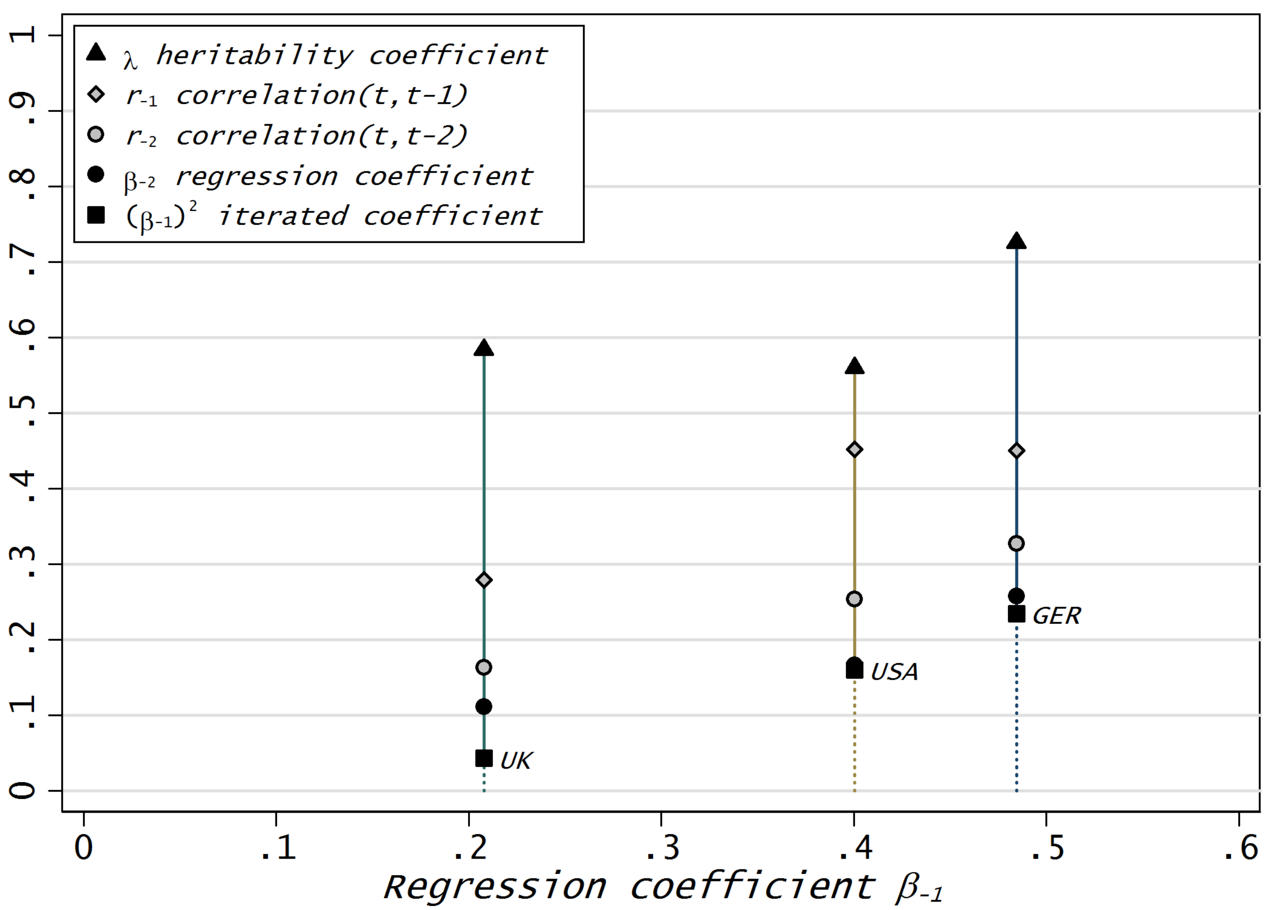
[14] Differences between the estimates for Germany and the two other countries are statistically significant at the 10 % level. Applying the Z-Score instead of completed years of education as outcome variable, the range is from 0.506 to 0.725 for λ and form 0.717 to 0.937 for ρ.

Table 4: *Estimated correlation (r), heritability (λ), and transferability (ρ) coefficients*

	Years of Education		
	GER	*USA*	*UK*
r_{-1}	0.451	0.453	0.279
r_{-2}	0.327	0.254	0.163
λ	0.726	0.560	0.584
s.e.	*0.0602*	*0.0314*	*0.0937*
ρ	0.788	0.899	0.692
s.e.	*0.0464*	*0.0274*	*0.0832*

Notes: Bootstrapped s.e. (200 replications).
Source: Own estimations based on SOEP (Germany), PSID (USA), and BHPS/UKHLS (UK).

Figure 4: *Summary and comparison of the estimated coefficients*



Source: Own estimations based on SOEP (Germany), PSID (USA), and BHPS/UKHLS (UK).

differences between countries are statistically significant, we reject Clark's universal law of social mobility. Furthermore, the heritability coefficient varies also over time: Performing the analysis for different cohorts separately we obtain different values of λ.[15] Hereby, in some of our estimations we cannot reject the hypothesis of a heritability coefficient being close, equal, or higher than 0.75. In Germany, for instance, some cohorts even display values of λ which are close to unity. However in the US, λ is constantly and significantly lower than 0.75 for the cohorts 1965-69 to 1980-84. The results for the UK also suggest λ to be smaller than 0.75. All in all, we find no clear evidence in favour of Clark's hypothesis that the historical and institutional context does not matter for the movements of families along the distribution in the long run.[16]

Extensions: Lineages, Assortative Mating and Sample Selectivity As further extensions, we account for lineages within families and estimate the rates of assortative mating. When we disentangle the intergenerational transmission in different lineages following son-father-grandfather and daughter-mother-grandmother triplets, the overall results basically do not change (see Tables A5-A8). However, gender specific pathways in the transmission of social status across two and three generations are revealed to some degree. For instance, in all three countries the regression coefficient of maternal education on the education of the daughter is higher than the coefficient of paternal education on sons, while the coefficient of grandfathers on fathers is higher than the coefficient of grandmothers on mothers. Regarding the transmission over three generations, the size of the coefficients of grandfathers on sons and granddaughters on daughters is rather similar in all three countries.

In Germany the positive and significant effect of grandparents on grandchildren, controlling for parents, seems to be mainly driven by the influence of grandfathers on their grandsons. The coefficient of grandmothers on their granddaughter is not significant when controlling for mother's education. These diverging findings might be explained by progressive changes in gender roles, as well as women's educational attainment and labour market participation experienced in industrialized countries in the last decades that led to a decrease in the association in observed outcomes between grandmothers and granddaughters. The results on the US in this sense are even more pronounced. In our previous analysis, we did not find any significant positive effect of grandparents on grandchildren, controlling for the social status of parents. However, there is a significant positive effect of both, grandfathers on grandsons, and grandmothers on granddaughters, if analysed separately. These results indicate that there might be a direct, gender-specific grandparental effect on the educational attainment of grandchildren in the US. The fact that for both lineages we reject the hypothesis of an AR(1) process for the US gives further support to this hypothesis. Finally, in the UK the coefficients of grandfathers

[15] Figure A1 shows the heritability coefficient estimated for different cohorts.

[16] As Braun and Stuhler (2016) point out, large variation in ρ among generations might lead to bias in the estimation of λ. We find large variations in ρ among cohorts in the children's generation, but cannot determinate the direction of the bias, since we have no information on the magnitude of ρ in the parents' and grandparents' generation. For a clear identification of Clark's hypothesis of time varying λ, these information are necessary. Future research with more comprehensive data on three ore more generations over multiple cohorts should address this point.

on grandsons and grandmothers on granddaughters are both not significant. This might however just be the result of relatively small sample sizes which result in larger standard errors. Finally, although some common behaviours of the intergenerational transmission exist, the country-specific differences found in the main analysis persist when disentangling by different lineages. Regarding the test of the latent factor model, the results point even stronger at different heritability coefficients between countries which are smaller than the hypothesized 0.75.[17]

The analysis of assortative mating – understood as non-random selection of individuals becoming parents – is relevant for the study of intergenerational persistence because the degree of spouse correlation in a society influences mobility parameters (Chadwick and Solon, 2002; Ermisch et al., 2006). Although the baseline model by Becker and Tomes assumes perfect assortative mating, the implications of the latent factor model crucially depend on this feature. Higher spouse correlations in endowments cause higher heritability coefficients. Therefore, large values of λ depend on high and constant rates of assortative mating (see Braun and Stuhler, 2016). Since endowments are unobservable characteristics, in order to analyse assortative mating we focus on spouse correlations in observable outcomes, i.e. completed years of education and the Z-Score of educational attainment. However, since we mostly have information on both father's and mother's outcomes in our data, our intergenerational mobility parameters are estimated taking the parent with highest education, as usually done in the literature on educational mobility when the characteristics of both parents are available.[18] The highest observable outcome should be an useful approximation of the average unobservable endowment of the two parents. So, the issue of assortative mating in unobservable endowments should influence less our results in comparison to studies that only have information on one parent. Still, it is an interesting dimension to account for; especially its differences between countries and over time.

Indeed, we find substantial differences in assortative mating between countries and generations.[19] Spouse correlations in the parents' and grandparents' generation are about 0.6 and 0.8 in Germany, about 0.4 and 0.8 in the UK, and about 0.6 in both generations in the US, respectively. Hence, assortative mating decreased in all three countries – with the UK showing the largest changes between the grandparents' and parents' generation – but is still a prevalent phenomenon, possibly fostering the intergenerational transmission of social status.[20] Interestingly, among the three countries under evaluation there seems to be a negative association between intergenerational mobility and assortative mating: In our analysis, the UK is the country with highest mobility and lowest assortative mating in

[17]Hereby, the coefficient r_{-1} used to estimate the heritability coefficient λ is the average of the correlation coefficients of sons (daughters) on fathers (mothers) and of fathers (mothers) on grandfathers (grandmothers).

[18]Estimates of income mobility instead mostly focus on son-father pairs, because lower labour-force participation rates among women cause their earnings to be a unreliable indicator of social status.

[19]The results discussed in this part of the analysis can be found in the Supplemental Material.

[20]These findings are in line with earlier studies on educational assortative mating (alias educational *homogamy*) for the cohorts included in our analysis. In the UK, past studies show a decreasing trend from the cohorts around 1925 to 1960 (Chan and Halpin, 2003). In the US, despite of a general rising trend, assortative mating decreased from 1940 to 1960, which should be exactly the time of marriage of the grandparents and parents in our sample (Schwartz and Mare, 2005). In Germany, assortative mating in education has been rising constantly among natives in the last decades (Grave and Schmidt, 2012). Excluding people with migration background from our analysis we come to the same result.

the parents' generation, while Germany is the one with lowest mobility and highest assortative mating. Another interesting finding is the difference in correlation coefficient among both grandfathers and both grandmothers that is high in Germany and, particularly, in the US, and very low in the UK. A possible reason for the higher degree of intergenerational mobility found in our UK sample could therefore be the weaker intermarriage of elites in the grandparent's generation, which seems to be substantially stronger in the other two countries.

Finally, a sensitivity analysis shows that samples drawn from household surveys might be positively selected in educational attainments. We find that the average years of education of individuals in our samples – restricted by the condition of available information on parents' and grandparents' education – is higher than the mean of the unrestricted sample, weighted by the inverse probability of selection. Furthermore, restricting the sample on the condition to have just information on parental education yields lower regression coefficients. Therefore, our results might be understood as an upper bound for intergenerational persistence. Since the selectivity issue and the direction of a potential bias seem to be the same in the three surveys, the cross-country analysis should hold, as well as the following identification of mechanisms.

5.3 *Direct Grandparental Effect*

Next, we test for the presence of a direct and independent effect of grandparents following two different strategies. First, we include more variables capturing different features of parental background to test whether the positive significant coefficient of grandparental outcomes is just an artefact of omitted variable bias or not. Second, we test if the grandparental coefficient varies with the likelihood of grandchild's exposure to the respective grandparent. For this purpose, we use the time of death of the grandparent as exogenous source of variation.[21]

Omitted variables First, we test for the general existence of a grandparental effect. For this exercise, we pool all data sets and perform a similar analysis as before; results can be found in Table 5. Our data is particularly suitable to control for omitted variable bias, since we mostly have information on both parents and all four grandparents. Furthermore, we can control for the influence of ethnic capital, an essential parental background characteristic, as a possible source of omitted variable bias. In column (1), the coefficient of grandparental education is positive and significant, and gets slightly smaller when allowing country-specific intercepts as in column (2). To control for ethnic capital, in column (3) a dummy is included in the regression which is one if the individual is non-white in the US and the UK, or has migration background in Germany, and zero otherwise. This dummy is then interacted with

[21] As argued, for example, by Braun and Stuhler (2016), time of death might be correlated with unobserved factors that influence the intergenerational transmission and, therefore, not suitable as exogenous source of variation. However, in our samples we do not find any clear association. The regression coefficient of time of death and grandparental education, measured in completed years of education and by the Z-Score, is mostly not significantly different from zero. Also, the association between year of death and educational attainment when controlling for year of birth is very weak and mostly not statistically significant.

Table 5: *Testing for a grandparental effect: Controlling for multiple features of parental background*

Outcome: *Completed years of education*	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Grandparents	0.060***	0.058***	0.056***	0.051***	0.029**	0.031**	0.030**	0.025**
	(0.0114)	(0.0113)	(0.0115)	(0.0116)	(0.0120)	(0.0120)	(0.0122)	(0.0123)
Parents	0.315***	0.285***	0.284***	0.286***				
	(0.0172)	(0.0176)	(0.0179)	(0.0178)				
Father					0.170***	0.169***	0.169***	0.171***
					(0.0138)	(0.0137)	(0.0139)	(0.0139)
Mother					0.188***	0.167***	0.167***	0.168***
					(0.0152)	(0.0156)	(0.0157)	(0.0155)
GER (0/1)		-0.761***	-0.753***	-0.696***		-0.727***	-0.724***	-0.614***
		(0.0884)	(0.0877)	(0.1003)		(0.0920)	(0.0913)	(0.1044)
UK (0/1)		-0.500***	-0.526***	-0.585***		-0.164*	-0.172*	-0.219**
		(0.0873)	(0.0910)	(0.0926)		(0.0880)	(0.0912)	(0.0929)
Non-white or Migrant (0/1)			-0.137	-0.188*			-0.032	-0.019
			(0.0973)	(0.1030)			(0.1011)	(0.1081)
Non-white or Migrant (0/1) × GER (0/1)				-0.186				-0.380*
				(0.1857)				(0.1979)
Non-white or Migrant (0/1) × UK (0/1)				1.029**				1.117***
				(0.4337)				(0.4098)
Adj. R^2	.1788	.1926	.1931	.1953	.1912	.2027	.2028	.2061
Observations	11045	11045	11039	11039	9769	9769	9764	9764
Clusters	5768	5768	5762	5762	5168	5168	5163	5163

Notes: Cluster adjusted s.e. at family level in parenthesis. Statistical significance level * 0.1 ** 0.05 *** 0.01.
Source: Own estimations based on SOEP (Germany), PSID (USA), and BHPS/UKHLS (UK).

Table 6: *Testing for a grandparental effect: Controlling for multiple features of parental background – country-wise*

Outcome: *Completed years of education*	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	USA	USA	USA	GER	GER	GER	UK	UK	UK
Grandparents	0.020	0.001	0.002	0.096***	0.049*	0.048	0.044**	0.018	0.016
	(0.0152)	(0.0161)	(0.0162)	(0.0316)	(0.0296)	(0.0323)	(0.0198)	(0.0212)	(0.0211)
Parents	0.383***			0.414***			0.192***		
	(0.0202)			(0.0394)			(0.0290)		
Father		0.193***	0.195***		0.304***	0.304***		0.107***	0.110***
		(0.0177)	(0.0180)		(0.0463)	(0.0463)		(0.0223)	(0.0225)
Mother		0.233***	0.233***		0.270***	0.270***		0.117***	0.118***
		(0.0249)	(0.0249)		(0.0437)	(0.0438)		(0.0216)	(0.0215)
Non-white or Migrant (0/1)	-0.095		0.074	-0.081		-0.025	0.763*		0.984**
	(0.1040)		(0.1096)	(0.1724)		(0.1853)	(0.4097)		(0.3921)
Adj. R^2	.2055	.2267	.2267	.2149	.23	.2297	.08382	.08496	.09016
Observations	6303	5554	5554	3210	2818	2818	1526	1397	1392
Clusters	2065	1898	1898	2192	1890	1890	1505	1380	1375

Notes: Cluster adjusted s.e. at family level in parenthesis. Statistical significance level * 0.1 ** 0.05 *** 0.01.
Source: Own estimations based on SOEP (Germany), PSID (USA), and BHPS/UKHLS (UK).

the country fixed effects in column (4) to control for country-specific ethnic capital. The coefficient of grandparents decreases when controlling for ethnic capital and country-specific ethnic capital, but is still positive and significantly different from zero.

The next four columns (5) to (8) control successively for the same characteristics as above, but include the completed years of education of both father and mother, instead of only including information of the parent with the highest degree. The resulting coefficients of grandparental education are positive and significant, but rather small. The coefficients of the control variables are mostly significantly different from zero and their inclusion increases the adjusted R-squared of the regressions. So, the persistence of a positive and significant coefficient for grandparental education could indicate a relationship between grandparents and grandchildren which goes beyond the role of both parents, and still holds if we control for country-specific differences in institutional background. However, there might still be other omitted variables which may cause bias and for which we cannot control for. We try to further reduce the bias caused by unobserved characteristics of parental social status performing the same analysis applying the Z-Scores of educational attainments. Indeed, in the joint analysis pooling the three samples, the coefficient of grandparental educational position measured by the Z-Score is not significantly different from zero as soon as we control for the education of both parents (see Table A3). The evidence, so far, points therefore against the existence of an independent and direct effect of grandparents, once parental social status is accounted for properly.

However, the fact that a general rule regarding the direct effect of grandparents might not exist does not rule out specific differences caused by institutions. As argued, for instance, by Mare (2011), the effect of grandparents might vary by context and institutional characteristics could determine the magnitude of the effect. Indeed, we find heterogeneous profiles comparing the three countries. Table 6 reports the estimated coefficients country wise. For Germany, the coefficient of grandparents is significantly different from zero when controlling, first, for the parent with highest education, and, then, for the education of both parents. The last evidence seems initially to be in contrast with the findings of Braun and Stuhler (2016) who find statistically insignificant coefficients in most of their applications controlling for both parents. However, Braun and Stuhler (2016) find, indeed, a positive significant coefficient in two of their five samples which are closer to our sample in terms of the years of birth of individuals and their grandparents. In our analysis, the coefficient of grandparents for Germany is no longer significantly different from zero if we additionally control for ethnic capital, besides mother's and father's educational attainment. The results on the UK show a positive and significant coefficient of grandparents controlling for parents and ethnic capital. The coefficient is, however, substantially smaller and not significantly different from zero as soon as we control for the education of both parents. Our results, therefore, only partly confirm the findings of Chan and Boliver (2013) on the persistence of social status over three generations in the UK. For the US, the coefficient is persistently not significantly different from zero in all applications. This pattern confirms earlier findings on older cohorts for the US by Behrman and Taubman (1985); Peters (1992); Warren and Hauser (1997).

Our results are qualitatively similar for the three countries when the outcome variable is the Z-Score of educational attainment (see Table A4). Interestingly, the results adopting the Z-Score for the US show a negative coefficient of grandparents when controlling for both father and mother, as found by previous studies on income mobility over three generations (Peters, 1992; Behrman and Taubman, 1985) and hypothesized by Becker and Tomes (1979). We interpret this as further evidence in favour of our supposition that the Z-Score mirrors socio-economic status properly.

Death of grandparents For the second exercise, we test whether the coefficient of grandparental education varies with the likelihood of interaction between grandparents and grandchildren (following Braun and Stuhler, 2016). Here, we use the information on the year of death of grandparents and the year of birth of grandchildren to check if a direct interaction was possible between the two or not. Since the information on parental year of death is only available in the SOEP and the PSID we restrict our analysis for this exercise to Germany and the US.

The estimation strategy is straightforward: Equation (2) is estimated interacting the education of the respective grandparent with a dummy variable which is one if there was no possibility of direct interaction – i.e. the grandparent died before the grandchild turned one year old – and zero otherwise. The results are shown in Table 7. If a direct interaction has a substantial effect, we would expect the coefficient of "dead grandparents" to be significantly lower than the coefficient of grandparents who were alive when the grandchild was born.

This hypothesis does not find a clear support in our findings. Only dead grandparents on the mother's side show the expected negative coefficient with respect to the coefficient of living grandparents. If we subdivide the analysis, it is evident that this result is completely driven by our German sample. Again, we find cross-country differences in the evaluation of a direct effect of grandparents. Identical patterns are observed when applying the Z-Score as outcome variable.[22] Of course, this strategy rules only those effects out that depend on direct interaction. There still might be important and persistent effects which derive from grandparents regardless of whether they were alive or not; for instance, family wealth, reputation, networks, as well as genetic traits that skip one generation. These cannot be clearly ruled out in this analysis. Our results show that direct interaction might only have a limited effect on grandchildren's human capital and confirm that these effects might vary with the cultural, historical, or institutional context.

Our findings for Germany regarding maternal grandparents seem, however, to confirm earlier findings and the hypotheses raised by family sociologists and human evolutionary scientists on differential effects of maternal and paternal grandparents on grandchildren. The former argue that the emotional closeness between mothers and their parents explains the stronger effect of maternal grandparents on grandchildren. Evolutionary explanations instead mostly focus on the degree of assumed genetic relatedness. One theory states, for example, that the bias in grandparental investment might depend on *paternity uncertainty*: maternal grandparents know for sure that their daughter is the mother of their

[22]These results are furthermore robust to the exclusion of people with migration background.

Table 7: *Testing for a grandparental effect: Grandparents' death as exogenous source of variation in the likelihood of interaction*

Outcome: *Completed years of education*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Father	0.368***	0.367***	0.330***	0.359***				
	(0.0250)	(0.0296)	(0.0266)	(0.0306)				
Mother					0.391***	0.373***	0.431***	0.430***
					(0.0290)	(0.0350)	(0.0328)	(0.0366)
GF-F	0.047**	0.029						
	(0.0186)	(0.0220)						
GM-F			0.055**	0.033				
			(0.0229)	(0.0236)				
GF-M					0.086***	0.106***		
					(0.0200)	(0.0241)		
GM-M							0.040	0.048
							(0.0278)	(0.0333)
Death=1 × GF-F		0.047						
		(0.0355)						
Death=1 × GM-F				0.075				
				(0.0521)				
Death=1 × GF-M						-0.067*		
						(0.0378)		
Death=1 × GM-M								-0.033
								(0.0571)
Death=1		-0.479						
		(0.5481)						
Death=1 × Father		0.003						
		(0.0462)						
Death=1				0.459				
				(0.7046)				
Death=1 × Father				-0.093*				
				(0.0518)				
Death=1						-0.084		
						(0.5402)		
Death=1 × Mother						0.064		
						(0.0463)		
Death=1								0.425
								(0.8073)
Death=1 × Mother								0.005
								(0.0770)
Country F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3360	3360	2241	2241	2973	2973	2147	2147
Clusters	1871	1871	1309	1309	1797	1797	1311	1311

Notes: GF/GM-F/M: Grandfather/Grandmother-Father's/Mother's side. Cluster adjusted s.e. at family level in parenthesis. Statistical significance level * 0.1 ** 0.05 *** 0.01.
Source: Own estimations based on SOEP (Germany), PSID (USA), and BHPS/UKHLS (UK).

grandchild (although in the case of the maternal grandfather there might still be some uncertainty about genetic relatedness), while the probability of relatedness on the father's side is usually smaller than one. However, to go deeper into the exact reasons and mechanisms of differences in grandparental effects would go beyond the scope of this work.[23]

6 Conclusions

This study evaluated multigenerational mobility in a cross-country setting using harmonized survey data sets. On grounds of highly comparable estimates we found some clear patterns: First, we confirmed Robert Mare's view that intergenerational mobility varies with the historical and institutional context. Indeed, we saw that this applies even for direct effects that grandparents exert on their grandchildren. Second, our finding of different heritability parameters across countries and time pointed against Gregory Clark's hypothesis of a "universal law of social mobility". Third, the differences in long run mobility rates in the US, the UK, and Germany are in line with previous findings on cross-country differences over two generations (Blanden, 2013; Chevalier et al., 2009; Hertz et al., 2007; OECD, 2015). Hence, our findings show that cross-country relationships, at least in this small sample of countries, hold aside from the timing of measurement, and short-run mobility (i.e. over two generations) does not seriously over nor under predict long-run mobility patterns.

A strength of our findings, apart from the cross-country perspective, lies in the adoption of measures which should be suitable as *omnibus measures* for latent socio-economic status with less measurement error (see Nybom and Vosters, 2016; Solon, 2014). Especially, our analysis using the relative position of grandparents, parents, and children should be particularly useful in that sense, since it allows to compare individuals and their ancestors with the corresponding reference group, namely people competing in the labour market broadly at the same time. An issue challenging our findings, and generally the analysis of intergenerational mobility with household survey data, turned out to be sample selectivity. We find that higher educated people are more likely to have available information on parents' and grandparents' education. Especially, families with higher education are more likely (i) to participate in household surveys for more than one generation and (ii) to answer retrospective questions about their parents' education. Our intergenerational persistence estimates over two and three generations might, thus, be understood as an upper bound. The fact that we are able to reject Clark's hypothesis about a strong unobserved intergenerational transmission with these upper bound estimates should, therefore, be an even more compelling evidence against it. Since we find selectivity to be the same in all three countries, the cross-country analysis should still be valid. On top of this, the identification of the mechanisms of multigenerational persistence should not have been affected. Nevertheless, it might be important to address this issue in future studies dealing with intergenerational transmission using survey data.

[23] For a recent review of theories and empirical findings on differential grandparental effects, see Danielsbacka et al. (2015).

Other points worth mentioning are the uncovered different effects by gender and family lineages. Decomposing the analysis by the effect of (grand)fathers and (grand)mothers on (grand)sons and (grand)daughters we find that significant differences exist between correlations and even direct effects. Interestingly, we find these patterns to differ across countries, confirming that historical, institutional, and cultural features matter for the intergenerational transmission of socio-economic status.

Concluding, a relevant point is how our findings are related to income mobility. Previous studies covering two generations have shown that rates of intergenerational mobility in education and income show the same broad picture, but are less than perfectly correlated. Since data on permanent income over three generations is rare, we cross-checked our results adopting a transformation that yields an outcome measure which is intuitively closer to the concepts of human capital and socio-economic status than completed years of education. Our analysis showed that our results adopting this transformation mirror past findings on intergenerational income mobility. It might therefore be useful to deepen this methodological aspect in future.

References

ADERMON, A., M. LINDAHL AND D. WALDENSTRÖM, "Intergenerational Wealth Mobility and the Role of Inheritance: Evidence from Multiple Generations," (2015).

BARONE, G. AND S. MOCETTI, "Intergenerational Mobility in the Very Long Run: Florence 1427-2011," (2015), 1–25.

BECKER, G. S. AND N. TOMES, "An Equilibrium Theory of the Distribution of Income and Intergenerational Mobility," *The Journal of Political Economy* 87 (1979), 1153–1189.

———, "Human Capital and the Rise and Fall of Families," *Journal of Labor economics* 4 (1986), 1–47.

BEHRMAN, J. AND P. TAUBMAN, "Intergenerational Earnings Mobility in the United States: Some Estimates and a Test of Becker's Intergenerational Endowments Model," *The Review of Economics and Statistics* 67 (1985), 144–151.

BLACK, S. E. AND P. J. DEVEREUX, "Recent Developments in Intergenerational Mobility," in O. Ashenfelter and D. Card, eds., *Handbook of Labor Economics*volume 4, 1 edition (Elsevier, 2011).

BLANDEN, J., "Cross-Country Rankings in Intergenerational Mobility: A Comparison of Approaches from Economics and Sociology," *Journal of Economic Surveys* 27 (2013), 38–73.

BORJAS, G. J., "Ethnic Capital and Intergenerational Mobility," *The Quarterly Journal of Economics* 107 (1992), 123–150.

Bratberg, E., J. Davis, B. Mazumder, M. Nybom, D. Schnitzlein and K. Vaage, "A Comparison of Intergenerational Mobility Curves in Germany, Norway, Sweden, and the United States," *Scandinavian Journal of Economics* (2016).

Braun, S. T. and J. Stuhler, "The Transmission of Inequality across Multiple Generations: Testing Recent Theories with Evidence from Germany," *Economic Journal* (2016).

Celhay, P. and S. Gallegos, "Persistence in the Transmission of Education: Evidence across Three Generations for Chile," *Journal of Human Development and Capabilities* 16 (2015), 420–451.

Chadwick, L. and G. Solon, "Intergenerational Income Mobility among Daughters," *American Economic Review* 92 (2002), 335–344.

Chan, T. W. and V. Boliver, "The Grandparents Effect in Social Mobility: Evidence from British Birth Cohort Studies," *American Sociological Review* 78 (2013), 662–678.

Chan, T. W. and B. Halpin, *Who Marries whom in Great Britain?* (Dordrecht: Springer Netherlands, 2003), 171–194.

Chetty, R., N. Hendren, P. Kline and E. Saez, "Where is the Land of Opportunity? The Geography of Intergenerational Mobility in the United States," *The Quarterly Journal of Economics* (2014a), 0–22.

Chetty, R., N. Hendren, P. Kline, E. Saez and N. Turner, "Is the United States Still a Land of Opportunity? Recent Trends in Intergenerational Mobility," *American Economic Review Papers and Proceedings* 104 (2014b), 141–147.

Chevalier, A., K. Denny and D. McMahon, "A Multi-country Study of Intergenerational Educational Mobility," in P. Dolton, R. Asplund and E. Barth, eds., *Education and Inequality Across Europe*chapter 12 (Edward Elgar Pub, 2009).

Clark, G., *The Son also Rises: Surnames and the History of Social Mobility* (Princeton University Press, 2014).

Clark, G. and N. Cummins, "Intergenerational Wealth Mobility in England, 1858-2012: Surnames and Social Mobility," *Economic Journal* 125 (2015), 61–85.

Collado, M. D., I. Ortuño-ortín and A. Romeu, "Long Run Intergenerational Social Mobility and the Distribution of Surnames," (2013).

Corak, M., "Income Inequality, Equality of Opportunity, and Intergenerational Mobility," *Journal of Economic Perspectives* 27 (2013), 79–102.

Couch, K. A. and T. A. Dunn, "Intergenerational Correlations in Labor Market Status: A Comparison of the United States and Germany," *The Journal of Human Resources* 32 (1997), 210–232.

Danielsbacka, M., A. O. Tanskanen and A. Rotkirch, "Impact of Genetic Relatedness and Emotional Closeness on Intergenerational Relations," *Journal of Marriage and Family* 77 (2015).

Dearden, L., S. Machin and H. Reed, "Intergenerational Mobility in Britain," *Economic Journal* 107 (1997), 47–66.

Ermisch, J., M. Francesconi and T. Siedler, "Intergenerational Mobility and Marital Sorting," *Economic Journal* 116 (2006), 659–679.

Fields, G. S., "Does Income Mobility Equalize Longer-term Incomes? New Measures of an Old Concept," *Journal of Economic Inequality* 8 (2010), 409–427.

Frick, J. R., S. P. Jenkins, D. R. Lillard, O. Lipps and M. Wooden, "The Cross-National Equivalent File (CNEF) and its Member Country Household Panel Studies," *Journal of Applied Social Science Studies* 127 (2007), 627–654.

Grave, B. S. and C. M. Schmidt, "The Dynamics of Assortative Mating in Germany," (2012).

Hällsten, M., "Inequality across Three and Four Generations in Egalitarian Sweden: 1st and 2nd Cousin Correlations in Socio-economic Outcomes," *Research in Social Stratification and Mobility* 35 (2014), 19–33.

Hertel, F. R. and O. Groh-Samberg, "Class Mobility across Three Generations in the U.S. and Germany," *Research in Social Stratification and Mobility* 35 (2014), 35–52.

Hertz, T., T. Jayasundera, P. Piraino, S. Selcuk, N. Smith and A. Verashchagina, "The Inheritance of Educational Inequality: International Comparisons and Fifty-year Trends," *The BE Journal of Economic Analysis & Policy* 7 (2007).

Hodge, R. W., "Occupational Mobility as a Probability Process," *Demography* 3 (1966), 19–34.

Jäntti, M. and S. P. Jenkins, "Income Mobility," in A. B. Atkinson and F. Bourguignon, eds., *Handbook of Income Disribution*volume 2B, 2 edition, chapter 10 (Elsevier, 2015), 807–935.

Johnston, D. W., S. Schurer and M. A. Shields, "Exploring the Intergenerational Persistence of Mental Health: Evidence from Three Generations," *Journal of Health Economics* 32 (2013), 1077–1089.

Knigge, A., "Beyond the Parental Generation: The Influence of Grandfathers and Great-grandfathers on Status Attainment," *Demography* (2016).

Kroeger, S. and O. Thompson, "Educational Mobility across Three Generations of American Women," *Economics of Education Review* 53 (aug 2016), 72–86.

LaFave, D. and D. Thomas, "Extended Families and Child Well-being," (2014).

Lindahl, M., M. Palme, S. S. Massih and A. Sjögren, "Long-term Intergenerational Persistence of Human Capital: An Empirical Analysis of Four Generations," *Journal of Human Resources* 50 (2015), 1–33.

Loury, G. C., "Intergenerational Transfers and the Distribution of Earnings," *Econometrica* 49 (1981), 843–867.

Lucas, R. E. B. and S. P. Kerr, "Intergenerational Income Immobility in Finland: Contrasting Roles for Parental Earnings and Family Income," *Journal of Population Economics* 26 (2013), 1057–1094.

Mare, R. D., "A Multigenerational View of Inequality," *Demography* 48 (2011), 1–23.

Nybom, M. and K. Vosters, "Intergenerational Persistence in Latent Socioeconomic Status: Evidence from Sweden," *Journal of Labor Economics* (2016).

OECD, *Education at a Glance 2015: OECD Indicators* (2015).

Olivetti, C., D. M. Paserman and L. Salisbury, "Three-generation Mobility in the United States, 1850-1940: The Role of Maternal and Paternal Grandparents," (2016).

Peters, H. E., "Patterns of Intergenerational Mobility in Income and Earnings," *Review of Economics & Statistics* 74 (1992), 456.

Pfeffer, F. T., "Multigenerational Approaches to Social Mobility. A Multifaceted Research Agenda.," *Research in Social Stratification and Mobility* 35 (2014), 1–12.

Piketty, T., *Capital in the Twenty-first Century* (Belknap Press, 2014).

Piraino, P., S. Muller, J. Cilliers and J. Fourie, "The Transmission of Longevity across Generations: The Case of the Settler Cape Colony," *Research in Social Stratification and Mobility* 35 (2014), 105–119.

Rawls, J., *A Theory Of Justice* (Harvard University Press (Cambridge MA), 1971).

Ridge, J., *Mobility in Britain Reconsidered* (Oxford University Press, 1974).

Schnitzlein, D. D., "A New Look at Intergenerational Mobility in Germany Compared to the US," *Review of Income and Wealth* (2015), online first.

Schwartz, C. R. and R. D. Mare, "Trends in Educational Assortative Marriage From 1940 to 2003," *Demography* 42 (2005), 621–646.

SHORROCKS, A., "Income Inequality and Income Mobility," *Journal of Economic Theory* 19 (1978a), 376–393.

SHORROCKS, A. F., "The Measurement of Mobility," *Econometrica* 46 (1978b), 1013–1024.

SOLON, G., "Intergenerational Income Mobility in the United States," *The American Economic Review* 82 (1992), 393–408.

———, "Theoretical Models of Inequality Transmission across Multiple Generations," *Research in Social Stratification and Mobility* 35 (2014), 13–18.

STUHLER, J., "Mobility across Multiple Generations: The Iterated Regression Fallacy," (2014).

WARREN, J. R. AND R. M. HAUSER, "Social Stratification across Three Generations: New Evidence from the Wisconsin Longitudinal Study," *American Sociological Review* 62 (1997), 561.

ZENG, Z. AND Y. XIE, "The Effects of Grandparents on Children's Schooling: Evidence from Rural China.," *Demography* 51 (2014), 599–617.

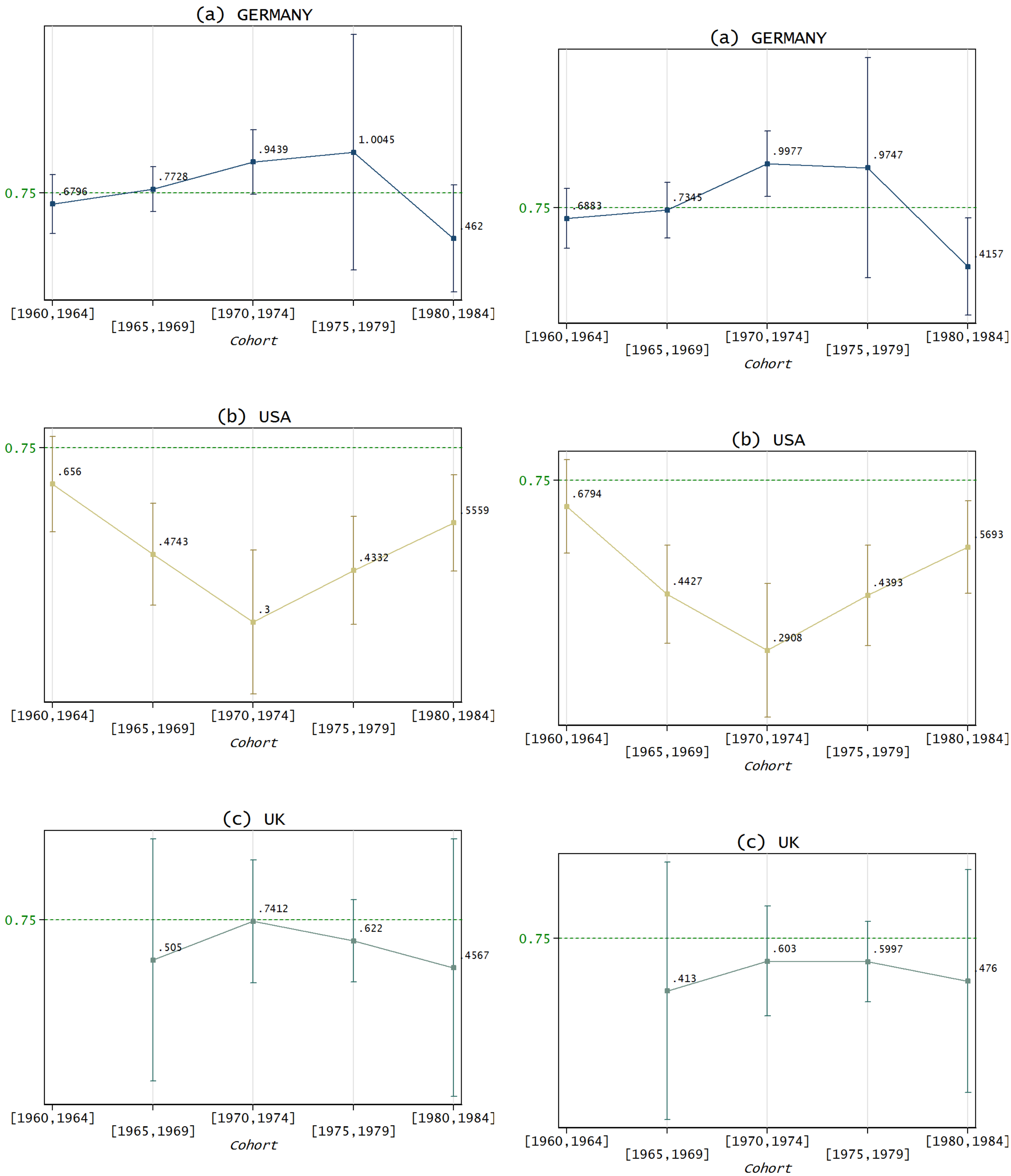
ZYLBERBERG, Y., "Dynastic Income Mobility," (2016).

A Appendix

Figure A1: *Estimated heritability coefficient (λ) by cohorts*

Panel A – Outcome: Completed years of education

Panel B – Outcome: Z-Score of educational attainment



Source: Own estimations based on SOEP (Germany), PSID (USA), and BHPS/UKHLS (UK).

Table A1: *Regression analysis - Outcome: Z-Score of educational attainment*

(a) Germany

	(1)	(2)	(3)
Parents (β_{-1})	0.423***		0.365***
	(0.0241)		(0.0329)
Grandparents (β_{-2})		0.331***	0.115***
		(0.0285)	(0.0366)
Observations	3210	3210	3210

Correlation coefficients: r_{-1} = 0.444 , r_{-2} = 0.322

Test $(\beta_{-1})^2 = \beta_{-2}$: F = 28.4403, Prob > F = 0.0000 ; $(\beta_{-1})^2$ = 0.179

(b) USA

	(1)	(2)	(3)
Parents (β_{-1})	0.491***		0.480***
	(0.0197)		(0.0222)
Grandparents (β_{-2})		0.256***	0.024
		(0.0236)	(0.0237)
Observations	6303	6303	6303

Correlation coefficients: r_{-1} = 0.445 , r_{-2} = 0.225

Test $(\beta_{-1})^2 = \beta_{-2}$: F = 0.4075, Prob > F = 0.5233 ; $(\beta_{-1})^2$ = 0.241

(c) UK

	(1)	(2)	(3)
Parents (β_{-1})	0.313***		0.290***
	(0.0421)		(0.0422)
Grandparents (β_{-2})		0.148***	0.056**
		(0.0303)	(0.0281)
Observations	1532	1532	1532

Correlation coefficients: r_{-1} = 0.276 , r_{-2} = 0.148

Test $(\beta_{-1})^2 = \beta_{-2}$: F = 2.7467, Prob > F = 0.0977 ; $(\beta_{-1})^2$ = 0.098

Notes: Tables show regressions of children's educational outcomes on the outcomes of the parent or grandparent with highest education within the family. Cluster adjusted s.e. at family level in parenthesis. Statistical significance level * 0.1 ** 0.05 *** 0.01.

Source: Own estimations based on SOEP (Germany), PSID (USA), and BHPS/UKHLS (UK).

Table A2: *Z-Score - Estimated correlation (r), heritability (λ), and transferability (ρ) coefficients*

	Z-Score		
	GER	*USA*	*UK*
r_{-1}	0.444	0.445	0.276
r_{-2}	0.322	0.225	0.148
λ	0.725	0.506	0.537
s.e.	*0.0529*	*0.0298*	*0.1041*
ρ	0.783	0.937	0.717
s.e.	*0.0377*	*0.0375*	*0.0839*

Notes: Bootstrapped s.e. (200 replications).
Source: Own estimations based on SOEP (Germany), PSID (USA), and BHPS/UKHLS (UK).

Table A3: *Z-Score - Testing for a grandparental effect: Controlling for multiple features of parental background*

Outcome: *Z-Score of educational attainment*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Grandparents	0.057***	0.058***	0.055***	0.050***	0.012	0.012	0.013	0.008
	(0.0163)	(0.0164)	(0.0168)	(0.0167)	(0.0171)	(0.0171)	(0.0176)	(0.0176)
Parents	0.395***	0.395***	0.394***	0.394***				
	(0.0176)	(0.0178)	(0.0182)	(0.0182)				
Father					0.253***	0.253***	0.255***	0.255***
					(0.0176)	(0.0175)	(0.0177)	(0.0178)
Mother					0.227***	0.227***	0.227***	0.227***
					(0.0166)	(0.0166)	(0.0167)	(0.0166)
GER (0/1)		-0.004	-0.000	0.006		0.007	0.004	0.028
		(0.0320)	(0.0318)	(0.0369)		(0.0330)	(0.0329)	(0.0382)
UK (0/1)		-0.042	-0.047	-0.067*		0.021	0.022	0.008
		(0.0347)	(0.0353)	(0.0361)		(0.0342)	(0.0347)	(0.0354)
Non-white or Migrant (0/1)			-0.037	-0.072			0.021	0.011
			(0.0388)	(0.0442)			(0.0399)	(0.0453)
Non-white or Migrant (0/1) $\times$ GER (0/1)				-0.010				-0.077
				(0.0728)				(0.0760)
Non-white or Migrant (0/1) $\times$ UK (0/1)				0.336**				0.327**
				(0.1650)				(0.1668)
Adj. R^2	.1563	.1566	.1569	.1582	.1769	.1768	.1768	.1783
Observations	11045	11045	11039	11039	9769	9769	9764	9764
Clusters	5768	5768	5762	5762	5168	5168	5163	5163

Notes: Cluster adjusted s.e. at family level in parenthesis. Statistical significance level * 0.1 ** 0.05 *** 0.01.
Source: Own estimations based on SOEP (Germany), PSID (USA), and BHPS/UKHLS (UK).

Table A4: *Z-Score - Testing for a grandparental effect: Controlling for multiple features of parental background – country-wise*

***Outcome**: Z-Score of educational attainment*

	(1) USA	(2) USA	(3) USA	(4) GER	(5) GER	(6) GER	(7) UK	(8) UK	(9) UK
Grandparents	0.021	-0.006	-0.004	0.106***	0.057	0.055	0.053*	0.010	0.008
	(0.0241)	(0.0253)	(0.0256)	(0.0387)	(0.0348)	(0.0378)	(0.0280)	(0.0307)	(0.0306)
Parents	0.477***			0.365***			0.294***		
	(0.0230)			(0.0330)			(0.0423)		
Father		0.287***	0.290***		0.299***	0.299***		0.171***	0.175***
		(0.0231)	(0.0236)		(0.0387)	(0.0387)		(0.0351)	(0.0352)
Mother		0.253***	0.254***		0.199***	0.199***		0.181***	0.182***
		(0.0248)	(0.0247)		(0.0340)	(0.0340)		(0.0308)	(0.0307)
Non-white or Migrant (0/1)	-0.038		0.044	-0.044		-0.011	0.248		0.310*
	(0.0455)		(0.0464)	(0.0644)		(0.0689)	(0.1583)		(0.1621)
Adj. R^2	.198	.2208	.2209	.2056	.2258	.2256	.08014	.0876	.09126
Observations	6303	5554	5554	3210	2818	2818	1526	1397	1392
Clusters	2065	1898	1898	2192	1890	1890	1505	1380	1375

Notes: Cluster adjusted s.e. at family level in parenthesis. Statistical significance level * 0.1 ** 0.05 *** 0.01.
Source: Own estimations based on SOEP (Germany), PSID (USA), and BHPS/UKHLS (UK).

Table A5: *Lineages - Regression analysis by son/daughter – father/mother – grandfather/grandmother Outcome: Completed years of education*

(a) Germany

	(1) Son	(2) Son	(3) Son	(4) Father
Father	0.486***		0.439***	
	(0.0355)		(0.0455)	
Grandfather		0.225***	0.076**	0.338***
		(0.0314)	(0.0342)	(0.0233)
Observations	1625	1503	1497	1497

Test $\beta^f_{-1} \cdot \beta^s_{-1} = \beta^f_{-2}$: F = 3.6893, Prob > F = 0.0550 ; $\beta^f_{-1} \cdot \beta^s_{-1}$ = 0.164

	(1) Daughter	(2) Daughter	(3) Daughter	(4) Mother
Mother	0.539***		0.513***	
	(0.0421)		(0.0506)	
Grandmother		0.215***	0.051	0.321***
		(0.0345)	(0.0359)	(0.0250)
Observations	1391	1311	1310	1310

Test $\beta^m_{-1} \cdot \beta^d_{-1} = \beta^m_{-2}$: F = 1.5214, Prob > F = 0.2177 ; $\beta^m_{-1} \cdot \beta^d_{-1}$ = 0.173

(b) USA

	(1) Son	(2) Son	(3) Son	(4) Father
Father	0.281***		0.262***	
	(0.0220)		(0.0268)	
Grandfather		0.147***	0.039**	0.412***
		(0.0158)	(0.0184)	(0.0238)
Observations	2705	2681	2681	2681

Test $\beta^f_{-1} \cdot \beta^s_{-1} = \beta^f_{-2}$: F = 3.8558, Prob > F = 0.0498 ; $\beta^f_{-1} \cdot \beta^s_{-1}$ = 0.116

	(1) Daughter	(2) Daughter	(3) Daughter	(4) Mother
Mother	0.363***		0.335***	
	(0.0187)		(0.0241)	
Grandmother		0.168***	0.056***	0.333***
		(0.0172)	(0.0184)	(0.0275)
Observations	3250	3153	3153	3153

Test $\beta^m_{-1} \cdot \beta^d_{-1} = \beta^m_{-2}$: F = 7.3774, Prob > F = 0.0067 ; $\beta^m_{-1} \cdot \beta^d_{-1}$ = 0.121

(c) UK

	(1) Son	(2) Son	(3) Son	(4) Father
Father	0.145***		0.084**	
	(0.0304)		(0.0356)	
Grandfather		0.076**	0.046	0.357***
		(0.0306)	(0.0332)	(0.0481)
Observations	734	506	506	506

Test $\beta^f_{-1} \cdot \beta^s_{-1} = \beta^f_{-2}$: F = 0.6329, Prob > F = 0.4267 ; $\beta^f_{-1} \cdot \beta^s_{-1}$ = 0.052

	(1) Daughter	(2) Daughter	(3) Daughter	(4) Mother
Mother	0.157***		0.147***	
	(0.0318)		(0.0343)	
Grandmother		0.085***	0.046	0.265***
		(0.0312)	(0.0299)	(0.0475)
Observations	721	651	651	651

Test $\beta^m_{-1} \cdot \beta^d_{-1} = \beta^m_{-2}$: F = 1.9852, Prob > F = 0.1593 ; $\beta^m_{-1} \cdot \beta^d_{-1}$ = 0.041

Notes: Tables show regressions of sons'/daughters' educational outcomes on the outcomes of father/mother and grandfather/grandmother. Cluster adjusted s.e. at family level in parenthesis. Statistical significance level * 0.1 ** 0.05 *** 0.01. $\beta^{s/d}$ regression coefficient of the education of fathers/mothers on sons/daughters. $\beta^{f/m}$ regression coefficient of the education of grandfathers/grandmothers on fathers/mothers.
Source: Own estimations based on SOEP (Germany), PSID (USA), and BHPS/UKHLS (UK).

Table A6: *Lineages - Estimated correlation (r), heritability (λ) and transferability (ρ) coefficients Outcome: Completed years of education*

	GER		*USA*		*UK*	
	Sons	*Daughters*	*Sons*	*Daughters*	*Sons*	*Daughters*
r_{-1}	0.456	0.455	0.451	0.451	0.286	0.240
r_{-2}	0.286	0.256	0.251	0.275	0.121	0.118
λ	0.627	0.563	0.557	0.609	0.424	0.491
s.e.	*0.0712*	*0.0770*	*0.0457*	*0.0472*	*0.1613*	*0.1508*
ρ	0.853	0.899	0.900	0.861	0.821	0.699
s.e.	*0.0506*	*0.0635*	*0.0425*	*0.0348*	*0.5916*	*0.4914*

Notes: Bootstrapped s.e. (200 replications). r_{-1} is here the average of the correlation coefficients of son (daughter) on father (mother) and of father (mother) on grandfather (grandmother).
Source: Own estimations based on SOEP (Germany), PSID (USA), and BHPS/UKHLS (UK).

Table A7: *Lineages - Regression analysis by son/daughter – father/mother – grandfather/grandmother Outcome: Z-Score of educational attainment*

(a) Germany

	(1) Son	(2) Son	(3) Son	(4) Father
Father	0.444***		0.399***	
	(0.0331)		(0.0410)	
Grandfather		0.302***	0.108***	0.486***
		(0.0365)	(0.0402)	(0.0297)
Observations	1625	1503	1497	1497

Test $\beta^f_{-1} \cdot \beta^s_{-1} = \beta^f_{-2}$: F = 5.6279, Prob > F = 0.0178 ; $\beta^f_{-1} \cdot \beta^s_{-1}$ = 0.216

	(1) Daughter	(2) Daughter	(3) Daughter	(4) Mother
Mother	0.396***		0.374***	
	(0.0356)		(0.0421)	
Grandmother		0.232***	0.064	0.451***
		(0.0384)	(0.0401)	(0.0339)
Observations	1391	1311	1310	1310

Test $\beta^m_{-1} \cdot \beta^d_{-1} = \beta^m_{-2}$: F = 1.9480, Prob > F = 0.1631 ; $\beta^m_{-1} \cdot \beta^d_{-1}$ = 0.179

(b) USA

	(1) Son	(2) Son	(3) Son	(4) Father
Father	0.410***		0.391***	
	(0.0290)		(0.0335)	
Grandfather		0.232***	0.056*	0.450***
		(0.0291)	(0.0302)	(0.0282)
Observations	2705	2681	2681	2681

Test $\beta^f_{-1} \cdot \beta^s_{-1} = \beta^f_{-2}$: F = 2.6858, Prob > F = 0.1015 ; $\beta^f_{-1} \cdot \beta^s_{-1}$ = 0.184

	(1) Daughter	(2) Daughter	(3) Daughter	(4) Mother
Mother	0.396***		0.371***	
	(0.0210)		(0.0259)	
Grandmother		0.229***	0.078***	0.409***
		(0.0257)	(0.0257)	(0.0348)
Observations	3250	3153	3153	3153

Test $\beta^m_{-1} \cdot \beta^d_{-1} = \beta^m_{-2}$: F = 6.8630, Prob > F = 0.0089 ; $\beta^m_{-1} \cdot \beta^d_{-1}$ = 0.162

(c) UK

	(1) Son	(2) Son	(3) Son	(4) Father
Father	0.233***		0.137**	
	(0.0501)		(0.0575)	
Grandfather		0.124***	0.080	0.320***
		(0.0451)	(0.0502)	(0.0482)
Observations	734	506	506	506

Test $\beta^f_{-1} \cdot \beta^s_{-1} = \beta^f_{-2}$: F = 1.1846, Prob > F = 0.2769 ; $\beta^f_{-1} \cdot \beta^s_{-1}$ = 0.075

	(1) Daughter	(2) Daughter	(3) Daughter	(4) Mother
Mother	0.209***		0.197***	
	(0.0424)		(0.0455)	
Grandmother		0.105**	0.057	0.245***
		(0.0431)	(0.0417)	(0.0455)
Observations	721	651	651	651

Test $\beta^m_{-1} \cdot \beta^d_{-1} = \beta^m_{-2}$: F = 1.5634, Prob > F = 0.2116 ; $\beta^m_{-1} \cdot \beta^d_{-1}$ = 0.051

Notes: Tables show regressions of sons'/daughters' educational outcomes on the outcomes of father/mother and grandfather/grandmother. Cluster adjusted s.e. at family level in parenthesis. Statistical significance level * 0.1 ** 0.05 *** 0.01. $\beta^{s/d}$ regression coefficient of the education of fathers/mothers on sons/daughters. $\beta^{f/m}$ regression coefficient of the education of grandfathers/grandmothers on fathers/mothers.
Source: Own estimations based on SOEP (Germany), PSID (USA), and BHPS/UKHLS (UK).

Table A8: *Lineages - Estimated correlation (r), heritability (λ) and transferability (ρ) coefficients*
Outcome: Completed years of education

	GER		*USA*		*UK*	
	Sons	*Daughters*	*Sons*	*Daughters*	*Sons*	*Daughters*
r_{-1}	0.456	0.433	0.428	0.418	0.276	0.227
r_{-2}	0.292	0.240	0.227	0.243	0.131	0.105
λ	0.641	0.555	0.531	0.581	0.476	0.464
s.e.	*0.0631*	*0.0776*	*0.0496*	*0.0506*	*0.1668*	*0.1676*
ρ	0.844	0.883	0.897	0.849	0.761	0.699
s.e.	*0.0419*	*0.0650*	*0.0468*	*0.0388*	*0.2216*	*0.3099*

Notes: Bootstrapped s.e. (200 replications). r_{-1} is here the average of the correlation coefficients of son (daughter) on father (mother) and of father (mother) on grandfather (grandmother).
Source: Own estimations based on SOEP (Germany), PSID (USA), and BHPS/UKHLS (UK).

B Supplemental Material

SUPPLEMENTAL MATERIAL (FOR ONLINE PUBLICATION)

Dynastic Inequality Compared: Multigenerational Mobility in the US, the UK, and Germany

Authors: Guido Neidhöfer, Maximilian Stockhausen (Freie Universität Berlin)

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A DATA

The SOEP is an annually repeated longitudinal study of private households in Germany that was launched in 1984. Since 1991, it also includes a sample of the East German population.[1] For the current study we restrict our sample to people residing in West Germany. The PSID is a representative sample of the US population and was annually repeated between 1968 and 1995. Since 1995, it is repeated biennial only and was reduced in its scope.[2] The BHPS is an annually repeated longitudinal study of private households in Great Britain and was run between 1991 and 2008.[3] In 2009, the BHPS was detached by Understanding Society which is an annually repeated longitudinal study of private households in Great Britain and covers an even larger array of people's social and economic circumstances, attitudes, behaviours and health.[4] It builds on the BHPS and a large number of former BHPS respondents were incorporated into Understanding Society from the second wave of interviews onwards. We treat information collected from BHPS sample members in Understanding Society as if it were information collected in successive BHPS waves.[5]

A.1 Harmonization

We maximize the comparability of our educational measure by following the harmonization procedures adopted in the Cross-National Equivalent File (CNEF).[6]

PSID provides detailed information on completed years of education for each family unit member at the time of the interview. It encompasses information on primary, secondary, and tertiary education as well as vocational training. We use this information to construct both the variables on schooling and education for parents (generation t-1) and children (generation t). In addition, retrospective questions on parental education are available. In this case, the answer of the responding household head is categorized into one of eight possible grade categories. We use this information to attribute the completed years of education of grandparents (generation t-2) to their grandchildren. Since we can directly observe generation *t* and *t-1* in our samples, we use these retrospective information to compute the completed years of education for generation *t-2* (grandparents). Also, whenever individual response on completed years of education is not available for parents, we take the information given by retrospective questions.

SOEP provides a comparable measure of completed years of education for each household member at the time of the interview. In contrast to the PSID, the scale of completed years of education is restricted to values ranging from seven years of education to eighteen years of education. We limit the scale at the upper bound to be consistent with the scale from the PSID. Retrospective questions on the educational level of both mothers and fathers are also available, at which the respondents have to refer to school leaving degrees ranging from "secondary school degree" to "did not attend school". As described before, the available information on the respondent and its parents is, then, transformed to our common scale of years of education.

The panel surveys for the UK, BHPS and Understanding Society, can be combined with each other for longitudinal analyses. Both do not provide a direct measure of completed years of education, but information on the highest educational qualification of a respondent and its respective parents.[7] This variable combines both information on the highest school leaving degree as well as information on vocational training. Again, the information provided in the retrospective questions on parents are less detailed and contain only five different categories. By using additional information on parental occupation and skills, measured

[1] See: Wagner, Gert G., Joachim R. Frick, and Jürgen Schupp (2007) The German Socio-Economic Panel Study (SOEP) - Scope, Evolution and Enhancements. *Journal of Applied Social Science Studies* 127 (1), 139-169.

[2] Panel Study of Income Dynamics, public use dataset. Produced and distributed by the Survey Research Center, Institute for Social Research, University of Michigan, Ann Arbor, MI (2016).

[3] Since 2001, the BHPS is also representative of the United Kingdom. This was achieved by adding 1,500 additional households from Scotland and 1,500 households from Wales in 1999 and another 2,000 households from Northern Ireland in 2001. See: University of Essex. Institute for Social and Economic Research. (2010). British Household Panel Survey: Waves 1-18, 1991-2009. 7th Edition. UK Data Service. SN: 5151.

[4] See: University of Essex. Institute for Social and Economic Research, NatCen Social Research. (2015). Understanding Society: Waves 1-5, 2009-2014. [data collection]. 7th Edition. UK Data Service. SN: 6614.

[5] There is no information on BHPS sample members for 2009.

[6] The CNEF project provides a harmonized subset of the information included in various household surveys and suitable for international comparisons. For information on CNEF, see Frick et al. (2007).

[7] Information on parents are provided in Wave 13 in the BHPS and in Wave 2 of Understanding Society.

in ISCO levels, we are however able to construct comparable measures of schooling and education for children, parents and grandparents. Figure A1 shows the codification scheme applied in each survey, Figure A2 the mean completed years of education by age and a comparison with the Barro-Lee data on educational attainment.

Finally, the household surveys are non-random draws of the population and oversample certain groups, like PSID does with low-income households and SOEP with migrants. Sample design weights are therefore provided to represent the actual population. Computing descriptive statistics and performing regressions without using weighting factors would results in inconsistent estimates. Our estimates are, therefore, obtained by weighting each observation by its inverse probability of selection into the sample. Since we pool several waves of the surveys, we normalize these weights for every survey year to maintain its relative population share. To account for heteroscedasticity, standard errors are obtained by clustering observations within the household of origin. For comprehensive overviews on household survey design and weighting procedures, see Deaton (1997) and Solon et al. (2015).

Fig. A1: *Codification of completed years of education*

(a) PSID - USA

$$Years\,of\,Schooling = \begin{cases} 1 & if\,school\,not\,attended \\ 5 & if\,school\,dropout\,and\,no\,school\,degree \\ 9 & if\,secondary\,school\,degree \\ 10 & if\,intermediate\,school\,degree \\ 12 & if\,technical\,school\,degree \\ 13 & if\,upper\,secondary\,school\,degree \end{cases}$$

$$Years\,of\,Education = \begin{cases} 1 & if\,0-5\,grades \\ 5 & if\,6-8\,grades\,or\,''grade\,school'' \\ 9 & if\,9-11\,grades\,(some\,high\,school)\,or\,junior\,high \\ 12 & if\,12\,grades\,(completed\,high\,school) \\ 13 & if\,12\,grades\,plus\,nonacademic\,training\,or\,R.N.\,(no\,further\,elaboration) \\ 14 & if\,some\,college,\,no\,degree\,or\,Associate's\,degree \\ 15 & if\,College\,BA\,and\,no\,advanced\,degree\,mentioned\,or\,normal\,school\,or\,R.N.\,with\,3\,years\,college \\ 17 & if\,College,\,advanced\,or\,professional\,degree,\,some\,graduate\,work\,orclose\,to\,receiving\,degree \end{cases}$$

(b) SOEP - Germany

$$Years\,of\,Schooling = \begin{cases} 1 & if\,school\,not\,attended \\ 5 & if\,school\,dropout\,and\,no\,school\,degree \\ 9 & if\,secondary\,school\,degree \\ 10 & if\,intermediate\,school\,degree \\ 12 & if\,technical\,school\,degree \\ 13 & if\,upper\,secondary\,school\,degree \end{cases}$$

$$Years\,of\,Education = \begin{cases} Years\,of\,Schooling & if\,no\,vocational\,degree \\ Years\,of\,Schooling+3 & if\,vocational\,degree \\ Years\,of\,Schooling+4 & if\,Tech\,Engineer,\,Civil\,Service\,Training,\,Special\,Tech\,School \\ 17 & if\,College,\,University \end{cases}$$

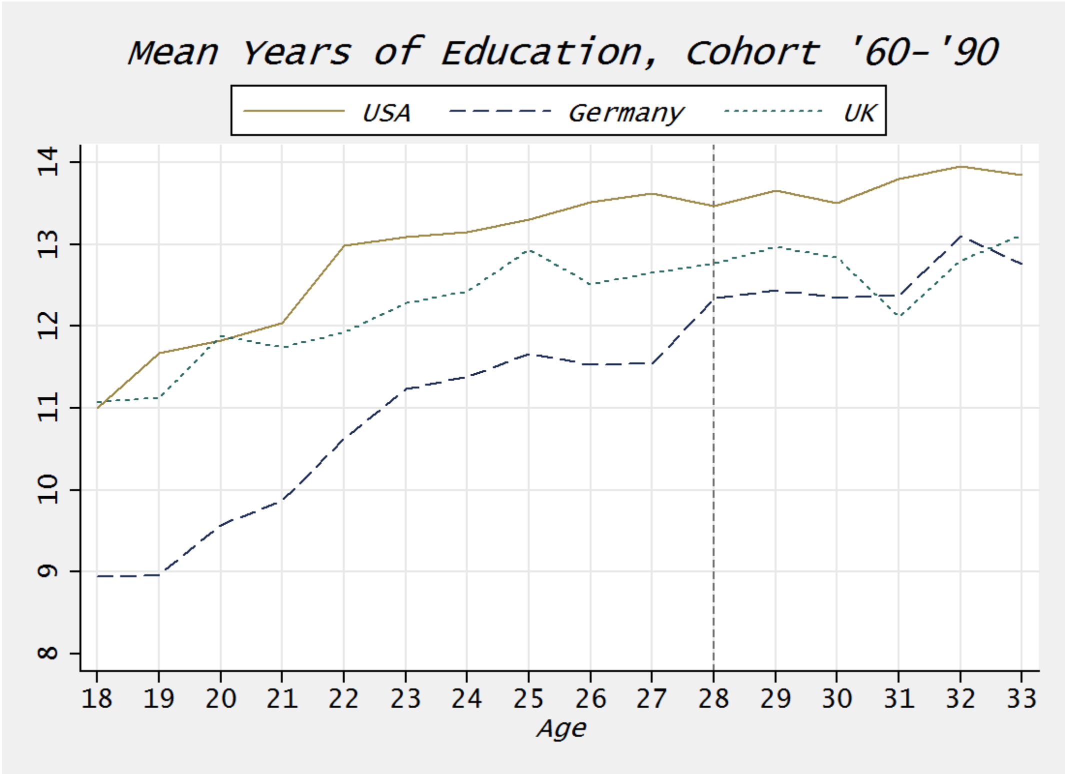
(c) BHPS/UKHLS - UK

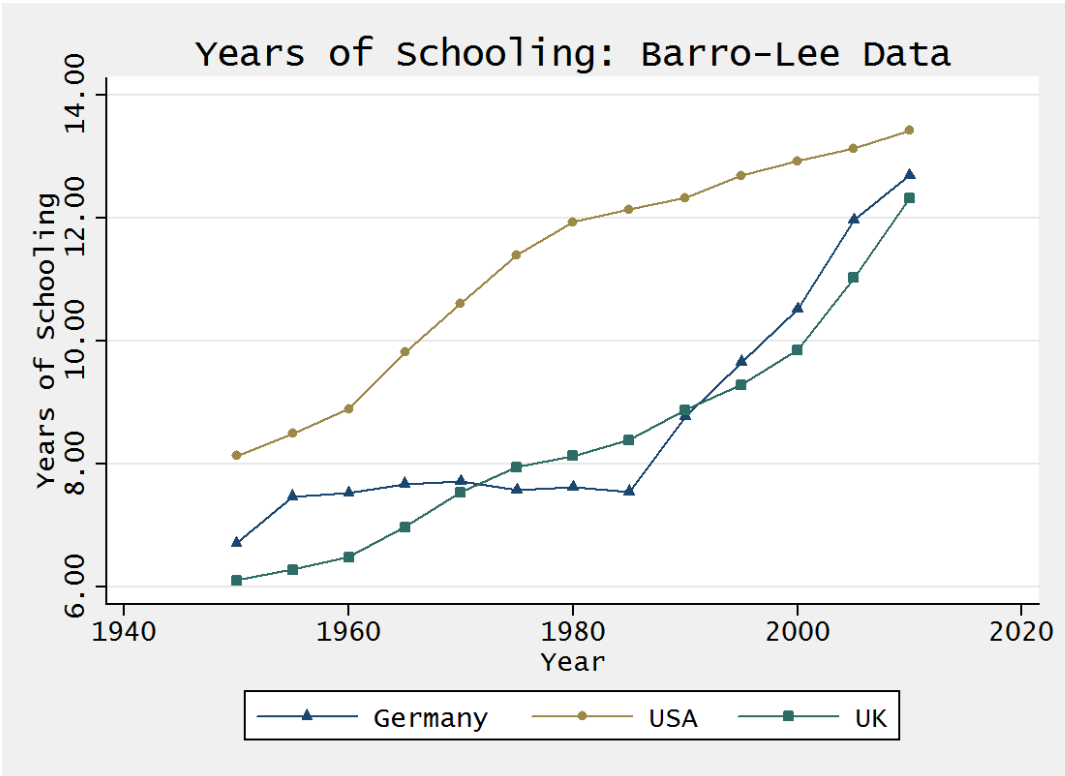
$$Years\,of\,Schooling = \begin{cases} 1 & if\,did\,not\,go\,to\,school\,at\,all \\ 5 & if\,left\,school\,with\,no\,qualifications\,or\,certificates \\ 9 & if\,left\,school\,with\,some\,qualifications\,or\,certificates \\ 12 & if\,post\,school\,quals\,or\,certs\,(e.g.\,city\,\&\,guilds) \\ 13 & if\,university\,degree\,or\,higher\,degree \end{cases}$$

$$Years\,of\,Education = \begin{cases} Years\,of\,Schooling & if\,ISCO\,level\,9\,(skill\,level\,1) \\ Years\,of\,Schooling+3 & if\,ISCO\,levels\,4-8\,(skill\,level\,2) \\ Years\,of\,Schooling+4 & if\,ISCO\,level\,0,1\,and\,3\,(skill\,level\,3) \\ 17 & if\,ISCO\,levels\,2\,(skill\,level\,4) \end{cases}$$

Fig. A2: *Mean education by age and comparison with other data sets on mean educational attainment*

(a) *Mean education by age*





(b) *Barro-Lee Data on years of schooling (see Barro and Lee, 2013)*

A.2 Selectivity of sample

A sensitivity analysis shows that the samples might be positively selected in educational attainments. We find that the weighted mean years of education of individuals in our sample – restricted by the condition of available information on parents' and grandparents' education – is higher than the weighted mean of the unrestricted sample. Restricting the sample on the condition to have information on parental education retrieved from retrospective questions – and not necessarily grandparental education – yields lower regression coefficients. These differences are statistically significant at the 1 % level for SOEP, at the 5 % level for BHPS/UKHLS and not significant for PSID. The interpretations and consequences of this bias for our study are discussed in the paper.

Tab. A1: *Testing selection into sample (Cohort 1960-1985); Weighted statistics.*

Sample 1: Sample used in this study (parents and children in survey and information on grandparental education).
Sample 2: Parental information retrieved from retrospective questions; information on grandparental education not necessarily available.

Mean completed years of education	*Sample 1*	*Sample 2*	*p-value*	*Unrestricted*	*p-value*
GER	12.552	12.497	0.2261	12.141	0.0000
USA	13.660	13.181	0.0000	13.088	0.0000
UK	12.673	12.630	0.5094	12.008	0.0000

First p-value shows the probability that the weighted means of Sample 1 and Sample 2 are equal. Second p-values shows the probability that the weighted mean of Sample 1 and of the Unrestricted sample are equal.

Regression coefficient (β_-1)	*Sample 1*	*N*	*Sample 2*	*N*	*p-value*
GER	0.484	3,210	0.380	12,044	0.0004
USA	0.400	6,299	0.378	10,475	0.1931
UK	0.208	1,532	0.169	4,757	0.1774

P-value shows the probability that the weighted regression coefficient of Sample 1 and Sample 2 are equal.

B ADDITIONAL MATERIAL

B.1 *Analysis performed applying the Z-Score of educational attainment*

To obtain a measure that is conceptually even closer to the notion of human capital – and comparable across countries and time periods – we perform a linear transformation of the dependent and independent variables constructing the Z-Score of educational achievements by cohorts:

$$z_{ijT} = \frac{y_{ijT} - \bar{y}_{jT}}{\sigma_{jT}} \tag{1}$$

where $\bar{y}_{jt}$ and σ_{jt} are the mean and standard deviation of completed years of education of all individuals from generation $T\epsilon\{t, t-1, t-2\}$ in cohort j. The cohort refers hereby to the cohort of the children's generation. This measurement gives the relative standing (in standard deviations) of an individual, his parents, and grandparents with respect to their reference groups, i.e. people competing with them in the labour market.

Tab. B1: *Testing for a grandparental effect:*
Grandparents' death as exogenous source of variation in the likelihood of interaction
***Outcome**: Z-Score of educational attainment*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Father	0.433***	0.450***	0.402***	0.440***				
	(0.0280)	(0.0346)	(0.0311)	(0.0369)				
Mother					0.381***	0.361***	0.409***	0.412***
					(0.0283)	(0.0356)	(0.0298)	(0.0339)
GF-F	0.079***	0.048						
	(0.0285)	(0.0367)						
GM-F			0.084***	0.076**				
			(0.0299)	(0.0337)				
GF-M					0.152***	0.183***		
					(0.0302)	(0.0371)		
GM-M							0.064*	0.076*
							(0.0377)	(0.0452)
Death=1 × GF-F		0.077						
		(0.0536)						
Death=1 × GM-F				0.023				
				(0.0667)				
Death=1 × GF-M						-0.105*		
						(0.0607)		
Death=1 × GM-M								-0.047
								(0.0757)
Death=1		0.042						
		(0.0455)						
Death=1 × Father		-0.039						
		(0.0553)						
Death=1				0.058				
				(0.0605)				
Death=1 × Father				-0.128**				
				(0.0640)				
Death=1						-0.014		
						(0.0493)		
Death=1 × Mother						0.064		
						(0.0527)		
Death=1								0.073
								(0.0707)
Death=1 × Mother								-0.013
								(0.0735)
Country F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3360	3360	2241	2241	2973	2973	2147	2147
Clusters	1871	1871	1309	1309	1797	1797	1311	1311

GF/GM-F/M: Grandfather/Mother-Father's/Mother's side. Own estimations based on pooled sample of SOEP and PSID.
Cluster adjusted s.e. at family level. Statistical significance level * 0.1 ** 0.05 *** 0.01.

	(1) USA	(2) USA	(3) USA	(4) USA	(5) GER	(6) GER	(7) GER	(8) GER
Father	0.501***	0.459***			0.394***	0.423***		
	(0.0503)	(0.0517)			(0.0482)	(0.0525)		
Mother			0.349***	0.395***			0.357***	0.420***
			(0.0551)	(0.0565)			(0.0464)	(0.0417)
GF-F	0.022				0.092			
	(0.0420)				(0.0737)			
GM-F		0.047				0.122*		
		(0.0394)				(0.0668)		
GF-M			0.131***				0.285***	
			(0.0474)				(0.0580)	
GM-M				0.038				0.135**
				(0.0647)				(0.0628)
Death=1 × GF-F	0.070				0.129			
	(0.0642)				(0.1049)			
Death=1 × GM-F		0.047				0.045		
		(0.0844)				(0.1154)		
Death=1 × GF-M			-0.036				-0.220**	
			(0.0780)				(0.1049)	
Death=1 × GM-M				0.029				-0.170
				(0.0935)				(0.1461)
Death=1	0.104*				-0.052			
	(0.0588)				(0.0740)			
Death=1 × Father	-0.034				-0.047			
	(0.0732)				(0.0838)			
Death=1		0.171**				-0.090		
		(0.0818)				(0.0861)		
Death=1 × Father		-0.097				-0.178*		
		(0.0905)				(0.0958)		
Death=1			0.034				-0.049	
			(0.0678)				(0.0753)	
Death=1 × Mother			0.083				0.057	
			(0.0817)				(0.0701)	
Death=1				0.110				0.057
				(0.0951)				(0.1110)
Death=1 × Mother				-0.015				-0.006
				(0.1106)				(0.1005)
Observations	1832	1105	1390	931	1528	1136	1583	1216
Clusters	811	501	646	434	1060	808	1151	877

Own estimations based on SOEP and PSID.
Cluster adjusted s.e. at family level. Statistical significance level * 0.1 ** 0.05 *** 0.01.

B.2 *Testing for a grandparental effect*

Tab. B2: *Testing for a grandparental effect:*
Grandparents' death as exogenous source of variation in the likelihood of interaction – Effects estimated separately for USA and Germany

***Outcome**: Completed years of education*

	(1) USA	(2) USA	(3) USA	(4) USA	(5) GER	(6) GER	(7) GER	(8) GER
Father	0.341***	0.302***			0.440***	0.453***		
	(0.0357)	(0.0331)			(0.0547)	(0.0580)		
Mother			0.297***	0.339***			0.462***	0.520***
			(0.0485)	(0.0514)			(0.0547)	(0.0518)
GF-F	0.016				0.063			
	(0.0235)				(0.0557)			
GM-F		0.020				0.107*		
		(0.0246)				(0.0563)		
GF-M			0.070**				0.240***	
			(0.0283)				(0.0469)	
GM-M				0.025				0.137**
				(0.0409)				(0.0595)
Death=1 × GF-F	0.040				0.139			
	(0.0403)				(0.0875)			
Death=1 × GM-F		0.044				0.102		
		(0.0640)				(0.1113)		
Death=1 × GF-M			-0.020				-0.187**	
			(0.0457)				(0.0842)	
Death=1 × GM-M				0.041				-0.200
				(0.0663)				(0.1218)
Death=1	-0.185				-0.698			
	(0.6549)				(0.9900)			
Death=1 × Father	-0.002				-0.084			
	(0.0555)				(0.0962)			
Death=1		0.534				1.168		
		(0.9010)				(1.2223)		
Death=1 × Father		-0.049				-0.208**		
		(0.0639)				(0.1012)		
Death=1			-0.712				1.535	
			(0.7458)				(0.9382)	
Death=1 × Mother			0.078				0.036	
			(0.0703)				(0.0833)	
Death=1				0.062				1.607
				(1.0757)				(1.3930)
Death=1 × Mother				-0.024				0.042
				(0.1004)				(0.1137)
Observations	1832	1105	1390	931	1528	1136	1583	1216
Clusters	811	501	646	434	1060	808	1151	877

B.3 *Lineages*

Tab. B3: *Lineages - Pooled sample*
Outcome: Completed years of education

Sons

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Father	0.212***	0.212***			0.203***		0.132***
	(0.0203)	(0.0212)			(0.0219)		(0.0239)
Mother			0.246***	0.253***		0.244***	0.182***
			(0.0230)	(0.0230)		(0.0237)	(0.0264)
GF-F	0.061***				0.045***		0.027
	(0.0149)				(0.0173)		(0.0276)
GM-F		0.067***			0.034		0.019
		(0.0179)			(0.0213)		(0.0345)
GF-M			0.070***			0.055***	0.011
			(0.0143)			(0.0179)	(0.0281)
GM-M				0.067***		0.027	-0.003
				(0.0160)		(0.0199)	(0.0335)
Country F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4684	4559	5318	5263	4507	5180	4216
Clusters	3123	3061	3533	3508	3027	3457	2789

GF/GM-F/M: Grandfather/Mother-Father's/Mother's side. Own estimations based on pooled sample of SOEP, PSID and UKHLS/BHPS. Cluster adjusted s.e. at family level. Statistical significance level * 0.1 ** 0.05 *** 0.01.

Daughters

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Father	0.237***	0.251***			0.243***		0.184***
	(0.0182)	(0.0187)			(0.0193)		(0.0206)
Mother			0.233***	0.239***		0.230***	0.154***
			(0.0222)	(0.0224)		(0.0231)	(0.0229)
GF-F	0.066***				0.046***		0.016
	(0.0140)				(0.0172)		(0.0244)
GM-F		0.064***			0.030		0.014
		(0.0150)			(0.0188)		(0.0262)
GF-M			0.080***			0.062***	0.028
			(0.0138)			(0.0176)	(0.0238)
GM-M				0.074***		0.027	0.010
				(0.0148)		(0.0189)	(0.0259)
Country F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4480	4386	5164	5114	4328	5039	4095
Clusters	2831	2790	3244	3228	2752	3174	2572

GF/GM-F/M: Grandfather/Mother-Father's/Mother's side. Own estimations based on pooled sample of SOEP, PSID and UKHLS/BHPS. Cluster adjusted s.e. at family level. Statistical significance level * 0.1 ** 0.05 *** 0.01.

Tab. B4: *Lineages - Pooled sample*
Outcome: Z-Score of educational attainment

Sons

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Father	0.329***	0.332***			0.323***		0.209***
	(0.0232)	(0.0236)			(0.0246)		(0.0270)
Mother			0.328***	0.338***		0.329***	0.251***
			(0.0221)	(0.0220)		(0.0227)	(0.0264)
GF-F	0.078***				0.062**		0.044
	(0.0211)				(0.0253)		(0.0353)
GM-F		0.069***			0.031		0.001
		(0.0219)			(0.0265)		(0.0392)
GF-M			0.098***			0.087***	0.003
			(0.0211)			(0.0256)	(0.0363)
GM-M				0.077***		0.021	-0.003
				(0.0201)		(0.0243)	(0.0383)
Country F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4683	4557	5318	5263	4505	5180	4214
Clusters	3122	3059	3533	3508	3025	3457	2787

GF/GM-F/M: Grandfather/Mother-Father's/Mother's side. Own estimations based on pooled sample of SOEP, PSID, and UKHLS/BHPS.
Cluster adjusted s.e. at family level. Statistical significance level * 0.1 ** 0.05 *** 0.01.

Daughters

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Father	0.361***	0.379***			0.372***		0.283***
	(0.0224)	(0.0225)			(0.0233)		(0.0257)
Mother			0.316***	0.321***		0.312***	0.194***
			(0.0218)	(0.0217)		(0.0226)	(0.0246)
GF-F	0.079***				0.048*		0.008
	(0.0209)				(0.0267)		(0.0347)
GM-F		0.069***			0.039		0.010
		(0.0204)			(0.0261)		(0.0356)
GF-M			0.102***			0.076***	0.034
			(0.0201)			(0.0256)	(0.0331)
GM-M				0.088***		0.038	0.018
				(0.0204)		(0.0259)	(0.0362)
Country F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4475	4379	5164	5113	4321	5038	4090
Clusters	2826	2784	3244	3228	2746	3174	2568

GF/GM-F/M: Grandfather/Mother-Father's/Mother's side. Own estimations based on pooled sample of SOEP, PSID, and UKHLS/BHPS.
Cluster adjusted s.e. at family level. Statistical significance level * 0.1 ** 0.05 *** 0.01.

B.4 ***Assortative Mating***

Assortative mating is an important characteristic to account for studying the intergenerational persistence of socio-economic status. Higher spouse correlations in endowments cause higher heritability coefficients and large values of λ depend on high and constant rates of assortative mating. Here, we report spouse correlations in observable outcomes.

Tab. B5: *Correlation of parents' and grandparents' education.*
*Spouse correlations (**assortative mating**) are Father/Mother, GF-F/GM-F and GF-M/GM-M.*

Panel A – Outcome: Completed years of education

(a) GER	Father	Mother	GF-F	GM-F	GF-M	GM-M
Father	1.000	0.598	0.469	0.416	0.440	0.404
Mother	0.598	1.000	0.484	0.428	0.520	0.486
GF-F	0.469	0.484	1.000	0.792	0.686	0.659
GM-F	0.416	0.428	0.792	1.000	0.665	0.706
GF-M	0.440	0.520	0.686	0.665	1.000	0.783
GM-M	0.404	0.486	0.659	0.706	0.783	1.000

(b) USA	Father	Mother	GF-F	GM-F	GF-M	GM-M
Father	1.000	0.559	0.481	0.450	0.429	0.407
Mother	0.559	1.000	0.449	0.437	0.479	0.477
GF-F	0.481	0.449	1.000	0.637	0.877	0.585
GM-F	0.450	0.437	0.637	1.000	0.565	0.870
GF-M	0.429	0.479	0.877	0.565	1.000	0.636
GM-M	0.407	0.477	0.585	0.870	0.636	1.000

(c) UK	Father	Mother	GF-F	GM-F	GF-M	GM-M
Father	1.000	0.409	0.332	0.302	0.302	0.280
Mother	0.409	1.000	0.253	0.228	0.306	0.284
GF-F	0.332	0.253	1.000	0.839	0.293	0.295
GM-F	0.302	0.228	0.839	1.000	0.290	0.278
GF-M	0.302	0.306	0.293	0.290	1.000	0.823
GM-M	0.280	0.284	0.295	0.278	0.823	1.000

Panel B – Outcome: Z-Score of educational attainment

(a) GER	Father	Mother	GF-F	GM-F	GF-M	GM-M
Father	1.000	0.577	0.468	0.410	0.443	0.390
Mother	0.577	1.000	0.502	0.443	0.539	0.490
GF-F	0.468	0.502	1.000	0.776	0.674	0.643
GM-F	0.410	0.443	0.776	1.000	0.641	0.693
GF-M	0.443	0.539	0.674	0.641	1.000	0.760
GM-M	0.390	0.490	0.643	0.693	0.760	1.000

(b) USA	Father	Mother	GF-F	GM-F	GF-M	GM-M
Father	1.000	0.540	0.439	0.412	0.380	0.359
Mother	0.540	1.000	0.389	0.384	0.421	0.424
GF-F	0.439	0.389	1.000	0.587	0.860	0.525
GM-F	0.412	0.384	0.587	1.000	0.507	0.847
GF-M	0.380	0.421	0.860	0.507	1.000	0.582
GM-M	0.359	0.424	0.525	0.847	0.582	1.000

(c) UK	Father	Mother	GF-F	GM-F	GF-M	GM-M
Father	1.000	0.384	0.316	0.299	0.295	0.269
Mother	0.384	1.000	0.228	0.210	0.287	0.266
GF-F	0.316	0.228	1.000	0.837	0.271	0.264
GM-F	0.299	0.210	0.837	1.000	0.269	0.253
GF-M	0.295	0.287	0.271	0.269	1.000	0.815
GM-M	0.269	0.266	0.264	0.253	0.815	1.000

References

BARRO, R. J. AND J. W. LEE, "A new data set of educational attainment in the world, 1950-2010," *Journal of Development Economics* 104 (2013), 184–198.

DEATON, A., *The Analysis of Household Surveys: A Microeconometric Approach to Development Policy* (Published for the World Bank [by] Johns Hopkins University Press, 1997).

FRICK, J. R., S. P. JENKINS, D. R. LILLARD, O. LIPPS AND M. WOODEN, "The Cross-National Equivalent File (CNEF) and its Member Country Household Panel Studies," *Journal of Applied Social Science Studies* 127 (2007), 627–654.

SOLON, G., S. J. HAIDER AND J. M. WOOLDRIDGE, "What Are We Weighting For?," *Journal of Human Resources* 50 (apr 2015), 301–316.

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