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ABSTRACT

Like (Grand)Parent, like Child? Multigenerational Mobility across the EU*

This study shows that the intergenerational transmission of inequality in most of the 28 EU countries is higher than what a parent-to-child paradigm would suggest. While a strand of the literature claims that this is due to a direct grandparental effect, economic historian Gregory Clark maintains that multigenerational mobility follows a Markovian process. In his view, previous estimates of social status persistence are not only (severely) attenuated by an errors-in-variables problem, but are also constant across time and space. Using a survey covering all 28 EU countries, we provide evidence against such a "universal law of mobility". We show that, while in most EU countries traditional estimates of social status persistence are indeed downward biased, there are sizable differences across countries driven by country-specific factors. Further, for a few EU countries we cannot reject the hypothesis of a direct grandparental effect after accounting for a number of parents related covariates possibly affecting the multigenerational transmission process.

JEL Classification: J62, I24

Keywords: multigenerational mobility, education, inequality

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1 Introduction

The degree to which socio-economic status is transmitted from parent to offspring has been the subject of a large theoretical and empirical literature in social sciences. Scholars have debated the theoretical mechanisms behind intergenerationally transmitted inequalities (e.g. Becker and Tomes, 1976, 1979, 1986; Loury, 1981), as well as between- and within-country differences in social mobility (e.g. Solon, 2002; Hertz et al., 2007; Chetty et al., 2014) and their underlying drivers (e.g. Durlauf, 1994; Borjas, 1995; Chadwick and Solon, 2002). Yet, the idea that long-term mobility could be described by a parent-to-child Markovian process has long been unchallenged (Pfeffer, 2014). Most of the earlier contributions implicitly assumed that the effect of earlier generations over offspring socio-economic status is indirect.

Recently, thanks to the increased availability of data providing information on more than two generations (Song and Campbell, 2017), scholars have been able to put such assumption to test. According to this literature, long-term social mobility is lower than what traditional parent-to-child correlations would suggest (Anderson et al., 2018). Estimating social status persistence across two generations and extrapolating it over three (or more) generations, yields lower estimates than the observed persistence across three (or more) generations (e.g. Lindahl et al., 2015; Braun and Stuhler, 2016; Neidhöfer and Stockhausen, 2018). Although Becker and Tomes (1986, p. 28) claim that "practically all the advantages or disadvantages of ancestors tend to disappear in only three generations", recent evidence do not support such insight.

Following these findings, scholars began investigating the possibility of a direct grandparental effect on social mobility. Early studies exploring the hypothesis rejected it (e.g. Hodge, 1966; Ridge, 1974; Behrman and Taubman, 1985). Yet, as Mare notes, the process underlying social mobility might not be invariant across time and space and depend on institutional and historical factors. In addition, a higher order autocorrelation, and thus a direct grandparent effect, is not the only potential explanation behind the observed excess persistence (Solon, 2014). Among the potential explanations proposed by the literature, one gained particular attention. According to economic historian Gregory Clark, the empirical evidence on social mobility has failed to distinguish between the "family's surface or apparent social status and their deeper social competence" (Clark, 2014, p. 108). Socio-economic status across generations is transmitted through an underlying latent factor that is not only much higher (≈ 0.75) than the usually observed parent-to-child correlation in socio-economic status, but also constant across time and space. Relying on partial measures of the socio-economic status leads to "systemically overestimate the underlying mobility rate" (Clark, 2014, p. 110). Once the underlying social status of the parent is correctly estimated, social status mobility follows a Markovian process.

In this study, we use the first EU-wide survey containing retrospective information about the educational attainment, the occupation, and the (subjective) social status of the respondents' parents and grandfathers. The survey provides the opportunity to test recent theories of multigenerational persistence across the 28 EU Member States and shed light on whether social mobility "is governed by a simple underlying law, independent of social structure and government policy" (Clark, 2014, p. 212) or, instead, varies across "times, places, and institutional circumstances" (Mare, 2011, p. 16).

The empirical analysis shows that social status persistence is higher than what the traditional parent-to-child framework would suggest. In the European Union, the iterated procedure leads to overestimate multigenerational mobility. The observed autocorrelation between grandfathers and offspring is significantly higher than what iterating parent-to-child estimates would imply for 17 out of the 28 EU countries. In 20 European countries the estimated latent factor is significantly higher than the average parents-to-child and grandfathers-to-parents estimates.

Our findings support Clark's first hypothesis: traditional estimates of social status persistence suffer from attenuation bias. Once accounting for the fact that the observed social status is transmitted through a latent factor, mobility across generations in the EU-28 is about 30 percent lower than what *naive* estimates suggest. However, our findings do not fully corroborates Clark's second and third hypotheses. While the (unweighted) mean magnitude of the estimated latent factor (≈ 0.73) is in line with Clark's conclusions, there are substantial cross-country differences. We then assess whether this variation is driven by country-specific factors. Theoretically, if intergenerational mobility is "independent of social structure and government policy" (Clark, 2014, p. 212), country-fixed effects should not change the results. Yet, the latent factor is significantly lower when including country dummies, hinting at the fact that the correlation between social status persistence and the unobserved country-specific factors is positive. We therefore investigate the possibility that the findings of excess persistence are driven by a non-Markovian process of social mobility. To do so, we include several proxies of the socio-economic status of both parents and control for the quality of the neighbourhood during childhood. Against this background, we cannot reject the possibility that, in the European Union, social mobility follows an AR(2) process, which is to say that grandparents directly affect the outcome of their grandchildren. This is however not true across all the Member States, corroborating Mare's idea that the process underlying social mobility might not be space-invariant, but rather depends on country-specific social and political institutions.

The remaining of this paper is structured as follows: Section 2 introduces the different approaches to measure multigenerational social status persistence; 3 details the data sources used; Section 4 discuss our findings and Section 5 concludes.

2 Models of multigenerational mobility

2.1 The iterated regression procedure

To measure the degree to which socio-economic status is transmitted across generations, social scientists typically estimate β_{-g} in a linear regression model such as:

$$y_{i,t} = \alpha + \sum_{g=1}^{G} \beta_{-g} y_{i,t-g} + \epsilon_{i,t} \tag{1}$$

where $y_{i,t}$ is the socio-economic status - usually proxied by education, occupation, income, or wealth - of the child of family i at the time period t, $y_{i,t-g}$ is the socio-economic status of the child's ancestor belonging to generation g. The coefficient β_{-g} captures the persistence of inequalities; its opposite, the regression to the mean $1 - \beta_{-g}$, is a measure of social mobility (i.e. the rate at which families that diverge from the average socio-economic status move towards the mean in each generation). In most of the empirical literature, equation (1) is estimated using two adjacent generations, such that $G = 1$; $y_{i,t-1}$ then reflects the socio-economic outcome of the children's parent(s). The choice of such a parent-to-child framework stems from both theoretical contributions and empirical evidence. The seminal theoretical papers on intergenerational mobility (Becker and Tomes, 1976, 1979, 1986; Loury, 1981) assume that the inheritance of the endowments follows a Markovian process of order one - henceforth AR(1). Early empirical studies on the topic (Hodge, 1966; Ridge, 1974; Behrman and Taubman, 1985; Warren and Hauser, 1997) confirmed that grandparent(s) have either no or limited influence on the grandchildren once the parent(s) effect is accounted for.[1]

[1]Using three-generation US data Hodge shows that grandfathers' occupation "do not have any appreciable direct effect" in predicting the grandchildren's occupation (Hodge, 1966, p. 25). Similarly, using British data on education and occupational prestige across three generations, Ridge (1974) finds no evidences supporting a higher order autoregressive process of social mobility. Behrman and Taubman (1985), using the US NAS-NRC Twin Sample, document that both grandfathers' and grandmothers' schooling do not impact on offspring schooling once parents schooling is accounted for. Warren and Hauser, using the Winsconsin Longitudinal study, find that "the data are not consistent with the hypothesis that grandparents' schooling, occupational statuses, or incomes directly affect grandchildren's educational or occupational attainments" (Warren and Hauser, 1997, p. 561)

Assuming such a parent-to-offspring (Markovian) process and that social status persistence decays at a geometric rate, long term dynamics have been then extrapolated as follows:

$$\beta_{-g} \approx (\beta_{-1})^g \quad \forall g > 1 \tag{2}$$

Based on this iterated regression procedure, for a first-order autocorrelation $\beta_{-1} = 0.50$, the second- and third-order autocorrelation β_{-2} and β_{-3} should, respectively, equal to 0.25 and 0.125. Even for high values of β_{-1}, "[...] all the advantages or disadvantages of ancestor tend to disappear in only three generations" (Becker and Tomes, 1986, p. 28). This iterated procedure has however been recently challenged from both methodological and empirical perspectives. First, equation 1 assumes that the socio-economic outcome of the parent $y_{i,t-1}$ is uncorrelated with the error term $\epsilon_{i,t}$. Yet, the same might not apply to the grandparental outcome $y_{i,t-2}$, which, in this case, would imply that equation (1) cannot inform on intergenerational mobility patterns beyond the two observed generations (Stuhler, 2012). Second, recent studies, relying on the direct observations of family lineages (e.g. Lindahl et al., 2015; Dribe and Helgertz, 2016; Kroeger and Thompson, 2016; Braun and Stuhler, 2018), found that $(\beta_{-1})^g$ typically underestimates social status persistence across generations.

The findings of what Stuhler (2012) calls "excess persistence" (i.e. $\beta_{-g} > (\beta_{-1})^g$) have often been attributed to the existence of a direct grandparents effect on offspring social status (Anderson et al., 2018). Yet, an AR(2) data generating process is not the only potential explanation behind the observed excess persistence. First, any causal process in which social status persistence decays slower than geometrically generates a positive grandparent coefficient in a regression in which offspring social status is predicted by parents and grandparents' status (Mare, 2011; Clark and Cummins, 2015; Braun and Stuhler, 2018). Second, the grandparents' effect could be driven by the (still largely unknown) genetic transmission of family traits. Certain characteristics that might explain the observed socio-economic status may skip a generation, resulting in a positive grandparental coefficient (Solon, 2014).[2] Furthermore, a positive grandparent coefficient might be driven by an omitted variable bias. Borjas (1995) suggests that the ethnic capital can create group effects that correlates with the realized social status. Third, and more impor-

[2]The importance of genetics is already mentioned in Becker and Tomes (1979), which shows that besides parental investment, offspring schooling is also influenced by endowments that are transmitted across generations, such as genetic constitutions as well as other *family commodities* acquired through belonging to a particular family culture.

tantly, measurement errors can also be the cause behind a positive grandparent coefficient (Clark, 2014). This last hypothesis recently gained increasing attention by scholars in the field (Solon, 2018). Therefore, before assessing the possibility that social mobility follows an AR(2) process (Section 2.3), Section 2.2 introduces Clark's view of multigenerational mobility and its identification strategies.

2.2 Measurement error models

In the book "The Son Also Rises: Surname and the History of Social Mobility" (Clark, 2014) and related papers (Hao and Clark, 2012; Clark and Cummins, 2014, 2015), Clark and his co-authors argue that existing research often fails to distinguish between the "family's surface or apparent social status and their deeper social competence" (Clark, 2014, p. 108). According to Clark and coauthors, commonly used proxies $y_{i,t}$ of social status (such as earnings, wealth, occupation, and education) are noisy proxies of the family's real social competence, linked with the latter with some random deviation.[3]

Equation (1) should thus be complemented as follows:

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

where $e_{i,t}$ is the family's underlying social competence, and $u_{i,t}$ and $v_{i,t}$ are the error terms uncorrelated with other variables and past values (Braun and Stuhler, 2018). In such a model, λ, the heritability coefficient, captures the degree of the unobserved endowments that offspring receive from their parents while ρ, the transferability coefficient, instead measures how much of the latent endowment is converted into the observed outcome.[4] Omitting to account for the latent endowment leads to "systematically overestimate the underlying mobility rate" (Clark, 2014, p. 110), and, in turn, to report excess

[3]Sociologists long challenged the idea that a single vertical structure is fitted to describe social status (Lenski, 1954). There are instead several hierarchies - such as the income hierarchy, the occupation hierarchy and the education hierarchy - that contributes in defining the individual underlying social status. Early models of status inconsistency also show that such hierarchies might be non-consistent among them (Hendrickx et al., 1993). Being at the top of one hierarchy does not necessarily imply that the same position is also held in other hierarchies.

[4]The idea that parents transmit to their offspring unobserved social competences does not represent a novelty in the social mobility literature. When modelling capital endowments transmitted from parent to children, Becker and Tomes already observed that these are also determined by "the reputation and connections of their families, contribution to the ability, race, and other characteristics of children from the genetic constitutions of their families, and the learning, skills, goals, and other *family commodities* acquired through belonging to a particular family culture." (Becker and Tomes, 1979, p. 1158).

persistence. This approach contrasts with the traditional one which, instead, assumes that $\rho = 1$. In other words, according to Clark, the findings of $\beta_{-g} > (\hat{\beta}_{-1})^g$ are not driven by slower-than-geometric decay of status persistence or higher order auto-correlations, but rather by a biased estimation of β_{-1}.

To address this attenuation bias, different strategies have been employed in the literature. A first strategy is, along Clark (2014) and co-authors, to aggregate individuals by (rare) surname and then compute the association across generations between average outcomes of surname-based groups. If the number of individuals in each surname-based group is sufficiently large and classical measurement error assumptions applies (i.e. $u_{z,t} \approx 0$), then $y_{z,t} \approx \rho e_{z,t}$, where $y_{z,t}$ is the average value of the observed socio-economic outcome of the group of individuals sharing the same surname z at time t. A second strategy is "to measure the social status of families as an aggregate of earnings, wealth, education, occupation and health" (Clark and Cummins, 2014, p. 79). Such an aggregation would return a social mobility rate "closer to that of the underlying latent variable" (Clark and Cummins, 2014, p. 80) even when using parent-to-child estimates.

A third strategy, consists, as shown by Braun and Stuhler (2018), to estimate the latent factor by exploiting repeated observations of the same proxy of socio-economic status, which is possible when the data include information on three (or more) generations. Given that $\beta_{-g} = \rho^2\lambda^g$, the parent-to-child estimate is $\beta_{-1} = \rho^2\lambda$, while the grandparent-child coefficient is $\beta_{-2} = \rho^2\lambda^2$. It follows that $\lambda = {}^{\beta_{-2}}/_{\beta_{-1}}$ and $\rho = ({}^{\beta^2_{-1}}/_{b_{-2}})^{\frac{1}{2}}$. If $\rho = 1$ then the latent factor model equals the iterated regression procedure: $\rho^2\lambda^g = (\hat{\beta}_{-1})^g$.[5] Finally, the fourth strategy relies on an instrumental variable approach (see Lindahl et al., 2015). If intergenerational mobility follows an AR(1) data-generating process as Clark and Cummins (2014) claim, instrumenting a partial measure (e.g. $y_{i,t-1}$) with another noisy measure (e.g. $y_{i,t-2}$), provides an unbiased estimate of the parent-to-child persistence β_{-1}.

After accounting for the attenuation bias by using groups-average estimation of rare surnames, Clark (2014) and co-authors find that social status persistence across generations is constant across societies and as high as 0.8. This "universal law of mobility" implies that the regression to the mean is extremely slow for families with a very low or very high social status. However, other studies relying on a similar group-average identification strategy, often failed to corroborate the findings by Clark and coauthors

[5] While in some circumstances this approach remains sensitive to measurement error, it "avoids the particular caveats that follow from the usage of grouped data." (Braun and Stuhler, 2018, p. 585). Braun and Stuhler show that, in retrospective surveys, λ can abstract from measurement errors only if the recall bias is constant across at least two adjacent generations.

of such a high social status persistence (Solon, 2018).[6] Similarly, Clark and Cummins's hypothesis that intergenerational mobility could be correctly estimated by incorporating information from multiple socio-economic outcomes, do not find support. Using such an approach, Vosters and Nybom show that there are no signs of substantial downward bias in previous estimates, both in Sweden (Vosters and Nybom, 2017) and in the US (Vosters, 2018). Further, they find no evidence of similarity across these two countries contrary to what the "universal law of mobility" suggests. Studies exploiting data directly linking three generations (e.g. Lindahl et al., 2015; Braun and Stuhler, 2018; Neidhöfer and Stockhausen, 2018), show instead that typical estimates of intergenerational mobility are downward biased, albeit not as much as suggested by Clark and Cummins (2014). According to the estimations of the latent factor conducted by Braun and Stuhler (2018) and Neidhöfer and Stockhausen (2018) traditional intergenerational mobility estimates in Germany, Sweden, and the UK suffer from an attenuation bias. In addition, Neidhöfer and Stockhausen (2018) provide evidence of the existence of cross-country differences. Finally, Lindahl et al. (2015)'s conclusions are also partially supportive of Clark's, their IV based estimation of β_{-1} being lower than 0.8 but substantially higher than the OLS estimate.[7]

2.3 The grandparents effect model

Another potential explanation behind the findings of excess persistence is that multigenerational mobility follows a non-Markovian process. By ignoring the potential role of higher-order ancestors, we might have "overstated intergenerational mobility" or misunderstood its underlying mechanisms (Mare, 2011, p. 19). Thanks to the increased availability of data directly observing three (or more) generations, scholars have estimated equation 1 whilst assuming that $G = 2$. Country specific cultural norms, and in particular, whether the grandparents are expected to play a significant part in children lifes, could affect the importance of the grandparents-grandchild dyad. Similarly, the rising number of single headed households and longer life expectancy in good health might have favoured the involvement of grandparents in the development of the grandchildren. In

[6]Accordingly to Chetty et al. (2014), this might be because surnames in Clark (2014) are correlated with race or ethnicity. Therefore, they "partly identifies the degree of convergence in income between racial or ethnic groups rather than across individuals" (Chetty et al., 2014, p. 1575). Similarly, Güell et al. (2014) claim that rare surnames contain information on the socio-economic status.

[7]Before Lindahl et al. (2015), Behrman and Taubman (1985) used an IV approach to estimate the intergenerational educational persistence. After instrumenting the parental educational attainment with that of the offspring's uncle, the coefficient rose from 0.17 (OLS estimate) to 0.21 (IV estimate).

contrast, increased geographic labour mobility in the last decades could also have reduced grandparents' vicinity to grandchildren.

While early studies rejected the hypothesis of a higher-order autocorrelation, more recent contributions, at times, conclude that social mobility follows an AR(2) process. Lindahl et al. (2015), using administrative data from the Swedish city of Malmö, find a significant correlation between great-grandparents' schooling and that of their great-grandchildren. Dribe and Helgertz (2016) reach a similar conclusion whilst using Swedish data as well. Kroeger and Thompson (2016) also report a non-Markovian correlation of education across three generations of US women in the 20th. In constrast, using Finish data, Lucas and Kerr (2013) conclude that grandparental log income has not a significant effect on offspring's log earnings. Overall, the systematic review of the literature conducted by Anderson et al. (2018) show that, in a sample of 69 analyses, one in three reports that grandparents socio-economic characteristics matters, over and beyond that of the parents, in predicting offspring socio-economic outcomes.

The findings of a significant grandparental effect do not however necessarily imply that there is a causal relation between offspring's and grandparents' social status. According to Clark's Markovian model of mobility, these results are just a by-product of a biased estimation of β_{-1}. By failing to model families' underlying social competences, grandparents appear to have a direct influence on their grandchild because their status "contains information on what the likely true underlying status of the parents is" (Clark and Cummins, 2015, p. 64). Further, other reasons beside measurement errors might explain a positive grandparent coefficient. Following Borjas (1995), not accounting for between-ethnic group differences might give rise to a (positive) omitted variable bias (see Solon, 2014).

Two different approaches have been employed in the literature to disentangle the causal effect of grandparents from measurement or omitted variables-driven bias. The first consists in adding information associated (at least to a certain degree) to the non-observable endowments underlying the transmission of inequalities across generations. Commonly, these information are obtained through the addition of further measures of the socio-economic status of the parents (e.g. Warren and Hauser, 1997) or the initially omitted second parent (Braun and Stuhler, 2018; Neidhöfer and Stockhausen, 2018; Sheppard and Monden, 2018). The resulting evidence is mixed, highlighting the possibility of a non-ubiquitous process of social mobility. The second strategy involves to test whether the grandparents effect differs with exogenous variations in grandparents' exposure. As an example, several scholars (e.g. Kroeger and Thompson, 2016; Braun and Stuhler, 2018;

Neidhöfer and Stockhausen, 2018) examine whether the grandparents-to-offspring association remains after interacting the grandparents socio-economic status with a dummy variable controlling for whether the grandparents were still alive at the date of birth of the grandchild. Other studies test instead whether the grandparents were co-resident with the offspring and parents during the childhood of the former (e.g. Ferguson and Ready, 2011; Zeng and Xie, 2014). While Zeng and Xie (2014) find that the "[. . .] causal process of intergenerational influence occur primarily inside households through daily interaction" (Zeng and Xie, 2014, p. 614), other researchers testing such contact-based mechanism of transmission (Ferguson and Ready, 2011; Kroeger and Thompson, 2016; Braun and Stuhler, 2018) are usually not supportive of a direct grandparents effect. Yet, the transmission of inequalities across generations might happen through channels that do not require contact, such as wealth bequests and gifts (Pfeffer and Killewald, 2017) or social capital in the form of neighbourhood and network externalities (Chetty and Hendren, 2016).

3 Data and descriptive evidences

The data used in the empirical analysis are drawn from a Special Eurobarometer on "Fairness, inequality and inter-generational mobility". The sample aims at being representative of the population living in the 28 European Union Member States and amounts to about 1000 observations per country ($28,031$ observations).[8] In addition to gathering detailed information on the socio-economic characteristics of the respondents, the special Eurobarometer investigates the European Citizens' attitudes towards fairness and inequality. Importantly, it is the first EU-wide survey containing retrospective information over the educational attainment, the occupation and the (subjective) social status of the parents and grandfathers (or grandparents). In addition, it provides a measure of the wealth of the neighbourhood where the respondent was living at age 15. The *educational attainment* of the respondents, their fathers, mothers, as well as of their maternal and paternal grandfathers, is measured on an ordinal scale with a variable ranging from 1 to 4 where: (1) completed primary studies; (2) completed secondary studies; (3) completed

[8]With the exceptions of: Poland (997 respondents), Luxembourg (504), Cyprus (502) and Malta (508). Even so the observations have been randomly selected in all the Member States, the response rate varies substantially between-country. There are three countries (Finland, Germany, and Italy) in which the response rate is lower than 25%; in other four countries (the Netherlands, Romania, Slovakia, and Slovenia) the response rate is instead higher than 65%. While this might raise doubts about the sample representativeness, our result for those countries in which low response rates are recorded are in line with other findings in the literature (see Section 4). Additional information about this Eurobarometer survey can be found in Appendix A.

post secondary vocational studies, or higher education to bachelor level or equivalent; and (4) completed upper level of education to master, doctoral degree or equivalent. The *occupational status* of the three generations is measured with a categorical (non-ordered) variable capturing eight different occupation categories; the *perceived social status* is instead approximated with an hypothetical social ladder ranging from 1 to 10, with 1 and 10 representing respectively the the bottom and the top of the social ladder.[9] Finally, the survey also includes an item measuring *the (subjective) wealth status of the neighbourhood* where the respondent was living at age 15. The variable can take five values ranging from very poor (1) to very rich (5) neighbourhood.

To investigate the dynamics of social mobility we focus on the educational attainment. The other socio-economic variables - occupation, perceived social status, and neighbourhood wealth - instead are used to assess whether measurement errors and omitted variables biases drive our findings. Table 1 shows the summary statistics of our main variable of interest. Around 16% of the respondents reached tertiary education. As expected, given the expansion of education witnessed over the last decades, the share of tertiary educated parents is lower. Furthermore, while the share of females and males in the parents' generation with a secondary attainment is similar, males are two times more likely than females to have tertiary education. Finally, paternal and maternal grandfathers present comparable distributions of educational attainment.

Table 1: Educational attainment across generations (%)

	Primary	Secondary	Post-sec.	Tertiary	N
Respondent	16.86 (0.45)	38.69 (0.58)	28.79 (0.55)	15.66 (0.46)	18691
Father	42.61 (0.60)	33.36 (0.56)	15.97 (0.45)	8.05 (0.36)	18474
Mother	47.08 (0.60)	34.65 (0.57)	13.99 (0.43)	4.28 (0.26)	18625
Pat. gf.	64.95 (0.60)	23.60 (0.53)	7.97 (0.34)	3.47 (0.24)	17474
Mat. gf.	65.19 (0.60)	23.45 (0.53)	8.50 (0.36)	2.86 (0.21)	17643

Note: Standard errors in parentheses. Students aged 25 are excluded from the sample. Respondents failing to indicate the educational attainment of at least one parent and at least one grandparents (alongside their own) are excluded from the sample. Survey weights accounting for population size and demographics are used. Pat. gf and Mat. gf. indicate, respectively, the paternal and the maternal grandfathers.

A word of cautious is needed before going further. Retrospective data present some limitations. In fact, while the survey is representative of the offspring's generation (the

[9]The eight occupation categories are: self-employed, managers, other white collars, manual workers, homemaker, unemployed, retired, and students. To test whether the results are robust to a different categorization, we also employ a variable containing 18 occupation categories. Results are available under request.

respondents), it might not be the case for the parental and grandparental generations (Song and Mare, 2015). Further, retrospective surveys might be biased by a recall error, i.e, respondents might not recall properly past events. Even if occupation and education are the socio-economic dimensions least affected by this bias (Pfeffer, 2014), their reliability is likely to decrease when respondents are elicited to go further back in their family trees.[10]

Table 2 provides the Spearman rank-order correlation matrix of the educational attainment variables. The educational attainment of the two parents of the respondents are highly correlated to each others (0.71, $p < 0.05$), hence signaling a high degree of assortative mating among the respondents' parents. The tendency to marry someone with similar income and educational attainment and its impact on intergenerational mobility is well known in the literature (e.g. Mare, 1991, 1998; Chadwick and Solon, 2002). In particular, assortative mating risks leading to further social stratification.

Table 2: Educational attainment across three generations: correlation matrix

	Edu	Edu_{fat}	Edu_{mot}	Edu_{patGF}	Edu_{matGF}
Edu	1				
Edu_{fat}	0.50*	1			
Edu_{mot}	0.46*	0.71*	1		
Edu_{patGF}	0.30*	0.60*	0.57*	1	
Edu_{matGF}	0.30*	0.55*	0.58*	0.76*	1

Note: Spearman rank-order correlation, * $p < 0.05$. Students aged 25 are excluded from the sample. Respondents failing to indicate the educational attainment of at least one parent and at least one grandparents (alongside their own) are excluded from the sample. Survey weights accounting for population size and demographics are used.

The findings of Table 2 are reflected in the four transition matrices displayed in Table 3. The column element P_{ij} of each matrix represents the probability that the offspring will attain the education level i given that his father, mother, paternal grandfather or maternal grandfather attained the education level j. If the transition matrix is an identity matrix, then we can perfectly predict at birth the educational attainment for any child: there is no social mobility. Conversely, given $n = 4$ educational levels, if the column element

[10] In appendix C we discuss the consequences of sampling selection in greater details. In the empirical analysis, we exclude from the sample respondents failing to indicate the educational attainment of at least one parent and at least one grandparents (alongside their own). Respondents aged 25 or below and reporting *student* as main occupation are also excluded from the sample to limit the risk of overestimating downward social mobility because of the response of those who have not yet completed their studies.

$P_{ij} = {}^1\!/_n = 25\%$, then birth circumstances do not predict offspring's schooling: there is perfect social mobility.

Table 3: Transition matrices: educational attainments across three generations

	Educational attainment: respondent				
	Primary % SE	Secondary % SE	Post-sec. % SE	Tertiary % SE	Obs
Educational attainment: father					
Primary	36.9 (0.9)	40.3 (0.9)	16.7 (0.7)	6.1 (0.4)	7,657
Secondary	2.4 (0.3)	55.1 (1.0)	29.3 (0.9)	13.3 (0.7)	6,378
Post-secondary	1.8 (0.3)	13.3 (1.0)	57.8 (1.5)	27.2 (1.5)	3,152
Tertiary	0.3 (0.1)	12.5 (1.5)	32.5 (2.2)	54.7 (2.3)	1,287
Educational attainment: mother					
Primary	33.4 (0.8)	41.4 (0.9)	18.4 (0.7)	6.8 (0.4)	8,714
Secondary	2.6 (0.3)	49.1 (1.0)	32.1 (1.0)	16.2 (0.8)	6,407
Post-secondary	1.2 (0.3)	12.7 (1.1)	54.4 (1.7)	31.6 (1.6)	2,752
Tertiary	0.7 (0.4)	11.2 (1.7)	31.3 (2.9)	56.8 (3.1)	752
Educational attainment: paternal grandfather					
Primary	25.2 (0.7)	41.1 (0.7)	23.0 (0.7)	10.6 (0.5)	11,465
Secondary	2.8 (0.4)	45.0 (1.3)	32.7 (1.2)	19.5 (1.1)	4,051
Post-secondary	2.9 (0.7)	15.5 (1.6)	53.6 (2.3)	28.0 (2.2)	1,470
Tertiary	0.6 (0.4)	12.1 (2.1)	33.2 (3.4)	54.1 (3.5)	488
Educational attainment: maternal grandfather					
Primary	24.8 (0.7)	41.0 (0.7)	23.2 (0.6)	11.0 (0.5)	11,684
Secondary	2.8 (0.4)	44.5 (1.3)	33.6 (1.2)	19.1 (1.1)	4,015
Post-secondary	2.6 (0.6)	15.9 (1.6)	54.2 (2.2)	27.3 (2.1)	1,494
Tertiary	1.4 (0.7)	11.6 (2.2)	35.5 (3.6)	51.5 (3.7)	450

Note: Students aged 25 are excluded from the sample. Respondents failing to indicate the educational attainment of at least one parent and at least one grandparents (alongside their own) are excluded from the sample. Survey weights accounting for population size and demographics are used.

Overall, there are signs of a low degree of both downward and upward mobility, particularly at both extremes of the educational attainment distribution. The two transition matrices using information on the educational attainment of respectively the mothers and fathers exhibit similar patterns. One out of two of the offspring whose mother or father have a tertiary education will reach the same educational level, whilst less than one out of ten will achieve less than post-secondary education. Conversely, around 35% of the offspring whose parents report primary education as highest educational attainment achieve the same. In such family circumstances, only 16-18% of the offspring reach post-secondary education and only 6% of them achieve tertiary education. The picture slightly changes when considering the paternal and maternal grandfathers, particularly with regards to upward mobility. When the paternal or the maternal grandfathers have not completed secondary education, around 23% of the children achieve post-secondary education and around 10% hold tertiary education. Downward mobility is instead in line with what is documented when looking at the educational attainment of the parents of the respondents.

4 Empirical analysis

Empirical models of intergenerational mobility are usually built on a father-to-son paradigm. Yet, there are several potential lineages in each family. This is even truer for multi-generational mobility analysis. In a three-generation framework, 16 lineages are potentially available. Researchers in the field have used a variety of approaches: Kroeger and Thompson (2016) adopt a three-generations matrilineal sample (daughter-to-mother-to-grandmother); Lindahl et al. (2015) use a son-to-father-to-grandfathers framework; Braun and Stuhler (2018) evaluate mixed lineages; and Neidhöfer and Stockhausen (2018) select instead the ancestor with the highest educational attainment. Ultimately, deciding which lineage to investigate depends upon the research question and data availability.

In this paper, we estimate mobility within family and across generations, without a specific lineage focus. To do so, we express the educational attainment as a dichotomous variable. In other words, y_{it} is a variable equal to 1 if the educational attainment of the respondent i ranges in the ISCED (International Standard Classification of Education) 2011 classification from level 4 (*Post-secondary non-tertiary education*) to level 8 (*Doctoral or equivalent level*), and equal to 0 otherwise. A similar approach is adopted for parents and grandfathers: y_{it-1} is an indicator variable equal to one if the mother or the father of the respondent achieved higher education and 0 otherwise; y_{it-2} takes the value one when, instead, at least one of the two grandfathers achieved higher education.[11]

[11]A common strategy in the social mobility literature is to transform the educational attainment into years of schooling. However, we decided against this approach. Besides the potential biases arising from transforming ordered categorical variables into continuous variables, the educational variables in the Eurobarometer survey are based on only five educational attainment categories. Given that the sample contains citizens born between 1918 and 2002 from 28 countries, the same degree does not correspond to

Descriptive statistics for such variables are provided in Appendix A, Table A.1. As in Braun and Stuhler (2018), we begin our analysis by assessing whether long term mobility dynamics can be properly approximated through the iterated regression procedure (Section 4.1). We then document how the outcome of different measurement error models (namely the latent factor model and the instrumental variables method) compare with traditional estimates of intergenerational mobility (Section 4.2). Further, we investigate the possibility that the transmission of social status is unaffected by country-specific characteristics. Finally, we explore the idea that grandparents might have a direct effect on their offspring over and beyond the effect of the parents (Section 4.3).

Equation (1) is estimated with a linear probability model (LPM).[12] Correlation coefficients could have been employed instead in order to account for changes in the variance of the educational attainment across generations. However, to address this concern, country and birth-cohorts dummies are included in all estimates. Finally, in Appendix D, we show that the results obtained by adopting correlation coefficients are in line (albeit slightly lower in terms of magnitude) with those documented by using β coefficients.

4.1 The iterated regression procedure

Table 4 reports the intergenerational regression coefficients β_{-1} and β_{-2}, the iterated version of the latter (i.e. $(\beta_{-1})^2$) for all the 28 EU Member States and the (unweighted) EU-28 average. Note that to estimate $(\beta_{-1})^2$ we use the average regression coefficients between two adjacent generations derived from the regressions of (i) offspring's education on parents' education (β_{-1}^{G1-G2}) and (ii) parents' education on grandfathers' education (β_{-1}^{G2-G3}). The estimates of β_{-2} are instead the result of regressing respondents' education upon grandfathers' education.

A number of findings emerge from Table 4. First, Europe displays high levels of intergenerational educational persistence, with the coefficients β_{-1}^{G1-G2} and β_{-1}^{G2-G3} being

the same years of schooling across all respondents, their parents and grandparents.

[12]We prefer a LPM to a probit or logistic models because our interest lies in comparing coefficients arising from different models, specifications and countries. Non-linear specifications assume that the unobserved heterogeneity is equal among the different models, specifications and countries (Long and Freese, 2006), an assumption which is unlikely to hold in our case. We do acknowledge that non-linear models might provide a better fit to the conditional expectation function (CEF) than a linear model. However, such an issue is rather trivial when it comes to marginal effects (Angrist and Pischke, 2008, p. 107). Furthermore, our specifications include dichotomous (or categorical) variables also on the right hand side of the equation. The more the model is saturated, the more the *CEF* tends to be linear. In the Appendix B.1 we show that the difference between the LPM and logistic average marginal effects is negligible; since no predicted probabilities fall outside the unit interval, the LPM is expected to be (approximately) unbiased and consistent (Horrace and Oaxaca, 2006).

Table 4: Regression coefficients over 3 generations

	Observed			Iterated	
	β_{-1}^{G1-G2}	β_{-1}^{G2-G3}	β_{-2}	$(\beta_{-1})^2$	N
Austria	0.539 (0.034)	0.537 (0.028)	0.312 (0.030)	0.289 (0.023)	819
Belgium	0.432 (0.037)	0.584 (0.038)	0.350 (0.039)	0.258 (0.028)	814
Bulgaria	0.409 (0.040)	0.632 (0.037)	0.361 (0.058)	0.271 (0.029)	712
Croatia	0.446 (0.042)	0.474 (0.063)	0.377 (0.060)	0.211 (0.034)	860
Cyprus	0.377 (0.069)	0.533 (0.139)	0.463 (0.148)	0.207 (0.070)	385
Czech Republic	0.446 (0.049)	0.471 (0.065)	0.174 (0.069)	0.210 (0.036)	768
Denmark	0.191 (0.028)	0.407 (0.030)	0.140 (0.025)	0.089 (0.012)	848
Estonia	0.196 (0.049)	0.322 (0.048)	0.123 (0.049)	0.067 (0.017)	429
Finland	0.337 (0.042)	0.447 (0.059)	0.217 (0.058)	0.154 (0.028)	580
France	0.434 (0.043)	0.477 (0.053)	0.297 (0.064)	0.207 (0.032)	519
Germany	0.573 (0.027)	0.642 (0.026)	0.442 (0.031)	0.370 (0.024)	1011
Greece	0.481 (0.045)	0.640 (0.064)	0.467 (0.079)	0.314 (0.048)	834
Hungary	0.469 (0.046)	0.677 (0.050)	0.430 (0.057)	0.329 (0.040)	803
Ireland	0.387 (0.038)	0.553 (0.060)	0.311 (0.050)	0.221 (0.036)	662
Italy	0.610 (0.036)	0.580 (0.056)	0.345 (0.058)	0.354 (0.042)	749
Latvia	0.343 (0.050)	0.228 (0.059)	0.186 (0.058)	0.082 (0.024)	422
Lithuania	0.231 (0.043)	0.388 (0.050)	0.207 (0.042)	0.096 (0.022)	588
Luxembourg	0.383 (0.043)	0.706 (0.044)	0.358 (0.045)	0.297 (0.035)	316
Malta	0.344 (0.086)	0.339 (0.172)	0.262 (0.123)	0.117 (0.061)	252
Netherlands	0.247 (0.029)	0.490 (0.035)	0.115 (0.029)	0.136 (0.016)	620
Poland	0.452 (0.056)	0.610 (0.064)	0.430 (0.071)	0.282 (0.047)	632
Portugal	0.598 (0.059)	0.847 (0.063)	0.438 (0.108)	0.522 (0.065)	592
Romania	0.529 (0.042)	0.550 (0.062)	0.514 (0.058)	0.291 (0.041)	729
Slovakia	0.528 (0.048)	0.572 (0.076)	0.369 (0.074)	0.302 (0.051)	839
Slovenia	0.384 (0.049)	0.424 (0.064)	0.270 (0.075)	0.163 (0.031)	671
Spain	0.423 (0.050)	0.524 (0.065)	0.343 (0.062)	0.224 (0.043)	787
Sweden	0.181 (0.029)	0.403 (0.035)	0.154 (0.029)	0.085 (0.013)	786
United Kingdom	0.425 (0.031)	0.560 (0.042)	0.339 (0.038)	0.242 (0.023)	664
EU-28	0.502 (0.006)	0.625 (0.007)	0.414 (0.008)	0.317 (0.006)	18691

Note: Bootstrapped standard errors in parenthesis. Students aged 25 or below as well as respondents failing to indicate the educational attainment of at least one parent and at least one grandparents (alongside their own) are excluded from the sample. Age-cohorts dummies are included but not reported.

both higher than 0.5. Offspring whose parents achieved higher education are 50 percentage points more likely to achieve the same educational attainment than offspring whose parents did not. There are however large between-countries differences. With regards to the parent-to-offspring transmission, six countries (Austria, Germany, Italy, Portugal, Romania, and Slovakia) report an intergenerational regression coefficient higher than 0.5. In addition, 16 countries also display a grandfather-to-parent coefficient above 0.5 while for seven countries (including Germany, Greece, and Hungary) the estimated coefficient is higher than 0.6. Conversely, Denmark, Estonia, Lithuania, Netherlands, and Sweden exhibit an intergenerational coefficient $\beta_{-1}^{G1-G2} < 0.3$. Overall, the parents-to-child persistence is the lowest among Northern and Baltic countries.

Second, the evolution over time of the intergenerational persistence in higer education is not homogeneous. There are 16 countries (e.g. Belgium, Italy, Germany, and the UK) for which β_{-1}^{G1-G2} is significantly smaller than β_{-1}^{G2-G3}. Social status persistence seems thus to have decreased over time. The opposite is observed in Latvia where the regression to the mean of educational attainment has indeed slowed down. In several countries (11) social status persistence between parents and offspring is not statistically different from the one observed between grandfathers and parents. Importantly, also for β_{-1}^{G2-G3} Northern and Baltic countries exhibit some of the lowest coefficients. Findings in other macro-regions scatter more widely.

Third, the comparison of $(\beta_{-1})^2$ with β_{-2} suggests that, in the European Union, the iterated procedure leads to overestimate social mobility: β_{-2} is, on average, 1.3 times larger than what the iterated approach would predict. For 17 of the 28 countries in our sample, β_{-2} is significantly larger than $(\beta_{-1})^2$. In six countries (Cyprus, Malta, Sweden, and the three Baltic states) the association between the education of grandfathers and their grandchildren is twice as strong as what would be implied by iterating a first order autoregressive structure. In other terms, educational persistence decays almost twice as slowly as geometrically. Results would have been even more staggering if we would have based the iteration only on the correlation between offspring and parents (β_{-1}^{G1-G2}).[13] Indeed in only four countries (Czech Republic, Italy, Netherlands and Portugal) the observed correlation is smaller, albeit not at a statistical significant level, than the iterated coefficient. From these findings no clear macro-regional patterns on excess persistence can be observed.

Overall, the intergenerational coefficients shown in Table 4 are similar to most of the evidences documented in the literature. In the UK, Dearden et al. (1997) find that the father-to-son and the father-to-daughter regression coefficients are equal to 0.42: we document a similar outcome. In Germany, our estimates are in line with Braun and

[13] Such a two-generation analysis would have led to the underestimation of the persistence of socio-economic outcome in 20 countries. In Sweden, regression to the mean would have resulted to be 4 times slower than what the iterated coefficient would have implied. Results are available under request.

Stuhler (2018), who report an average parent-to-child estimate of 0.5.[14] We do however find a stronger education persistence in the grandparent-to-parent framework. In France, our result diverge from those by Ben-Halima et al. (2014) whose estimated parent-to-child coefficient is equal to 0.25. For Sweden, our parent-to-child estimates are instead in line with those shown by Holmlund et al. (2011) and Björklund et al. (2006) while they are lower than those reported by Lindahl et al. (2015), which however document a similar grandparent-to-parent coefficient. Our findings also corroborate those by Hertz et al. (2007) for Czech Republic (where they document intergenerational educational mobility estimates of ≈ 0.37), Finland (≈ 0.33), Hungary (≈ 0.49), Ireland (≈ 0.46), Italy (≈ 0.54) and Poland (≈ 0.43). They instead diverge for Netherlands (≈ 0.36) and Sweden (≈ 0.40).

Similarly, our evidences of excess persistence compare favourably with the existing literature relying on direct observations of family lineages across three or more generations. Lindahl et al. (2015) and Braun and Stuhler (2018) document that the iterated regression procedure overestimates educational mobility across three generations in, respectively, Sweden and Germany. Neidhöfer and Stockhausen (2018) corroborate Braun and Stuhler (2018) findings for Germany and show that there exist excess persistence also in the UK. Outside of Europe, the available evidence suggests that the iterated regression procedure overestimates schooling mobility in Chile (Celhay and Gallegos, 2015) and in the US (Kroeger and Thompson, 2016; Neidhöfer and Stockhausen, 2018).

Importantly, the findings of Table 4 are in line with those documented by using correlation coefficients r instead (Appendix D, Table D.1): the iterated procedure overestimates social mobility. In 24 countries $r_{-2} > (r_{-1})^2$, and in 17 of them the difference is statistically significant. Only four countries (Czech Republic, Italy, Netherlands and Portugal) display $r_{-2} < (r_{-1})^2$, albeit the two estimatd coefficients are not statistically different. Furthermore, similarly to the analysis based on regression coefficients, the estimated r coefficients display a high degree of cross-country variability.

4.2 Measurement errors models

The evidence collected in section 4.1 show that, if only one proxy of social status is used, a first order autoregressive process combined with the assumption of a geometric decay can severely underestimate the long run persistence of family-based inequalities. This provides the rationale for investigating Clark's account of multigenerational mobility. Results are reported in Table 5. The first two columns display β_{-1} and β_{-2}, whilst

[14] Our estimates diverge from earlier father-to-son coefficients reported by Couch and Dunn (1997) for Germany (0.24).

columns 3 and 4 report the heritability ($\lambda = {}^{\beta_{-2}}/_{\beta_{-1}}$) and transferability ($\rho = ({}^{\beta_{-1}^2}/_{\beta_{-2}})^{1/2}$) coefficients. Finally, Column 5 reports the findings of the instrumental variable approach (i.e. instrumenting y_{-1} through y_{-2}).[15] Importantly, the consistency of the estimates of the measurement error models (i.e. columns 3 to 5) rest upon the assumption that intergenerational mobility follows a Markovian process. If the model has a longer memory than Clark (2014) assumes, the exclusion restriction needed to correctly identify β_{IV-1} is not valid. Similarly, if earlier ancestors have a direct effect on their offspring, the latent factor model by Braun and Stuhler (2018) would be biased due to unaccounted off-diagonal elements in the variance-covariance matrix.

The figures reported in Table 5 have several implications. First, as suggested by Clark, estimates based on noisy proxies of social status lead to an overestimation of mobility. The latent factor λ is, on average, about 30 per cent larger than the estimated parent-to-offspring association in social status (β_{-1}). Looking across countries, β_{-1} is significantly smaller than λ in 20 of the 28 EU Member States. Importantly, in the same four countries (Czech Republic, Italy, Netherlands and Portugal) in which is not possible to reject a geometric (or slower) decay of social status persistence, $\lambda < \beta_{-1}$, albeit in none of them the difference is statistically significant. When the IV estimation is employed to tackle the measurement errors bias, β_{IV-1} overestimates mobility by about 20 per cent, but the instrumented estimates are significantly larger than the mean parent-to-child observed transmission in *only* nine countries.

Second, not all European countries show a heritability coefficient as high as Clark suggests ($0.7 - 0.8$). The EU-28 (un-weighted) average is indeed equal to 0.73, but several countries report estimates 20 or more decimal points below those shown in the analysis of rare surnames by Clark (2014). In two countries (Czech Republic and the Netherlands) the estimated value of λ is below 0.4. Similarly, while the IV estimation report an EU-28 mean of 0.66, five countries document values below 0.4. The transferability coefficient ρ shows instead an average value of 0.88, suggesting that most of the latent factor that in Clark's view explains the intergenerational association in social status is transmitted from one generation to the next. [16]

Third, Clark's hypothesis that "social mobility is governed by a simple underlying

[15] As for Table 4 we test the robustness of such findings estimating the latent factor model using correlation coefficients. Results are available in Appendix D, Table D.2.

[16] As shown in Section 2.2, when $\rho = 1$, then the latent factor models, then $\lambda^g = (\hat{\beta}_{-1})^g$. Indeed, in the four countries in which $(\beta_{-1})^2 = \beta_{-2}$, we also observe that $\beta_{-1} = \lambda$. The relationship between λ and β_{-1} on one hand and the value of ρ on the other can therefore be seen as a proxy for the speed of the decay of the intergenerational association. When it is equal or faster than geometrical, ρ is equal to or larger than 1 and $\beta_{-1} \geq \lambda$.

Table 5: Measurement errors models

	β_{-1}	β_{-2}	λ	ρ	β_{IV-1}	N
Austria	0.538 (0.022)	0.312 (0.03)	0.579 (0.040)	0.963 (0.028)	0.580 (0.046)	819
Belgium	0.508 (0.028)	0.350 (0.039)	0.690 (0.068)	0.858 (0.050)	0.600 (0.067)	814
Bulgaria	0.521 (0.027)	0.361 (0.058)	0.693 (0.098)	0.867 (0.066)	0.571 (0.090)	712
Croatia	0.460 (0.038)	0.377 (0.060)	0.819 (0.125)	0.749 (0.070)	0.795 (0.139)	860
Cyprus	0.455 (0.073)	0.463 (0.148)	1.017 (0.369)	0.669 (0.556)	0.869 (0.428)	385
Czech Rep.	0.458 (0.039)	0.174 (0.069)	0.379 (0.141)	1.099 (0.559)	0.369 (0.139)	768
Denmark	0.299 (0.021)	0.140 (0.025)	0.469 (0.080)	0.798 (0.073)	0.344 (0.066)	848
Estonia	0.259 (0.033)	0.123 (0.049)	0.473 (0.177)	0.740 (0.205)	0.381 (0.155)	429
Finland	0.392 (0.036)	0.217 (0.058)	0.555 (0.152)	0.840 (0.119)	0.486 (0.144)	580
France	0.455 (0.036)	0.297 (0.064)	0.653 (0.127)	0.835 (0.094)	0.623 (0.131)	519
Germany	0.608 (0.020)	0.442 (0.031)	0.728 (0.045)	0.914 (0.031)	0.689 (0.051)	1011
Greece	0.560 (0.043)	0.467 (0.079)	0.834 (0.120)	0.820 (0.071)	0.731 (0.120)	834
Hungary	0.573 (0.035)	0.430 (0.057)	0.751 (0.087)	0.874 (0.056)	0.635 (0.082)	803
Ireland	0.470 (0.039)	0.311 (0.050)	0.663 (0.097)	0.842 (0.074)	0.564 (0.081)	662
Italy	0.595 (0.036)	0.345 (0.058)	0.581 (0.080)	1.012 (0.067)	0.596 (0.077)	749
Latvia	0.286 (0.041)	0.186 (0.058)	0.651 (0.200)	0.662 (0.130)	0.816 (0.307)	422
Lithuania	0.310 (0.035)	0.207 (0.042)	0.668 (0.146)	0.681 (0.103)	0.533 (0.125)	588
Luxembourg	0.545 (0.033)	0.358 (0.045)	0.657 (0.071)	0.910 (0.061)	0.507 (0.058)	316
Malta	0.342 (0.092)	0.262 (0.123)	0.766 (0.506)	0.668 (0.339)	0.771 (2.760)	252
Netherlands	0.369 (0.021)	0.115 (0.029)	0.311 (0.070)	1.089 (0.133)	0.234 (0.057)	620
Poland	0.531 (0.045)	0.430 (0.071)	0.809 (0.135)	0.810 (0.084)	0.704 (0.153)	632
Portugal	0.723 (0.046)	0.438 (0.108)	0.607 (0.136)	1.091 (0.138)	0.518 (0.131)	592
Romania	0.540 (0.037)	0.514 (0.058)	0.953 (0.112)	0.753 (0.060)	0.934 (0.143)	729
Slovakia	0.550 (0.046)	0.369 (0.074)	0.672 (0.109)	0.905 (0.078)	0.646 (0.108)	839
Slovenia	0.404 (0.039)	0.270 (0.075)	0.669 (0.181)	0.777 (0.156)	0.638 (0.196)	671
Spain	0.474 (0.046)	0.343 (0.062)	0.725 (0.118)	0.808 (0.081)	0.655 (0.112)	787
Sweden	0.292 (0.023)	0.154 (0.029)	0.529 (0.099)	0.743 (0.082)	0.383 (0.074)	786
UK	0.492 (0.024)	0.339 (0.038)	0.689 (0.076)	0.845 (0.054)	0.606 (0.079)	664
EU-28	0.563 (0.005)	0.414 (0.008)	0.735 (0.014)	0.876 (0.009)	0.663 (0.014)	18691

Note: Bootstrapped standard errors in parenthesis. Students aged 25 or below as well as respondents failing to indicate the educational attainment of at least one parent and at least one grandparents (alongside their own) are excluded from the sample. Age-cohorts dummies are included but not reported.

law, independent of social structure and government policy" (Clark, 2014, p. 212) is rejected by our data. Theoretically, if neither social structure nor government policies would affect social mobility, regression coefficients partialled out for time-invariant country effects should not be substantially different from the raw correlation coefficients. The figures reported in Table 6 show that it is not the case in the EU: all the coefficients are significantly different from each other's. In particular, both the figures for the latent factor λ and the IV estimates result are significantly lower after the inclusion of country-specific effect. This result is not driven by changes in ρ which, after accounting for time-invariant country effects, is equal to 0.865 (0.013), a value not significantly different to that shown in Table 5.

Table 6: The role of institutions

	Observed			Iterated	
	β_{-1}^{G1-G2}	β_{-1}^{G2-G3}	β_{-2}	$(\beta_{-1})^2$	N
EU-28	0.502 (0.006)	0.625 (0.007)	0.414 (0.008)	0.317 (0.006)	18691
EU-28 (FE)	0.395 (0.008)	0.519 (0.009)	0.279 (0.009)	0.260 (0.006)	18691
	β_{-1}	β_{-2}	λ	β_{IV-1}	N
EU-28	0.563 (0.005)	0.414 (0.008)	0.735 (0.014)	0.663 (0.014)	18691
EU-28 (FE)	0.457 (0.006)	0.279 (0.009)	0.611 (0.017)	0.538 (0.016)	18691

Note: Bootstrapped standard errors in parenthesis. Students aged 25 or below as well as respondents failing to indicate the educational attainment of at least one parent and at least one grandparents (alongside their own) are excluded from the sample. (FE) represented the inclusion of country-specific intercepts. Age-cohorts dummies are included but not reported.

To the best of our knowledge, this is the first study applying measurement errors models to intergenerational mobility in such a large sample of countries. Other studies investigating it in a single-country context (Lindahl et al., 2015; Braun and Stuhler, 2018) or for a limited number of countries (Neidhöfer and Stockhausen, 2018) provide estimates in line with our findings. Both Braun and Stuhler (2018) and Neidhöfer and Stockhausen (2018) find that $\lambda > r_{-1}$ in Germany. Lindahl et al. (2015) and Neidhöfer and Stockhausen (2018) document the same pattern in Sweden, the UK and the US. Importantly, our estimated value of λ for Germany ($\lambda \approx 0.7$) is similar to those reported by Braun and Stuhler (2018) and Neidhöfer and Stockhausen (2018).[17] Further, our figures for Sweden and the UK are comparable to those reported by, respectively, Braun and Stuhler (2018), which estimates are based on the study by Lindahl et al. (2015), and Neidhöfer and Stockhausen (2018).[18]

Overall, our findings are only partially supportive of Clark's hypotheses. We confirm that, in a Markovian model of intergenerational mobility, noisy proxies of social status often lead to underestimate family-based inequalities. However, we reject the hypothesis

[17] Braun and Stuhler (2018) report an average $\lambda \approx 0.6$. Among their samples, the one for which estimate are the closest to ours, is the LVS-2 sample ($\lambda = 0.699$). Here offspring are born (on average) in 1959, which is also the closest value, among their samples, to our mean birth year for Germany (1964). Neidhöfer and Stockhausen (2018) estimate $\lambda \approx 0.7$.

[18] The estimated values of λ are in the cited studies, respectively, equal to 0.61 and 0.58 for Sweden and the UK.

that mobility across generations is governed by a universal law. Clark's law paints a too pessimistic picture of social mobility in Europe. In some countries children have the possibility to move beyond their social origins more easily than what Clark suggests. Furthermore, we observe substantial cross-country variations in social status persistence.

4.3 The grandparents effect model

As explained in Section 2.3, the fact that the socio-economic status transmission process is more persistent than what extrapolating intergenerational estimates suggest might also be explained by a direct grandparental effect. To test whether social status mobility follows an AR(2) data-generating process, we estimate the following model:

$$y_{i,t} = \beta_0 + \beta_{-1} y_{i,t-1} + \beta_{-2} y_{i,t-2} + \gamma Z + \delta_t + \epsilon_{i,t} \tag{4}$$

where $y_{i,t}$, $y_{i,t-1}$, and $y_{i,t-2}$ are respectively the respondent, the parents and the grandfather higher education dummies, Z is a vector of control variables and α_c and δ_t are, respectively, country and age cohorts fixed effects. Results are presented in Table 7.

In Column 1, Z includes information on gender and household composition. The results suggest that offsprings with at least one higher educated grandfather are, *ceteris paribus*, 9 percentage points more likely to reach the same education attainment than counterparts whose both grandfathers have a lower educational level. In columns 2 to 4 we try to account for the fact that we rely on a partial measure of the socio-economic status of respondents, parents and grandfathers. Including the parent's occupation and its perceived position on the social ladder can reduce the attenuation bias as long as such measures are associated, at least to a certain degree, to the non-observable endowments that explain the transmission of inequalities across generations. Similarly, spatial effects might also be important. As shown in Benabou (1994, 1996) and Durlauf (1994), local spillover effects could "interact with income-based stratification of neighbourhoods to transmit parental economic status from generation to generation" (Durlauf, 1994, p. 836). Individuals might sort accordingly to their educational levels, income and preferences. Network effects then improve both the educational choices and the professional opportunities of the offspring living in *rich* areas. This, in turn, affects mobility across generations.

To account for these dynamics, in Column 2 the vector Z additionally includes the parent's occupation and position on the social ladder as well as two variables to control for neighbourhood and spatial effects (the wealth of the neighbourhood in which the offspring

Table 7: The grandparents effect model: test procedures

	(1) Aggregate	(2) Aggregate	(3) Both	(4) Both
Education (t-1):				
HE_P	0.422***	0.384***		
	(0.0138)	(0.0150)		
HE_F			0.346***	0.314***
			(0.0159)	(0.0166)
HE_M			0.177***	0.167***
			(0.0167)	(0.0169)
Education (t-2):				
HE_{GP}	0.0925***	0.0731***	0.0534***	0.0380**
	(0.0155)	(0.0158)	(0.0166)	(0.0167)
Constant	0.159***	0.102*	0.195***	0.120**
	(0.0327)	(0.0599)	(0.0331)	(0.0602)
Observations	18691	17849	18408	17607
Adjusted R^2	0.301	0.310	0.301	0.310
Occupation (t-1)	No	Yes	No	Yes
Social status (t-1)	No	Yes	No	Yes
Spatial ctrl. (t-1)	No	Yes	No	Yes

Note: Heteroskedastic robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Country fixed effects and age cohorts dummies are included but not reported. Survey weights accounting for population size and demographics are used. Students aged 25 or below as well as respondents failing to indicate the educational attainment of at least one parent and at least one grandparents (alongside their own) are excluded from the sample.

lived when the respondent was 15 and the subjective level of urbanisation).[19] The figures displayed in Column 2 confirm the findings of a grandfathers effect over and beyond that of the parents ($p < 0.01$). Both the parents and the grandfathers coefficients are positive and statistically significant, albeit the parents' effect magnitude is significantly lower than in Column 1, suggesting that the addition of parental covariates as well as spatial controls, helps explaining the social status transmission process.

Column 3 replicates Column 1 but replaces $y_{i,t-1}$ with both parents higher education dummies (i.e. $y_{i,t-1}^{father}$ and $y_{i,t-1}^{mother}$). This approach is grounded on the intuition that, in a one-parent-setting, the initially omitted parent socio-economic outcome might be correlated not only with the offspring's outcome, but also with the unobserved endow-

[19]Occupation refers to the occupation of the principal contributor to the household income when the respondent was 15 years old. Social status instead concerns both parents.

ments of the other parent. If mating would be perfectly assortative, this strategy would have no impact: considering the highest education achievement reached by the two parents, as in columns 1 and 2, or just by one of the two parents would lead to estimate the same intergenerational coefficient. When this is not the case the above mentioned measures overestimate social mobility. The previous conclusions are unchanged: even after accounting for both parents' educational achievement we cannot reject the existence of an AR(2) transmission mechanism. Having at least one grandfather with a higher educational level increases the chances of reaching tertiary education by 5 percentage points ($p < 0.01$).Finally, in Column 4, we test whether there exists a grandfather effect after controlling for both parents' educational attainment as well as for the other socio-economic proxies, namely the parents' occupation and position on the social ladder, as well as the neighbourhood wealth when the respondents was 15. The grandfathers' coefficient remains positive and statistically significant, albeit with a lower level of statistical significance ($p < 0.05$).

Table 8 extends the analysis by providing country-specific estimates of the estimated reported in column 4 of Table 7. A non-Markovian process of intergenerational mobility is not rejected for only six countries: Croatia, Denmark, Romania, Sweden, United Kingdom, and Portugal.[20] In other EU-28 Member States, the grandfathers coefficient is not significantly different from zero. No clear macro-regional patterns emerge. Interestingly, Sweden and Denmark, which display some of the lowest β_1 values in Tables 4 and 5, exhibit a positive and significant β_2 coefficient. Comparing our results with the existing literature, we observe that Braun and Stuhler (2018) and Neidhöfer and Stockhausen (2018) also reject the possibility of a direct grandparental effect in Germany after controlling for both parents education. Our findings for the United Kingdom are supportive of Chan and Boliver (2013) but do not corroborate those reported in Neidhöfer and Stockhausen (2018). Finally, as Lindahl et al. (2014) we find that grandparents' educational attainment is positively correlated with the offspring's education in Sweden. Overall, these findings corroborate the view of Mare (2011). The data-generating process behind the intergenerational transmission of social status varies across space. While in most EU countries there is no evidence supporting a non-Markovian process of mobility, in few others it is not possible to reject such an hypothesis. Further, the length of the memory of the intergenerational transmission process does not appear to be linked with the magnitude of the process itself.

[20] In Portugal, $y_{i,t-2}$ is negative. This finding does not imply that having highly educated grandfathers lowers the offspring's probability of reaching higher education. Rather, it reflects a more-than-geometric decay of multigenerational associations.

Table 8: The grandparents effect: both parents, parental and spatial covariates

Country	Father	Mother	Grandfathers	N
Austria	0.422 (0.044)***	0.175 (0.040)***	-0.032 (0.035)	763
Belgium	0.298 (0.055)***	0.185 (0.054)***	0.019 (0.054)	800
Bulgaria	0.312 (0.063)***	0.063 (0.064)	0.020 (0.072)	671
Croatia	0.298 (0.062)***	0.067 (0.072)	0.139 (0.068)**	826
Cyprus	0.102 (0.087)	0.013 (0.092)	0.202 (0.131)	376
Czech Republic	0.352 (0.065)***	0.235 (0.070)***	-0.053 (0.065)	735
Denmark	0.021 (0.035)	0.060 (0.032)*	0.058 (0.031)*	821
Estonia	-0.003 (0.055)	0.125 (0.063)**	0.052 (0.051)	376
Finland	0.187 (0.066)***	0.220 (0.065)***	-0.037 (0.082)	545
France	0.272 (0.059)***	0.192 (0.060)***	0.051 (0.067)	486
Germany	0.468 (0.041)***	0.102 (0.047)**	0.037 (0.044)	947
Greece	0.305 (0.074)***	0.173 (0.085)**	0.121 (0.081)	820
Hungary	0.150 (0.079)*	0.213 (0.077)***	0.020 (0.077)	782
Ireland	0.162 (0.055)***	0.145 (0.054)***	-0.008 (0.064)	637
Italy	0.472 (0.058)***	0.217 (0.065)***	-0.054 (0.058)	705
Latvia	0.136 (0.073)*	0.210 (0.075)***	0.042 (0.079)	338
Lithuania	0.115 (0.056)**	0.104 (0.059)*	0.074 (0.058)	551
Luxembourg	0.152 (0.092)*	0.142 (0.087)	0.030 (0.066)	283
Malta	0.088 (0.096)	0.077 (0.092)	-0.010 (0.130)	218
Netherlands	0.139 (0.043)***	0.097 (0.038)**	-0.040 (0.035)	596
Poland	0.121 (0.096)	0.347 (0.080)***	0.025 (0.099)	576
Portugal	0.344 (0.102)***	0.213 (0.100)**	-0.307 (0.116)**	543
Romania	0.274 (0.064)***	0.299 (0.068)***	0.133 (0.079)*	695
Slovakia	0.242 (0.078)***	0.339 (0.082)***	0.064 (0.076)	765
Slovenia	0.180 (0.077)**	0.127 (0.074)*	0.039 (0.086)	631
Spain	0.304 (0.070)***	0.124 (0.071)*	0.076 (0.070)	761
Sweden	0.119 (0.050)**	0.100 (0.047)**	0.082 (0.047)*	758
United Kingdom	0.226 (0.050)***	0.186 (0.048)***	0.119 (0.046)**	602

Note: Heteroskedastic robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Age cohorts dummies are included but not reported. Survey weights accounting for demographics are used. Students aged 25 are excluded from the sample. Respondents failing to indicate the educational attainment of at least one parent and at least one grandparents (alongside their own) are excluded from the sample. Control variables included are gender, household composition, parent's occupation, parent's socials status, neighbourhood wealth when the offspring was 15 and subjective urbanisation.

5 Conclusion

The recent literature shows that estimating multigenerational persistence by extrapolating parent-to-child association in socio-economic status often leads to an underestimation of the transmission of socio-economic inequalities (Clark and Cummins, 2014; Clark, 2014; Braun and Stuhler, 2018; Neidhöfer and Stockhausen, 2018). This could be driven by a data-generating process having a longer memory (i.e. a direct grandparental effect) or the attenuation bias generated by measurement errors.

Using a novel Eurobarometer survey containing information on the socio-economic status of the respondents, parents and grandfathers, we show that the iterated regression procedure overestimates social mobility in the EU, albeit this is not true for all the 28 countries. This finding provides the rationale to investigate Clark's assumption of an attenuation bias due to measurement errors. Once measurement errors are accounted for, we find that naive parent-to-child estimates of social mobility do indeed overestimate social mobility at the aggregated EU level as well as in most of the EU countries. Yet, the magnitude of this overestimation varies across countries. Therefore, we cannot corroborate Clark's findings of an "universal law of mobility" independent of cultural norms, social and political institutions (Clark, 2014). We then test whether the overestimation of social mobility though the extrapolation of the parent-to-child association could be due to the presence of a grandparent effect over and beyond the parents' influence (i.e. that intergenerational mobility follows a non-Markovian process). The richness of the dataset allows us to account for the socio-economic status of both parents and to simultaneously control for both their educational and occupational status as well as for the quality of the neighbourhood during the childhood of the respondents. After having partialled out the influence of all these parental-level factors, we still cannot reject the possibility of a direct grandparent effect at the EU-aggregated level as well as in a few EU countries.

This study offers a picture of multigenerational social mobility in 28 EU countries. Europe is not a continent of equal opportunities. Disparities in education are still largely transmitted from one generation to another. Our estimates suggest that long term dynamics of social mobility in Europe are less optimistic than what the traditional literature based on information of two generations would suggest. In addition, the empirical results do not support the hypothesis that mobility is independent of social and cultural institutions. Future research should then focus on providing further causal evidence on the transmission channels behind multigenerational associations.

In companion papers, we describe in more details gender and lineage patterns in multigenerational social mobility as well as whether and how mobility varies across geographical areas and over time. We also link actual and perceived mobility to preferences for redistribution. This is important if we want to better understand the dynamics of inequalities in Europe and how they translate into policy related preferences.

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A Data

The analysis is conducted using the special Eurobarometer 471. Interviews are conducted by computer-assisted personal interviewing (CAPI). The sampling points are drawn after stratification by NUTS II regions (or equivalent) and by degree of urbanisation. They thus represent the whole territory of the country/territory surveyed and have been selected proportionally to the distribution of the population in terms of metropolitan, urban and rural areas. The standard random route procedure has been used to select addresses. This means that in each of the selected sampling points, one address is drawn at random. Only one interview per household has been conducted. The weights, when used, correct for population and demographics using the following target variables: region, size of locality, age, sex, size of household, marital status and occupation of the respondent.

Table A.1 provides summary statistics for the higher education dummy variables used in the empirical analysis.

Table A.1: Summary statistics: higher education dummy

	Obs.	Mean	SD	Min.	Max.
Education (t):					
Respondent	18691	0.44	0.50	0	1
Education (t-1):					
Father	18474	0.24	0.43	0	1
Mother	18625	0.18	0.39	0	1
Parents	18691	0.28	0.45	0	1
Education (t-2):					
Pat. gf.	17474	0.11	0.32	0	1
Mat. gf.	17643	0.11	0.32	0	1
Grandfathers	18691	0.15	0.36	0	1

Note: Students aged 25 or below as well as respondents failing to indicate the educational attainment of at least one parent and at least one grandparents (alongside their own) are excluded from the sample. Survey weights accounting for population size and demographics are used.

B Robustness tests

B.1 Logit-LPM comparison

Table B.1: Logit and LPM: comparison

	(1) Logistic	(2) Logistic	(3) LPM	(4) LPM
Education (t-1):				
HE_P	0.463***		0.456***	
	(0.0115)		(0.0121)	
Education (t-2):				
HE_{GP}		0.346***		0.325***
		(0.0163)		(0.0147)
Constant			0.188***	0.293***
			(0.298)	(0.203)
Observations	18691	18691	18691	18691
Adjusted R^2			0.298	0.301

Note: Standard errors in parentheses (specifications 1-2). Heteroskedastic robust standard errors in parentheses (specifications 3-4). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Country fixed effects and age cohorts dummies are included but not reported. Students aged 25 are excluded from the sample. Respondents failing to indicate the educational attainment of at least one parent and at least one grandparents (alongside their own) are excluded from the sample. Specifications 1-2 report average marginal effect. Survey weights accounting for population size and demographics are used.

C Sampling Selection

The item regarding the educational attainment of the parents and the grandparents present a substantial number of non-responses. There are 1727 non-responses regarding the father's educational level, 1346 regarding the mother's educational attainment, and 9549 and 9375 regarding, respectively, the paternal grandfather and maternal grandfather educational level. On average, there is no difference in the non-response rate between paternal and maternal grandfathers; when the respondents failed in replying to the item regarding the paternal grandfather, the same applied for the maternal grandfathers. Indeed, in 17343 of the cases respondents replied to both items. Further, the rate of response show a high degree of variation across countries. The EU-28 weighted average document that 39.32% of the respondents replied *don't know* to the grandfathers' education item. In Greece and Croatia less than 17% of the respondents did not reply to the grandfathers' educational attainment item; in France, Finland, Netherlands, Portugal, Malta and the UK the figure is higher than 50%. In Latvia and Estonia it is higher than 65%.

Therefore, we test whether our results are robust by regressing the parents education on the offspring education across four different samples - Table C.1. In specification (1), all the respondents are considering, including also those who did not reply to the grandfathers' educational attainment items. Specification (2), (3) and (4) include, only, the respondents who failed in replying, respectively, to both grandfathers' educational attainment items; to the one regarding the paternal grandfather; and to the one regarding the maternal grandfather. Overall, findings across different samples are highly comparable, albeit estimates in specifications (2) to (4) are slightly downward biased.

Table C.1: Higher education: missing grandparents' education item

	(1) Full sample	(2) Missing Both	(3) Missing PGF	(4) Missing MGF
Education:				
$\mathrm{HE_P}$	0.450***	0.401***	0.402***	0.410***
	(0.0106)	(0.0227)	(0.0204)	(0.0205)
Constant	0.196***	0.227***	0.221***	0.192***
	(0.0273)	(0.0621)	(0.0575)	(0.0578)
Observations	25663	6972	8189	8020
Adjusted R^2	0.277	0.230	0.240	0.239

Note: Heteroskedastic robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Country fixed effects and age cohorts dummies are included but not reported. Students aged 25 are excluded from the sample. Survey weights accounting for population size and demographics are used.

D Latent factor model: correlation coefficients

Table D.1: Correlation coefficients over 3 generations

	Observed			Iterated	
	r_{-1}^{G1-G2}	r_{-1}^{G2-G3}	r_{-2}	$(r_{-1})^2$	N
Austria	0.571 (0.031)	0.608 (0.023)	0.375 (0.031)	0.347 (0.024)	819
Belgium	0.404 (0.032)	0.495 (0.034)	0.271 (0.031)	0.202 (0.022)	814
Bulgaria	0.365 (0.035)	0.458 (0.032)	0.225 (0.035)	0.170 (0.020)	712
Croatia	0.422 (0.033)	0.340 (0.046)	0.250 (0.039)	0.145 (0.022)	860
Cyprus	0.337 (0.042)	0.325 (0.092)	0.191 (0.045)	0.110 (0.033)	385
Czech Republic	0.413 (0.043)	0.331 (0.044)	0.117 (0.043)	0.138 (0.022)	768
Denmark	0.266 (0.033)	0.442 (0.029)	0.187 (0.031)	0.125 (0.016)	848
Estonia	0.276 (0.044)	0.409 (0.035)	0.169 (0.041)	0.117 (0.019)	429
Finland	0.345 (0.035)	0.378 (0.046)	0.165 (0.039)	0.131 (0.021)	580
France	0.428 (0.039)	0.379 (0.044)	0.235 (0.045)	0.163 (0.025)	519
Germany	0.557 (0.026)	0.589 (0.024)	0.391 (0.025)	0.328 (0.022)	1011
Greece	0.348 (0.031)	0.436 (0.047)	0.211 (0.035)	0.154 (0.024)	834
Hungary	0.389 (0.037)	0.487 (0.045)	0.255 (0.034)	0.192 (0.026)	803
Ireland	0.359 (0.034)	0.371 (0.046)	0.196 (0.031)	0.133 (0.022)	662
Italy	0.529 (0.030)	0.457 (0.045)	0.238 (0.037)	0.243 (0.027)	749
Latvia	0.334 (0.046)	0.246 (0.046)	0.152 (0.044)	0.084 (0.020)	422
Lithuania	0.246 (0.037)	0.381 (0.033)	0.166 (0.030)	0.098 (0.017)	588
Luxembourg	0.406 (0.041)	0.569 (0.044)	0.294 (0.035)	0.238 (0.031)	316
Malta	0.412 (0.052)	0.302 (0.107)	0.251 (0.056)	0.127 (0.042)	252
Netherlands	0.339 (0.031)	0.511 (0.028)	0.171 (0.030)	0.181 (0.017)	620
Poland	0.379 (0.043)	0.435 (0.052)	0.242 (0.041)	0.166 (0.028)	632
Portugal	0.472 (0.051)	0.608 (0.066)	0.241 (0.058)	0.292 (0.040)	592
Romania	0.432 (0.037)	0.348 (0.039)	0.260 (0.030)	0.152 (0.021)	729
Slovakia	0.451 (0.039)	0.384 (0.055)	0.214 (0.042)	0.174 (0.030)	839
Slovenia	0.323 (0.040)	0.313 (0.049)	0.159 (0.042)	0.101 (0.019)	671
Spain	0.366 (0.036)	0.412 (0.053)	0.217 (0.037)	0.152 (0.027)	787
Sweden	0.190 (0.031)	0.400 (0.032)	0.153 (0.027)	0.087 (0.013)	786
United Kingdom	0.422 (0.029)	0.437 (0.035)	0.257 (0.030)	0.185 (0.019)	664
EU-28	0.463 (0.006)	0.508 (0.007)	0.306 (0.006)	0.236 (0.005)	18691

Note: Bootstrapped standard errors in parenthesis. Students aged 25 or below as well as respondents failing to indicate the educational attainment of at least one parent and at least one grandparents (alongside their own) are excluded from the sample.

Table D.2: Latent factor model: correlation coefficients

	r_{-1}	r_{-2}	λ	ρ	N
Austria	0.589 (0.020)	0.375 (0.031)	0.637 (0.038)	0.962 (0.025)	819
Belgium	0.450 (0.024)	0.271 (0.031)	0.603 (0.057)	0.863 (0.047)	814
Bulgaria	0.412 (0.024)	0.225 (0.035)	0.546 (0.071)	0.868 (0.058)	712
Croatia	0.381 (0.030)	0.250 (0.039)	0.656 (0.095)	0.762 (0.067)	860
Cyprus	0.331 (0.049)	0.191 (0.045)	0.577 (0.141)	0.758 (0.150)	385
Czech Republic	0.372 (0.030)	0.117 (0.043)	0.316 (0.106)	1.084 (0.263)	768
Denmark	0.354 (0.022)	0.187 (0.031)	0.529 (0.081)	0.818 (0.068)	848
Estonia	0.342 (0.027)	0.169 (0.041)	0.493 (0.110)	0.833 (0.124)	429
Finland	0.362 (0.029)	0.165 (0.039)	0.455 (0.097)	0.891 (0.096)	580
France	0.404 (0.031)	0.235 (0.045)	0.582 (0.100)	0.833 (0.079)	519
Germany	0.573 (0.019)	0.391 (0.025)	0.683 (0.038)	0.916 (0.030)	1011
Greece	0.392 (0.031)	0.211 (0.035)	0.539 (0.071)	0.853 (0.063)	834
Hungary	0.438 (0.030)	0.255 (0.034)	0.582 (0.064)	0.868 (0.054)	803
Ireland	0.365 (0.030)	0.196 (0.031)	0.538 (0.073)	0.823 (0.067)	662
Italy	0.493 (0.028)	0.238 (0.037)	0.482 (0.060)	1.011 (0.058)	749
Latvia	0.290 (0.035)	0.152 (0.044)	0.525 (0.145)	0.743 (0.119)	422
Lithuania	0.313 (0.027)	0.166 (0.030)	0.528 (0.093)	0.770 (0.088)	588
Luxembourg	0.487 (0.032)	0.294 (0.035)	0.603 (0.060)	0.899 (0.057)	316
Malta	0.357 (0.061)	0.251 (0.056)	0.703 (0.195)	0.712 (0.136)	252
Netherlands	0.425 (0.020)	0.171 (0.030)	0.403 (0.060)	1.027 (0.076)	620
Poland	0.407 (0.035)	0.242 (0.041)	0.594 (0.095)	0.828 (0.083)	632
Portugal	0.540 (0.039)	0.241 (0.058)	0.446 (0.097)	1.101 (0.140)	592
Romania	0.390 (0.026)	0.260 (0.030)	0.667 (0.077)	0.765 (0.060)	729
Slovakia	0.418 (0.035)	0.214 (0.042)	0.513 (0.080)	0.903 (0.073)	839
Slovenia	0.318 (0.030)	0.159 (0.042)	0.500 (0.127)	0.798 (0.138)	671
Spain	0.389 (0.035)	0.217 (0.037)	0.557 (0.085)	0.836 (0.077)	787
Sweden	0.295 (0.022)	0.153 (0.027)	0.518 (0.091)	0.754 (0.078)	786
United Kingdom	0.430 (0.023)	0.257 (0.03)	0.599 (0.062)	0.847 (0.049)	664
EU-28	0.485 (0.005)	0.306 (0.006)	0.630 (0.011)	0.878 (0.009)	18691

Note: Bootstrapped standard errors in parenthesis. Students aged 25 or below as well as respondents failing to indicate the educational attainment of at least one parent and at least one grandparents (alongside their own) are excluded from the sample.