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More inequality, more viscosity?
Intergenerational mobility in Europe and the US

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Abstract

The popularity of the so-called Great Gatsby Curve (GGC, Blanden 2013, Corak 2013, Torche 2015) that describes a strong macro relation between income inequality (Gini) and intergenerational earnings elasticity is demonstrated by the increasing number of studies investigating this relationship. Still, the exact mechanism underlying the association between income inequality and intergenerational immobility is not yet well understood (McCall and Percheski 2010: 339). This study will contribute (a) to filling this gap by complementing the "economic" income-based regressions approach with a "sociological" class-based categorical modelling approach (Xie 2003; Pisati's unidiff model, Pisati and Schizzerotto 2004) and (b) to test the robustness of the Great Gatsby Curve by proposing an innovative methodological approach. Applying this approach can be useful for the current methodological debate on imputation methods (typically two sample two stages least squares TSTSLS) that could produce upward-biased intergenerational elasticities, leading to an overestimation GGC relation. To avoid this bias, we use a new measure of elasticity net of Gini (logit rank of income) to reproduce the GGC with a more robust approach.

Besides, concerns about international comparability of the methods used have been raised; our approach is imputed in the context of a multilevel random slope model where the country-specific slopes (BLUPS Best Linear Unbiased Predictor) are identified as a measure of socioeconomic reproduction. A third, empirical contribution of this paper lies using a harmonised methods across countries and in widening the evidence base by including a large set of counties not included in previous publications: In additional to the US (PSID), we included 26 European countries (EU Survey on Income and Living Conditions, EU-SILC, module 2005 and 2011 on Intergenerational transmission of poverty/disadvantage).

The results confirm our expectations. First, the results based on a Gini-neutral measure are more modest in terms of explained variance of the GGC but are strong and significant: the economic tradition although the association between

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Gini and intergenerational reproduction remain rather solid. Secondly, in line with the literature (Blanden 2013, Torche 2015), we find that the "sociological" approach differs considerably from the "economic" one in the sense that the latter has a strong result in terms of impact of inequality on (im)mobility. We scrutinize the discrepancy from an analytical perspective and conclude with new challenges for sociological research.

Acknowledgement

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Introduction

The linkage of static and dynamic income inequalities has experienced an upsurge in the economic literature over the last decade. Most notably, the famed "Great Gatsby Curve" (Corak, 2013, Figure 2) mapping 22 countries on a graph with income inequality (Gini) on the x axis and generational earnings elasticity on the y axis has provoked many discussions, which spilled over to the policy domain. In brief, the "Great Gatsby Curve" with a R-squared of .75 and a slope close to 1 suggests that more static inequality is associated with more dynamic inequality (intergenerational reproduction) or in other words, the more equal societies in the past, the more equality of opportunity today. The nature of the recent controversial academic debate around the "Great Gatsby Curve" and its reliability is in essence methodological discussing the different approaches of estimating intergenerational mobility (panel methods versus imputation strategies), whose general logics we will briefly discuss below.

Although many authors confirm the GGC concluding "More inequality, less social mobility"(Andrews and Leigh 2009; Blanden 2013, Corak 2013, Torche 2015), relatively little is known about the link between income inequality and intergenerational mobility (Jäntti and Jenkins 2013) and especially about the mechanisms behind (Jerrim and Macmillan 2015). On top of this, the relative level of intergenerational mobility differs depending on the measure used: income, education or social class (Blanden 2013, Torche 2015). Critiques have been developed on some of these approaches[2] and these results are often

[2] The widely used two samples two stages least squares (TSTSLS) approach seems to overestimate the slope (intergenerational elasticity) and lacks robustness (Jerrim et al 2014). One key issue is that the father's income is mostly not available and therefore estimated on an auxiliary data set. The flaw inherent to this method is that the log(income) is dependent on Gini: The higher the Gini, the more stretched the distribution - even if the intrinsic regime of mobility is not affected. This change in Gini is a structural transformation. However, when Gini rises, also the elasticity increases. A second line of criticism concerns of uncertainty about the comparability of intergenerational earnings mobility across countries have been raised. Jerrim, Choi, and Rodríguez (2014) for instance point out that in the production (supposedly) cross-nationally comparable findings different empirical methodologies have been applied and

debated among economists, while sociologists remain less active in this respect. This calls for further research, in particular including a larger set of different countries.

Our aim is to contribute to these debates with this analysis of the well harmonized EU-SILC data using a combined measure of parental socio-economic origin, which we transform into a rank scale and link this rank to the individual's socio-economic position in a society – first in terms of income and then in terms of social class. In this way, we are able to assess the sensitivity of prior research and gain additional information on the interrelation of intergenerational mobility and inequality.

Economists' view on the association between static and dynamic inequality

Intergenerational elasticities (IGE) have been estimated with two strategies in the pertinent literature. The first "ideal" strategy relies on administrative or panel data comprising – if sufficiently long – actual information on income (or earnings) of parents in the past and children today respectively (Jäntti & Jenkins, 2013) – but is rarely feasible. This first approach uses ordinary least squares (OLS) techniques to estimate the son's income based on the father's as a predictor (Nicoletti & Ermisch, 2008).

Where panel data and thus actual information on the parents' income in the past is not available, two-sample strategies have been applied (Björklund & Jäntti, 1997; Lefranc, 2011; Lefranc & Trannoy, 2005) (Andrews and Leigh 2007) matching information on children's income and parents' characteristics such as education, experience and occupation from two different sources (Jerrim et al., 2014). These studies estimate first the earnings equation of the parents based on auxiliary data representing the parent's income distribution obtaining coefficients of these income determinants. In a second step, the coefficients are used to predict the income of the parent based on the main data (representative for the adult children), using the socio-economic characteristics of the parents reported by the children (Torche, 2013). Some authors prefer to refer to these approaches as imputation methods (Jerrim et al., 2014).

Inherent to the traditional GGC approach are three main problems that have been emphasized by different scholars: (a) the cross-national comparability when applying two different strategies, (b) the overestimation of estimated intergenerational elasticity and thus the GGC, and (c), which will be our main argument here, the inability to account for a structural transformations such as an increasing Gini as for instance witnessed in the US. We will next elaborate on argument (b) and (c) in more detail.

In a nutshell, the argument (b) adheres to the risk that estimates of intergenerational elasticity differ according to the method applied. Containing in addition to the association between origin and destination also the net impact of

emphasize the need to produce "more robust and reliable estimates of earnings mobility that can be legitimately compared across countries" (Jerrim et al. 2014: 22).

the (instrumental) variable used to predict parental income, the two-sample methods overestimate the true slope and produce an upward biased estimated elasticity (Jerrim et al., 2014). The estimator should therefore be interpreted as an upper bound for the intergenerational elasticity (Nicoletti & Ermisch, 2008; Torche, 2013).[3] When applying two-sample strategies, the variance in the parents' distribution decreases inflating estimated intergenerational elasticity (Andrews & Leigh, 2009).[4] Since the GGC mixes results based on the first and the second estimator (11 out of 21 included countries have applied the TSTSLS methodology), critics claim that the key findings do no longer hold when using the same approach for all countries (Jerrim et al., 2014).[5]

Argument (c) is linked to this feature. Structural transformations such as a rising Gini may (upward) bias the relation displayed in the GGC if it is based on log of income as it is usually the case. When Gini rises, also the elasticity increases as our simulation based on the PSID (in which the parental income is available) shows (Table 1).

Table 1: Two samples least squares estimation of currency elasticity after rescaling of fathers' and sons' Gini (US)

		fathers' Gini			
		0.2	**0.3**	**0.4**	**0.5**
sons' G	**0.2**	0.380	0.253	0.190	0.152
	0.3	0.570	0.380	0.285	0.228
	0.4	0.760	0.507	0.380	0.304
	0.5	0.950	0.634	0.475	0.380

Note: We simulate changes in the Ginis for fathers and sons based with the formula a ln(p/1-p) = ln(medianised income) where a = Gini (Fisk-Champernowne-Dagum distributions). Source: PSID.

Table 1 displays intergenerational measures based on currency elasticity (in dollars) and their dependency on changes in the Gini: when the Gini of the sons income distribution is larger than the Gini among the fathers' income distribution, the intergenerational elasticity increases.[6]

The central problem TS2SLS methodology is thus that (pseudo)-fathers estimates (or averages) are imputed and create a non-realistic distribution of fathers where Gini(fathers)<<Gini(sons). This intergenerational Gini gap is larger in countries with higher Gini of the sons' income distribution and could

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[3] The larger R-squared in the first-stage regression, the smaller this bias (Nicoletti & Ermisch, 2008).

[4] On the contrary, the intergenerational correlation (IGC) is a measure of intergenerational persistence, which adjusts for differences in income variance between the parents and children and is thus a more robust measure of intergenerational mobility (Bjorklund and Jantti 2009). As incomes of both are required, which is often not available, the correlation is only rarely included (Andrews & Leigh, 2009 as an exception). Moreover, it cannot reflect nonlinearities in the intergenerational economic association (Corak, Lindquist, & Mazumber, 2014; Torche, forthcoming). Yet, information on both the elasticity *and* the correlation is desirable (Blanden, 2013).

[5] In addition, Jerrim et al. (2014) stipulate that the TSTSLS approach should not be applied in cross-national comparisons since the poor TSTSLS proxies of parents' earnings produce biased coefficients of intergenerational associations.

[6] When both Ginis are equal (diagonal), this issue does not occur.

therefore potentially account for parts of the log-income GGC. In other words, we have to find a measure of *exchange* mobility, net of Gini change (*structural* transformation) to test this empirically. The main risk of the conventional elasticity approach is then to generate trivial results: income gaps are stronger (elasticity) where income gaps are deeper (Gini).

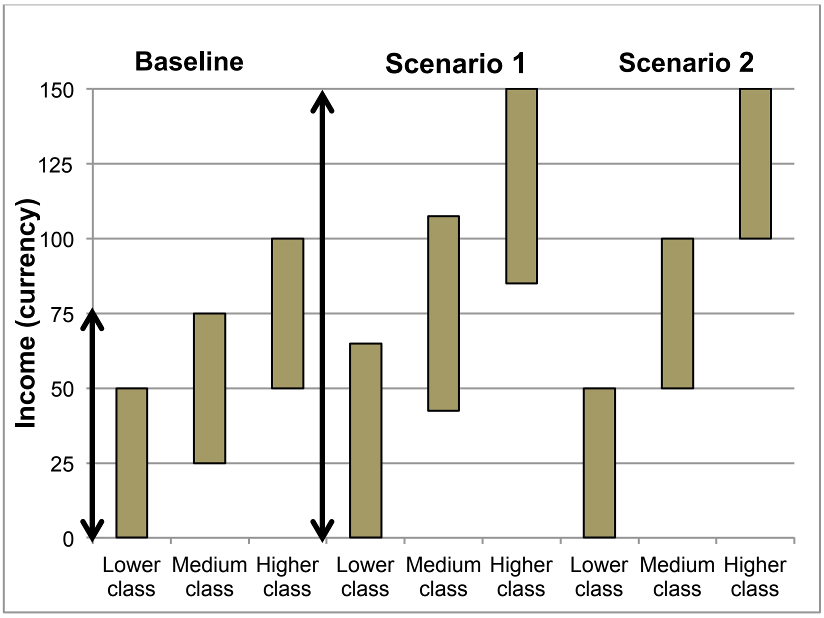
A sociological perspective

Sociologists investigating inequality of opportunity through a social class lens have long been providing ambiguous statements on the link between the intensity of economic inequality and intergenerational immobility (Erikson and Goldthorpe 1992, Goldthorpe 2013). In a European comparisons of social mobility, the team of Breen (2004, Figure 3) finds no relation between fluidity of nations and their rankings in terms of Gini indices. Recent research (Mitnik et al 2016) making use of occupational based information and unidiff log-linear models (Xie 1992) show the increase in inequality in the US seems to have enabled the professional-managerial class to better protect their interest in class reproduction and maintain their positions in the upper social hierarchy over generations. But this kind of approach is not very common in sociology, compared to the massive use of big data based long-term research in economics (Chetty et al 2014).

A general issue is thus the contradictory evidence on the association of social reproduction and inequality depending on the concept used. Findings based on regressions of continuous measures such as earnings and income do not necessarily coincide with those based on categorical measures such as class and occupation due to their conceptual difference (Neckermann and Torche 2007, Torche 2015). The class approach groups the set of occupations into a few discrete strata, which are not only defined by income but rather other differentiating characteristics such as industrial sector or authority. Within-class dispersion of income may thus vary and thus also the degree of intergenerational correlation (Blanden 2013).

However, an approach to economic hierarchy should be redeveloped in sociology (Pareto 1896; Nielsen 2007), in particular in the domain of intergenerational mobility (Girod 1986). For sociologists, the GGC hypothesis is interesting in terms of social class theory. If higher Gini indices indeed go with stronger income intergenerational elasticity (socio-economic reproduction), this has important implications for social class structure: stronger inequality means a higher predictability of children's socioeconomic position when parents' are known. Otherwise, it means that the percentage of predicted variance of incomes of kids (predicted by parents' position) might increase when Gini indices are higher. In a discrete model, the overlaps between socioeconomic origins should decline with inequality; conversely, equalitarian countries are then expected to show massive overlaps between social origins.

Figure 1: Possible scenarios of changes in the class structure as result of increasing inequality (widening of income distribution)



Source: own illustration

Figure 1 illustrates possible outcomes of changes in the class structure when income inequality is rising: Compared to the baseline situation, scenario 1 refers to a stretching of the whole structure, similar to an elastic loom, so that the classes can increase their income (move upward) but also proportionally spread their variance. Still, as it is the case in the baseline situation, persons from lower classes may have higher incomes than some persons from the next higher class. Scenario 2 is a "telescopic" change, in the sense that the spread (variance) of each class remains the same but the difference or gap between them increases; the ratio of the predicted variance (by origins) by total variance is increasing compared to scenario 1, and the relative overlaps decline. In scenario 2, intergenerational elasticity increases dramatically.

In a nutshell, we will answer the following questions in view of the different economic and sociological concepts: Can we confirm the link between income inequality (Gini index) and intergenerational mobility *net of structural changes in the shape of distribution*? Even with Gini independent measures of mobility? What is the difference between "economic" approaches (income based) and "sociological" ones (occupational class) and how can it be explained?

Methods

Income versus income ranks

Many authors have underlined the importance of using rank positions when analyzing the income distribution (Chauvel, 2015; Ebert, 1999; Jenkins & Van Kerm, 2006; Mujcic & Frijters, 2013; Van Kerm, 2004; Chetty and al 2014).

Comparing the income distribution with an "elastic band" where a mere stretching signifies an increasing inequality (Gini) in a given population, no positional changes should occur. When calculated in terms of incomes, an increasing Gini refers to a stretched distribution, even if the intrinsic regime of mobility is not affected (Jäntti & Jenkins, 2013). The change in Gini indicies measure thus *structural* transformation of inequality. This structural mobility differs from exchange mobility, the re-ranking within a population, through which inequality is not affected.

Using ranks avoids the issue with the conventional currency elasticity measurement, i.e. that intergenerational elasticity is very reactive to inequality trends: When inequality (Gini) rises, elasticity increases. "Changes in the extent of mobility mostly reflects the evolution of cross-section earnings inequality, rather than variations in positional mobility." (Lefranc, 2011: 1) This mechanism may account for a large extent of association shown in the Great Gatsby curve. Lefranc shows this for the evolution of intergenerational mobility but this is problematic for international comparisons as well. We will therefore apply a rank based elasticity.

The percentile rank based elasticity

We could standardize the variables as simple ranks or as fractional ranks (between 0 and 1), which would, however, contract the Pareto-tails. An alternative would be to reshape the distributions of income as a normal curve, but once again we lose the properties of Pareto tails specific to income and wealth distributions. The logitrank approach offers a standardization strategy consistent with the Pareto characteristics of income distributions that have important properties.

We proceed as follows. Let $p \in [0;1]$ be the percentile rank of individual i in the income distribution, so that the logged odds of the percentile $\ln(p_i/(1-p_i)$ measures the relative social power of individual i ("Logit rank" (Copas, 1999), O'Brien, 1978; compare also to the log of Positional Status Index used by Rotman, Shavit and Shalev 2015). Based on the so-created rank positions, we derive the Gini α, a measure of the degree to which these positions are stretched between the top and the bottom, from the following equation based on the Champernowne-I-Fisk quantile distribution (Champernowne, 1953; Chauvel, 2015; Dagum, 1977; Fisk, 1961):

$$\ln(m_j) = \alpha \ln(p_i/(1-p_i)) \text{ or } M_i = \alpha X_i$$

where the medianized income $m_j = y_i/median$, $M_i = \ln(m_i) = \ln(y_i/median)$, and the logit rank $X_i = \text{logit}(p_i) = \ln(p_i/(1-p_i))$. (Chauvel, 2015: 3)

Let us introduce percentile rank based elasticity (RE). While the Great Gatsby curve is based on Currency-Elasticity (CE)[7], which is Gini-dependent, i.e. when the Gini rises, CE increases, we avoid this issue by replacing the yearly country-

[7] The CE is based on logged incomes so that inflation and growth is absorbed by the constant.

logged incomes by logit rank $X_i = \text{logit}(p_i) = \ln(p_i/(1-p_i))$. This rank based elasticity is independent of the Gini in parents' or children's generation and thus a measure of mobility net of structural changes in both distributions and is therefore a more suitable strategy to compare different countries.[8]

Multilevel model

In order to obtain country-specific gradients of socioeconomic origin logit ranks on children income logit rank, we apply a multilevel random intercepts random slopes model (Rabe-Hesketh & Skrondal 2012) with the following general form:

$$y_{ij} = (\beta_1 + \zeta_{1j}) + (\beta_2 + \zeta_{2j})x_{ij} + \epsilon_{ij}$$

with random country-specific intercept ζ_{1j} and random country-specific slope for parental background $\beta_2+\zeta_{2j}$ for the 52 subsamples included (26 countries at two time points). Under this specification, $\beta_2+\zeta_{2j}$ can be understood as the strength of the impact of parents' relative position in the socioeconomic hierarchy of their nation on their children achievements. This model has already been applied to socioeconomic gradient (logitrank of both socioeconomic origin and ego's income) of health on the same datasets (Chauvel & Leist 2015) to demonstrate that higher Gini indices increases social origin's role on inequalities of health. The GGC hypothesis goes with the existence of a strong correlation between national $\beta_2+\zeta_{2j}$ and the Gini indices. The 52 (country x year) $\beta_2+\zeta_{2j}$ and the related standard errors are estimated in a single multilevel model with the best linear unbiased predictions (BLUPs), then correlated to the 52 Gini indices.

The dependent variable is here the "logit rank" (at the country-year level), logged odd of the percentile ln(p/1-p) in the income distribution (post-tax, post-transfer, disposable household income). The main explanatory variable is the logit rank of the scores in the Multiple Correspondence Analysis (MCA, Burt method) of education and occupation of the father and of the mother (6 classes EGP scheme) again at the country-year level (see below).

Loglinear association model

For analyzing social mobility in terms of social classes, we apply log-multiplicative layer model (Xie 1992, 2003), which is a more parsimonious log-linear model compared to the saturated model that suits well research designs that are interested in country- or layer- specific mobility (Xie 1992).

$$\log(F_{ij}) = \mu + \mu_i^R + \mu_j^C + \beta ij$$

with parental versus offspring's social class across 52 layers. Note, that we assume thus that the qualitative pattern of mobility is similar across countries as the row-column-layer effect is constrained here.

[8] If the income inequality in all countries does not change between the two generations, log(income) based strategies are equally suitable. Using PPP will also not solve the issue that inequity measured by the Gini differs among parents and their children.

Data and variables

Our analysis draws on the US Panel Study of Income Dynamics (PSID) and the EU Survey on Income and Living Conditions (EU-SILC). While the PSID contains generally information on the parent's socio-economic origin and the family context, for the EU-SILC comparable information exists only for the waves 2005 and 2011, which includes modules on the "intergenerational transmission of poverty/disadvantages" that comprises a set of questions on the parents' education and occupation. We include the following 27 countries in our analysis: Austria, Belgium, Czech Republic, Cyprus, Germany, Denmark, Estonia, Spain, Finland, France, Greece, Hungary, Ireland, Iceland, Italy, Lithuania, Latvia, Luxembourg, the Netherlands, Norway, Poland, Portugal, Slovenia, Slovakia, Sweden, the UK and the US.

A major advantage of using the EU-SILC is the availability of a large number of harmonized variables. On the other hand, the EU-SILC has the limitation of obtaining its data with different sampling strategies across the countries. In many Nordic countries, which are characterized by low inequality and high mobility, administrative data is complemented with additional forms filled out by citizens (e.g. NL, SE), leading to high rates of non-response and a potential bias that is not corrected by the available weights. To date there is no evidence of the existence of such a potential design artifact and many other researchers use the EU-SILC for intergenerational mobility analyses (some excluding certain countries).

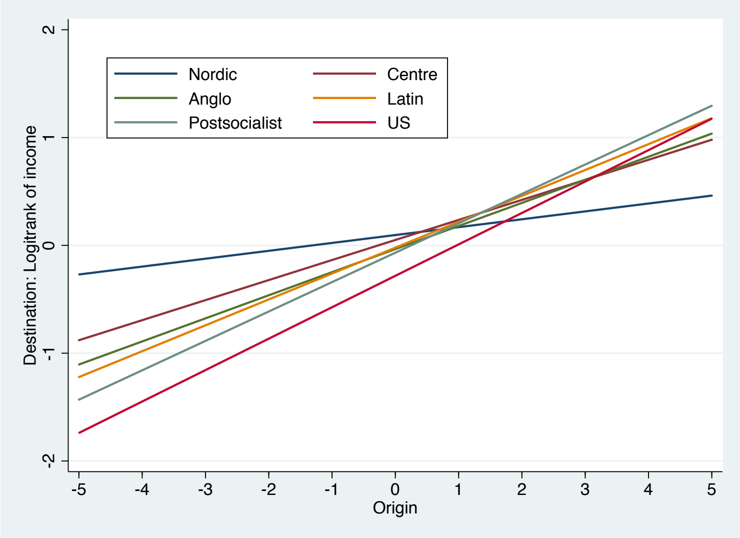
In order to obtain our parental origin variable, we combine the maximum amount of information available on the parents' socio-economic background and construct a scale with Multiple Correspondence Analysis (MCA; Burt method) of education and occupation of the father (6 classes EGP scheme) and mother's education and occupation. For robustness checks we tried different combinations of these variables, and the results do not diverge is we focus on mother or father alone. The first dimension of the MCA we use for our further analysis explains 88.6% inertia (predict factor coordinates), this means that the different dimensions of hierarchy (occupations, education of parents) are strongly related. Scores are logit-ranked by country-year. One data issue with the EU-SILC, however, is that the high percentage of missing information on the parents' background, in particular in Sweden (more than 50% of missing values). For consistency with other studies, we exclude those missing cases.

The harmonization of the PSID and EU-SILC variables across generations does unfortunately not allow for great detail. *Education* (ISCED) of father and son has been harmonized into three levels: (1) low: pre-primary, primary education or lower secondary education, (2) medium: upper secondary education and post-secondary non-tertiary education, and (3) high: first stage of tertiary education and second stage of tertiary education. However, as the comparability of educational qualifications is limited across generations and countries, these variables must be interpreted with caution.

Results

The aim of this section is to replicate the "Great Gatsby Curve" using the association between social origin rank and children's income rank rather than the intergenerational elasticity used in the economic literature. Before doing so, we investigate the link between the father's origin and his children's outcome with the logit-rank approach across the different types of welfare states based on Ebbinghaus' (2006) typology (Figure 2).

Figure 2: The origin gradient in different types of welfare states

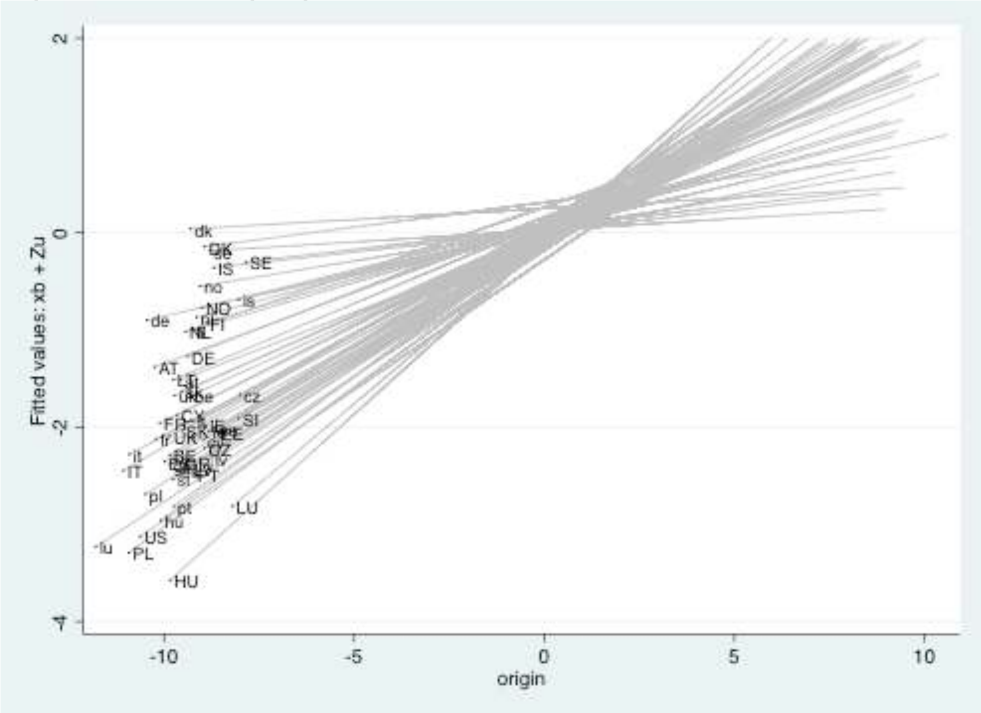


Source: EU-SILC 2005/2011, PSID 2005.

Consistent with the sociological literature the degree of social reproduction is lowest in the Nordic countries. Central European welfare states and even more so the other types exhibit a much higher degree of origin dependence. The US separated from the European welfare states exhibits the steepest origin gradient and thus greatest intergenerational persistence of all welfare states investigated.

In a next step, we run a multilevel regression with random intercepts and random slopes to obtain the country-specific origin gradients. The estimated best linear unbiased predictions (BLUPs) of the random effects showing the variation for both the intercept and the estimated beta coefficient(s) are displayed in Figure 3.

Figure 3: The origin gradient across EU countries



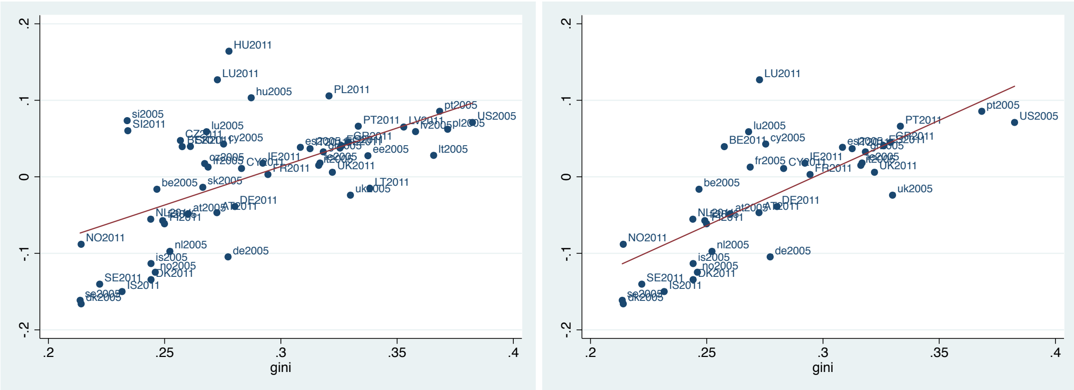
Notes: Best linear unbiased predictor (BLUP) based on random coefficient null model. Labels: lower cases - 2005 (e.g. uk), upper cases - 2011 (e.g. UK).
Source: EU-SILC 2005/2011.

Figure 3 allows detecting more details in the country differences and exceptions from the previous figure. The Nordic countries exhibit again a much less steep slope suggesting a lower degree of social reproduction than the rest of the countries investigated here. The Eastern European and Southern countries, which have often been excluded from the GGC (Jerrim and Macmilan 2015), fall mostly on the other side of the spectrum with rather large degrees of origin dependence. However, Slovakia (2005) and Lithuania (2011) as compared to other Eastern countries, has a much higher social mobility, which is comparable to those of Austria, Belgium (2005) and the UK (2005) for instance. The largest origin dependence can be found in Hungary and Luxembourg (both 2011), which is even higher than in the US.

If we plot these country-specific gradients against the Gini (Figure 4), we obtain our key result, the logit-rank based Great Gatsby Curve, that corrects for changes in the income distributions among fathers and sons. Two observations can be made: first, the conclusion compared to the log-income based GGC (Figure 4) remains relatively stable: the more inequality, the more viscosity. Second, the explained variance (see Annex A.1) is lower using our method (R squared(M1)=.343) compared to the log-income based approach (R squared(M3)=.661) indicating that the changes in Gini do indeed explain an enormous part of the association between inequality and social reproduction on the macro level.

Figure 4: Logit-rank based GGC: (a) Europe and the US and (b) excluding post-socialist countries

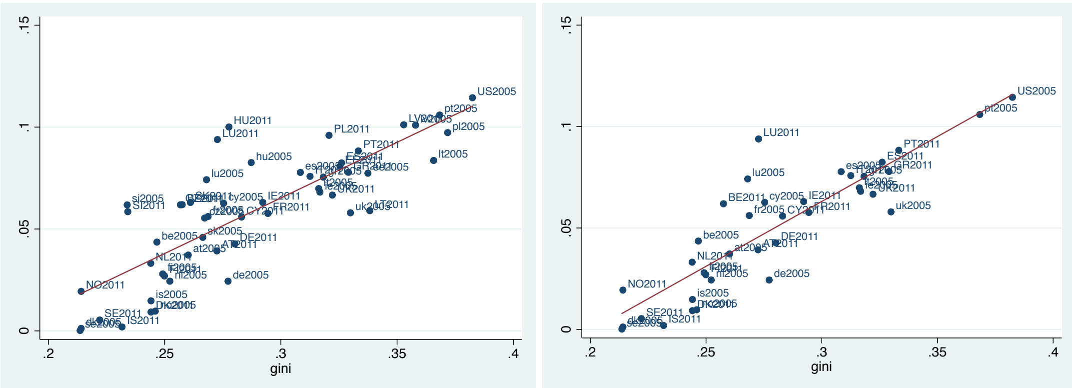
R2=.343 R2=.570



Source: EU-SILC 2005/2011

Figure 5: Log-income based GGC: (a) Europe and the US and (b) excluding post-socialist countries

R2=.661 R2=.773



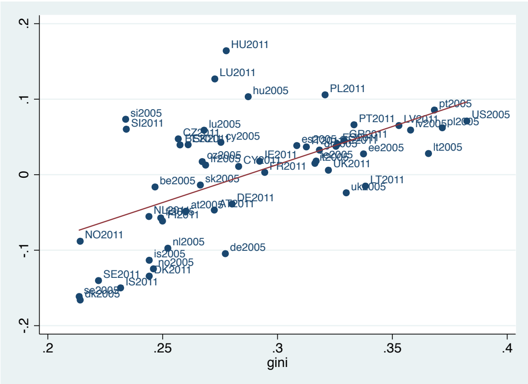
Source: EU-SILC 2005/2011

If we parallel the results based on social class/unidiff "sociological" and logitrank income based/elasticity "economic" concepts (Figure 6), not surprisingly, obvious differences appear. The link to economic inequality is not given when looking at social reproduction in terms of EGP classes instead of income. R squared close to zero confirms this. In other words, the relation described in the Great Gatsby curve does not hold for intergenerational class mobility. This is in line with findings of other studies comparing income and social class approaches to intergenerational mobility (Blanden 2013, Torche 2015). In this comparison, a naïve conclusion would be that the much stronger GGC curve of the "economic" approach compared to the "sociological" one suggests it is more powerful to consider incomes than social class. The gradient of social origin on today's income hierarchy is stronger in more unequal countries. This goes with the result that the intensity of social class reproduction is not correlated with economic inequality. The rigidity of the economic structure is correlated to economic inequality. In equalitarian countries, the different socioeconomic levels of origin loosely predict child's income and they overlap massively in this respect (see Figure 1) and conversely in unequal countries parents' relative position predicts better child's income, and subgroups of social origins overlap less on the children logitrank income scale.

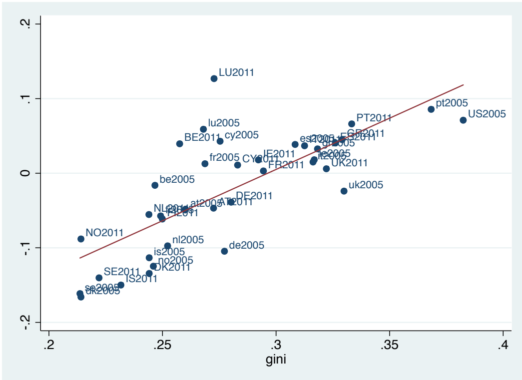
The occupational social class social mobility table analyzed by the unidiff model suppresses this correlation. This may seem paradoxical at first sight, but at a closer look the explanation is that within each social class of destination, the richer are the kids of richer parents: higher level income medical doctors are the children of professionals, for instance, while public sector general practitioners could be more often the kids coming from income-modest social milieus.

Figure 6: Income-based/elasticity (logitrank) GGC (top) vs. social class-based/unidiff GGC (bottom), Europe with and without post-socialist countries

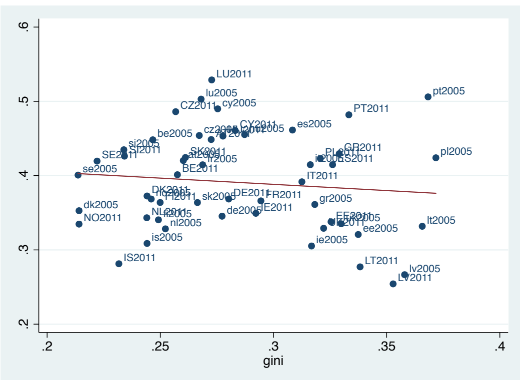
R2=.343



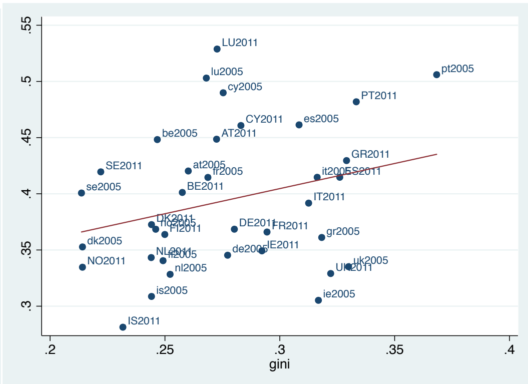
R2=.570



R2=.012



R2=.079



Source: EU-SILC 2005/2011, US and post-socialist countries excluded.

Interesting, however, is the link between the both concepts: the correlation of the residuals (in the simple regression of elasticity on Ginis) of both is rather strong (r=.645 when post-socialists countries are included), indicating that both concepts are strongly linked. Investigation the residuals, i.e. which countries fall above and below the fit line in Figure 6, gives an idea of which countries are more or less prone towards viscosity as expected given their Gini. The strong correlation of the residuals of elasticity versus unidiff approaches means that relatively to a Gini level, fluid and viscous countries of both approaches are similar. Relatively higher viscosity with respect to income ranks can especially be found in Hungary, Luxembourg and many Eastern European countries for instance, while relatively less origin dependence prevails in the Nordic countries given their (low or high) level of inequality. With respect to social class, there are a few differences. Luxembourg again displays a relatively higher viscosity given the level of Gini but now also many Central European countries can be found on this side of the spectrum. Relatively more open with respect to the class structure given the Gini level are Iceland and the Anglo-Saxon countries.

These findings suggest in a nutshell that social class mobility depicts a different link to inequality than income-based mobility due to intergenerational earnings persistence *within* social classes. In other words, in countries with high inequality, in a given class of destiny, descendants of higher-class origins obtain higher incomes than those from lower-class origins.

Conclusions

In this paper, our aim was first to reproduce the GGC with a more robust and income-distribution neutral measure that is independent of economic inequality, namely Gini. The risk of the conventional approach is to obtain trivial results: income predicts stronger gaps where gaps between incomes are stronger. There the logitrank approach offers a standardization strategy consistent with the Pareto characteristics of income distributions. Second, we tested if the proven relation between Gini and intergenerational mobility also holds for sociological concepts of reproduction.

We contribute to the existing literature in several ways. First, we include a large set of new countries vis-à-vis Corak (2013) making use of harmormised instead of country-specific data comprising the US (PSID) and Europe (EU-SILC). Second, the use of Gini-independent measure of social mobility (vis-à-vis income) allows us scrutinize the macro-relation between economic inequality and intergenerational mobility and feed the methodological debate with new insights. Our results confirm and refine the Great Gatsby Curve: We find a much more modest association with the Gini-independent logit rank measure we use. The association is thus partly due to the Gini itself, or in more technical terms, the upward bias of the intergenerational elasticity based on log of income.

This study, third, contributes to the interdisciplinary literature by providing additional insights based on both economic and sociological concepts. In line with the few previous studies (Blanden 2013, Torche 2015), social class mobility shows a different link to inequality. Our explanation is the intergenerational earnings persistence within social classes is that in countries with high economic inequality, in a given class of destiny, kids of higher-class origins obtain higher incomes than those from lower-class origins. Reflecting different processes, sociological and economic concepts need to be seen in conjunction to better reflect on the link of socio-economic inequality and social viscosity. Sociological and economic concepts reflect in other words utterly different processes and future research will profit much from investigating both traditions in conjunction.

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Annex

A.1 Explained country-level variance of the three approaches applied

	Logit rank approach (Figure 3)		Log income approach (Figure 4)		Social class approach (Figure5)	
	M1 - all countries	M2 - excluding Eastern EU	M3 - all countries	M4 - excluding Eastern EU	M5 - all countries	M6 - excluding Eastern EU
Gini	1.006***	1.375***	0.546***	0.640***	-0.168	0.447
	(0.178)	(0.158)	(0.055)	(0.059)	(0.240)	(0.246)
Intercept	-0.289***	-0.408***	-0.099***	-0.129***	0.439***	0.271***
	(0.057)	(0.048)	(0.016)	(0.017)	(0.067)	(0.067)
r2	0.343	0.570	0.661	0.773	0.012	0.079
N	53	37	53	37	52	36