The shape of the wealth distribution and differences in wealth inequality across euro area countries

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Abstract: Based on data from the Eurosystem Household Finance and Consumption Survey (HFCS), we revisit the question of how differences in household characteristics can account for cross-country differences in wealth inequality. We first show that commonly used RIF-decompositions are typically tested positive for specification error due to the large differences in household characteristics between countries. We then present an alternative analysis for which we introduce a convenient graphical representation of the wealth distribution. Our results show that not only differences in wealth inequality but also differences in distributional shape can be largely accounted for by differences in homeownership across countries, but that, for some country comparisons, differences in household incomes also matter.

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1 Introduction

Why is wealth inequality higher in some countries than in others? Given the increasing availability of internationally comparable wealth surveys, this question has drawn a considerable amount of attention in the recent literature. As an early example, Bover (2010) compares the wealth distributions in Spain and the U.S., finding that differences in household structures explain some of the differences in the lower part of the distribution but generally fail to account for the differences in other parts. Addressing a larger set of countries, Cowell et al. (2018) also aim at explaining cross-country differences in wealth inequality by differences in demographic and economic household characteristics. Their conclusion is that the biggest share of inequality differences is not attributable to the characteristics considered by them. More recent contributions have focussed on the potential impact of differences in homeownership on cross-country differences in the wealth distribution. Mathä et al. (2017) find that differences in homeownership, intergenerational transfers and house price dynamics are important for explaining differences in the *level* of wealth between euro area countries. Sierminska and Doorley (2018) study cross-country differences in asset participation. They identify important differences in household portfolios across countries, including the share of homeownership. Explicitly focussing on wealth *inequality*, Kaas et al. (2019) investigate the role of differences in homeownership for wealth inequality across euro area countries. Using modern decomposition techniques (RIF-decomposition), they identify a large role of such differences for cross-country differences in wealth inequality.

This paper revisits the question of how differences in household characteristics such as homeownership shape cross-country differences in wealth inequality. Like Mathä et al. (2017) and Kaas et al. (2019), our study is based on the Eurosystem Household Finance and Consumption Survey (HFCS), which provides highly comparable information on wealth holdings across European countries. We make the following contributions. As a first contribution, we scrutinize the use of RIF-decomposition techniques (Firpo et al. 2009; Fortin et al. 2011) for cross-country analyses. The RIF-methodology used in Mathä et al. (2017) and Kaas et al. (2019) is an extremely powerful tool of distributional analysis which has been successfully applied in a large number of applications. However, the method heavily relies on local approximations and linearity assumptions which may be questionable if two very different populations are compared, which is typically the case in cross-country comparisons (e.g., large differences in homeownership rates across countries). Indeed, Mathä et al. (2017) and Kaas et al. (2019) used an outdated version of the RIF-decomposition which does not allow to gauge potential misspecification problems in the RIF-regressions. By contrast, the present paper uses the so-called *hybrid* variant of the RIF-decomposition (Fortin et al. 2018), which explicitly quantifies the potential amount of specification error involved in the decomposition. We show that, as might be expected, specification error in RIF-regressions is the bigger the more different the units are that are being compared in the decomposition. Our application with eleven countries of the euro area provides a laboratory for studying the empirical properties of RIF-decompositions, which may be of independent interest to practitioners who want to apply this powerful method and who want to understand their empirical performance.[1]

As a second contribution, we shed light on cross-country differences not only in wealth inequality but in *distributional shape*. For this purpose, we develop a convenient representation of the wealth distribution. It is well known that the wealth distribution is notoriously hard to represent graphically. We believe that the representation proposed by us may be of independent interest for other applications. Using this representation, we show that there is a close empirical relationship between the shape of the wealth distribution and homeownership in a population, which we investigate in more detail using the method of reweighting (DiNardo et al. 1996). We show that counterfactually reducing the homeownership rate in a population 'morphs' its wealth distribution into the wealth distribution of a country with low homeownership (Germany and Austria in our case). For some countries, reweighting in addition with respect to income differences is necessary to explain cross-country differences. Our results confirm the findings of earlier studies

[1] Further differences of our study to Mathä et al. (2017) and Kaas et al. (2019) are the following. In contrast to our study, Mathä et al. (2017) only study cross-sectional differences in wealth *levels* but not in wealth *inequality*. Both Mathä et al. (2017) and Kaas et al. (2019) use an outdated version of RIF-decompositions, which we show to suffer from specification problems in the given context. A further difference to Kaas et al. (2019) is that they use an uncommon decomposition formula involving an interaction term which makes some of their results hard to interpret. Finally, Kaas et al. (2019) include income differences between countries in their decompositions in a very basic way, yielding no income effects for cross-country differences. By contrast, we show that income differences are important for cross-national differences in wealth inequality for some countries.

that differences in homeownership have the potential to explain a large part of cross-country differences in wealth inequality. We believe, however, that our graphical analysis does this in a more credible and transparent way than previous contributions which only focussed on numerical differences in wealth inequality across countries.

The rest of this paper is structured as follows. Section 2 introduces our data which were taken from the European Household Finance and Consumption Survey (HFCS). Section 3 describes our graphical representation of the wealth distribution which we use in later sections to study cross-country differences. Section 4 presents our analysis using the RIF- and the alternative graphical reweighting method. Section 5 concludes.

2 Data

Our study is based on data from the Household Finance and Consumption Survey (HFCS) of the ECB (see HFCS 2020). Our main analysis refers to the year 2017. In our descriptive results, we include comparisons to the year 2010 in order to assess to what extent wealth distributions observed in 2017 were representative for the longer term. For Spain, we used the year 2014 rather than 2017, as no data for 2017 were available at the time of our study. We focus on the eleven largest euro area countries in the HFCS that have been present over different waves of the survey and for which there is complete coverage of the variables used in the analysis below: Germany (DE), Spain (ES), France (FR), Italy (IT), Greece (GR), and the Netherlands (NL), Belgium (BE), Portugal (PT), Austria (AT), Finland (FI) and Slovakia (SK). Our set of countries represents over 95 percent of the population of the euro zone.

The main variable of the analysis is household net wealth, which we divide by the number of adult household members.[2] The HFCS provides a comprehensive measure of household wealth including the value of the household's self-owned main residence, the value of other real estate

[2]We obtain similar results if we do not divide by the number of adult household members. For inequality measurement, it appears appropriate to apply some household size correction, otherwise there would be perfect equality between two households of which one is a single household owning 1 million euros and the other one is a four person household owning the same amount.

property, the value of the household's vehicles, the value of business wealth as well as the value of other financial or non-financial assets minus the household's liabilities.[3] We transform all monetary values into 2017 euros. In addition to our dependent variable, we consider household covariates such as the age and education of the household reference person, the number of children and employed persons per household as well as equivalized household income (in terms of relative income positions within our overall sample including all eleven countries). Throughout our analysis, we make full use of the HFCS sampling weights and multiply imputed values for missing wealth components (HFCS 2020). Table 1 provides basic sample information for the most recent wave 2017.

Table 1 – Descriptive statistics, 2017

	DE	ES[a]	FR	IT	GR	NL	BE	PT	AT	FI	SK
Mean wealth[b]	139890	138073	142158	119947	48948	107870	201295	82781	137705	125577	48298
Median wealth[b]	44070	64681	70040	68250	30315	40612	115167	37334	47665	68254	30966
Proportion of households with											
Homeownership	.439	.803	.578	.684	.720	.574	.693	.744	.459	.662	.888
Other real estate	.224	.398	.224	.206	.387	.061	.189	.292	.130	.316	.280
Business wealth	.095	.140	.094	.143	.178	.041	.110	.148	.073	.096	.150
Risky assets[c]	.204	.146	.172	.084	.012	.156	.276	.056	.121	.412	.057
Inheritance[d]	.163	.282	.468	-	.012	.151	.310	.290	.290	.475	.290
Debt/assets>.1	.334	.356	.298	.125	.133	.519	.340	.347	.199	.454	.223
Age reference person											
<35 years	.192	.093	.160	.074	.095	.184	.121	.098	.150	.218	.122
35-49 years	.244	.331	.267	.278	.263	.265	.294	.296	.262	.227	.338
50-64 years	.281	.277	.272	.288	.295	.282	.289	.282	.283	.263	.301
≥65 years	.282	.297	.299	.358	.346	.268	.294	.322	.303	.290	.237
Education reference person											
Lower	.101	.520	.303	.515	.381	.241	.227	.648	.128	.245	.089
Upper secondary	.561	.162	.399	.351	.377	.380	.309	.155	.633	.423	.673
Tertiary	.337	.316	.297	.133	.240	.377	.462	.195	.237	.330	.236
Household structure and employment											
#children in hh	.358	.448	.496	.383	.422	.417	.461	.436	.369	.401	.518
#employed/adult	.580	.428	.474	.453	.397	.529	.483	.501	.532	.466	.562
Income position[e] in pooled DE/ES/FR/IT/GR/NL/BE/PT/AT/FI/SK sample											
1st quartile	.168	.441	.188	.384	.627	.160	.105	.666	.095	.094	.804
2nd quartile	.214	.260	.316	.276	.269	.152	.236	.183	.235	.249	.143

[3]The HFCS does not include information on pension entitlements. These may be an important part of wealth accumulation, but they also differ markedly from other wealth components in terms of liquidity.

3rd quartile	.249	.175	.313	.218	.081	.268	.270	.089	.355	.303	.036
4th quartile	.367	.122	.181	.120	.020	.417	.387	.060	.313	.352	.015
Observations	4942	6120	13685	7420	3007	2556	2329	5924	3072	10210	2179

Source: HFCS, 2014, 2017. Weighted data. Average over 5 implicates. Notes: [a]2014, [b]Net wealth per household adult
[c]Shares, mutual funds and managed accounts, [d]Variable not available for Italy, [e]Net equivalized income

The numbers in table 1 show that, in 2017, many of the countries considered shared similar levels of *mean wealth* per household adult. Notable exceptions were Greece, Portugal and Slovakia with significantly lower levels of mean wealth, as well as Belgium with a particularly high level of mean wealth per household adult. The second row of table 1 shows that there was considerably more heterogeneity in *median wealth* across euro area countries, pointing to marked differences in *wealth inequality* across countries. The countries with the largest gaps between mean and median wealth were Germany, the Netherlands and Austria. These turn out to be the countries with the highest levels of wealth inequality which we analyze in more detail below.

The rest of table 1 shows further marked differences in household characteristics, only some of which turn out to be major determinants of differences in wealth inequality and differences in the shape of wealth distributions across countries. As we show below, the main determinants of such differences are differential homeownership rates and differences in the income position of the population of a country with respect to the pooled income distribution of all countries. As to the former, the country with the lowest percentage of homeowners in the population is Germany (.439), closely followed by Austria (.459). France and the Netherlands range in the middle (.578 and .574), while a number of countries share homeownership rates between .662 and .744 (Finland, Italy, Belgium, Greece and Portugal). With .803 and .888, Spain and Slovakia exhibit the highest percentage of homeowners.

The other factor that turns out to be relevant for cross-country comparisons is differences in the income position of a country with respect to the European level, but only if the respective country ranges significantly *below* the European level in the sense that a majority of the population is concentrated in the first two quartiles of the European income distribution. This is in particular the case for Greece, Portugal and Slovakia (see lower panel of table 1).

3 Graphical representation of the wealth distribution

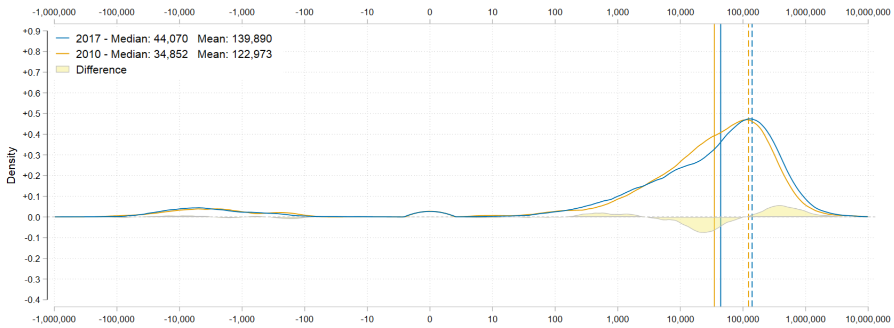
One of the goals of this study is to investigate differences of the wealth distribution across countries not only numerically but also graphically. It is well-known that the wealth distribution is notoriously difficult to represent graphically. The three features that characterize the wealth distribution (Jenkins and Jänti 2005), and that render its graphical representation difficult are: i) the potential existence of negative values, ii) the possibility of excess zeros, and iii) the typically extremely long right-hand tail. In view of these difficulties – which pose a problem to conventional histograms and kernel density estimates – the literature has often resorted to graphs of the cumulative distribution function or the Lorenz curve whose interpretation is not straightforward (e.g., Cowell and Van Kerm 2015). One of the aims of this paper is to propose a compact graphical exposition of the wealth distribution that addresses all of the above difficulties while retaining graphical interpretability across the whole range of wealth values. One of the benefits of the representation is its use in cross-country comparisons of the *shape* of the wealth distribution as we show below. Our graphical exposition of the wealth distribution is related but distinct from attempts to find suitable transformations of wealth values in econometric models (for an overview, see Ravallion 2017). To our best knowledge, these kind of transformations have not been used before for representing the wealth distribution graphically.

Our representation is based on the simple transformation

$$g(y) = \begin{cases} -\log_{10}(-y) & y < -1 \\ 0 & -1 \leq y \leq 1 \\ +\log_{10}(+y) & 1 < y \end{cases} \tag{1}$$

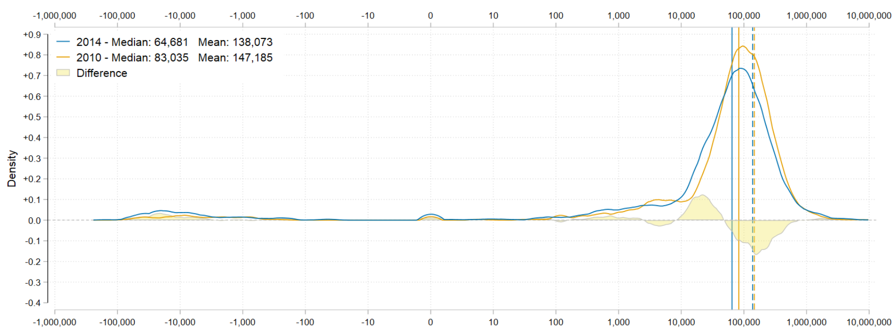
where y is wealth. Depending on the data, other logarithms may be used, but we found $\log_{10}$ convenient for our purposes. In figures 1 to 3, we illustrate our graphical representation of the wealth distribution focussing on three countries whose wealth distributions are representative for the group of countries with low homeownership rates (Germany), high homeownership rates (Spain) as well as moderate homeownership rates (France). The full set of graphs for all countries is provided in the supplementary appendix.

Figure 1 – Distribution of net wealth in Germany



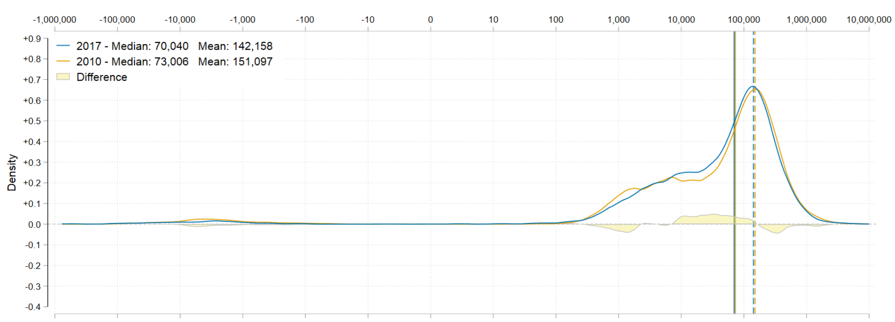
Source: HFCS, 2010, 2017. Density of transformed wealth values. Vertical lines: mean (dashed), median (solid)

Figure 2 – Distribution of net wealth in Spain



Source: HFCS, 2010, 2014. Density of transformed wealth values. Vertical lines: mean (dashed), median (solid)

Figure 3 – Distribution of net wealth in France



Source: HFCS, 2010, 2017. Density of transformed wealth values. Vertical lines: mean (dashed), median (solid)

The proposed graphical representation of the wealth distribution has the following useful features.[4]

(i) The graph nicely separates the three parts of the distribution (negative, positive, zero) which are often completely blurred in density estimates based on smoothing. This clear separation will be even more useful for wealth data with a higher proportion of zeros than in our survey, which often result from surveying household wealth in a less comprehensive way (e.g., no information on vehicles or smaller valuables). An additional option in (1) would be to replace the thresholds -1 and 1 by larger values, e.g. -1000 and 1000 to separate the 'have nots' (wealth below 1000 euros) from those with 'significant' wealth (more than 1000 euros). In this case, the graph will clearly show the size of the group of households that have 'nothing' which is often of particular interest (e.g., in global wealth analyses where wealth is close to zero for a large part of the world population).

(ii) The transformation is strictly monotonic (except for statements inside the narrow interval between the two thresholds which are practically irrelevant). As a consequence, the probability mass for a given range of wealth values in figures 1 to 3 can be interpreted in the usual way. For example, a certain fraction of the population has negative wealth as represented by the area under the respective part in the graph. Similarly, median wealth is the wealth value for which 50 percent of the area under the density lies on the left-hand side, and 50 percent on the right hand side.

(iii) The graph presents an 'analytical' yet comprehensive picture of the distribution in the sense that it forces the typically extremely spread-out tail of the distribution into a limited interval, making it easy to grasp the typical range of wealth values. This is much harder for untransformed wealth values which often do not fit well into a single picture.[5]

[4]The kernel density estimates use an Epanechnikov kernel. For the sake of comparability, we use a common bandwidth of .1 for all countries. The density plots are based on wealth values that were averaged across the multiply imputed wealth values at the household level (but plots would look exactly the same if only one particular implicate was used).

[5]Note that the user may choose different log bases depending on how compressed the resulting graph should be. One may also select different bases for positive or negative values in order to 'tune' the composition of the resulting graph (e.g., to make the part of the graph representing negative values smaller; for simplicity, we present

(iv) In the transformation chosen by us, the mean of the distribution typically coincides very well with the peak of the density plot, allowing the reader to form a quick visual estimate of the mean. This is particularly useful if two different distributions are compared (of course, this property depends on the type of log chosen for the transformation).

(v) The compact form of the plot makes it easy to identify country clusters sharing similar distributional shapes as can be verified in the full set of graphs provided in the supplementary appendix. In particular, it turns out that the shape of the distribution is strongly related to the proportion of households with homeownership as shown in the third row of table 1. More precisely, the graphs for countries with the highest proportion of homeowners (.888 in Slovakia, .803 in Spain, .744 in Portugal, .720 in Greece) exhibit very pronounced peaks, while the peak is more and more supplemented by additional mass below the mean for countries with more moderate proportions of homeowners (.693 in Belgium, .684 in Italy, .662 in Finland, .578 in France, .574 in the Netherlands). The shape for the countries with the lowest proportions of homeowners (.439 in Germany and .459 for Austria) is very distinct from that of countries with many homeowners, displaying a much higher fraction of moderate wealth values below the mean and a left-skewed, almost triangular appearance. We will show below that counterfactually altering the degree of homeownership in a country 'morphs' the wealth distribution from a pronounced peaked shape into a left-skewed one that resembles that of countries with low homeownership like Germany and Austria.

How does the proposed transformation compare to other transformations used in the literature? In principle, the inverse hyperbolic sine (IHS) transformation $g(y) = \sinh^{-1}(y) = \ln(y + (y^2+1)^{0.5})$ (Johnson 1949; Burbidge et al. 1988) may serve similar purposes as the transformation proposed above. It is also defined over the whole range of real values and compresses very positive/very negative values. To our best knowledge, it has not been used for graphical purposes before as in our proposal. Moreover, the arcane nature of the IHS function makes interpretation difficult and dependent on the units of measurement (Aihounton et al. 2021). By contrast, the interpretation of the logarithmic metric is well-known, and it is invariant to changes in measurement units (up to a constant). As pointed out by Ravallion (2017), transformations such as the IHS or the one

the most simple variant here).

proposed in this paper violate global concavity, which may be problematic if one is interested in welfare analysis. Ravallion (2017) develops a transformation that obeys concavity over the whole range, while preserving some of the desirable properties above. The main purpose of the transformation proposed here is graphical rather than welfare analysis, so that non-concavity is no disadvantage in the present context. Moreover, as shown by Ravallion (2017), any globally concave transformation will have to 'spread out' negative values which appears undesirable for graphical purposes.

4 Analysis of cross-country differences in wealth inequality

The previous section has identified differences in homeownership across countries as an important potential source of cross-country differences. The aim of this section is to investigate in more detail to what extent homeownership can account for these differences, and to what extent other factors have to be taken into account. We start with the state-of-the-art hybrid RIF-decomposition method described in Firpo et al. (2018) and show that it identifies the main sources of cross-country differences in wealth inequality, but that it breaks down if differences in the distribution of characteristics between countries are large (e.g., in homeownership rates). We then demonstrate how conditional reweighting (DiNardo et al., 1996) can be used in the given context to nearly fully account for cross-country differences by counterfactually changing homeownership rates, and, for some countries, incomes. We will show that this not only applies to numerical differences in wealth inequality but to differences in the *shape* of the wealth distribution across countries.

4.1 Hybrid RIF-decomposition

The Recentered-Influence-Function (RIF) approach proposed by Firpo et al. (2009) and Fortin et al. (2011) is based on the recentered influence function defined as $RIF\,(y,\nu) = \nu + IF\,(y;\nu)$ which integrates to the statistic of interest $\nu\,(F_Y) = \int RIF\,(y;\nu)\,dF(y) = E(RIF\,(y;\nu))$ (the Gini coefficient in our case), where F_Y is the distribution function of the dependent variable (net wealth in our case). In this decomposition, the RIF is modeled as a linear function of the explanatory variables $X = (X_1, \ldots, X_k)$, i.e. $E[RIF(Y;\nu)|X] = X\gamma$, where γ can be estimated by means of OLS. The statistic of interest is then obtained as $\nu(F_Y) = E(E[RIF(Y;\nu)|X]) = E(X)\gamma$, using the sample counterparts estimated by OLS (i.e. $\hat{\nu} = \bar{X}\hat{\gamma}$).

As shown in Firpo et al. (2009), the coefficients γ of the RIF regression represent the effects of shifts in the distribution of the components of $X = (X_1, \ldots, X_k)$ on the statistic of interest. In the given context, this answers the question how different wealth inequality as measured by the Gini $\nu(F_Y)$ in a given country would be if the distribution of household characteristics of this country was marginally changed into the direction of the distribution of characteristics of another country (= reference country), and how individual characteristics $X_1, \ldots, X_k$ contribute to this difference (detailed decomposition). On the other hand, the parameters γ represent the 'coefficients effects' reflecting how, in a given country, the distribution of characteristics X translates into wealth inequality $\nu(F_Y)$.

The hybrid decomposition method introduced by Firpo et al. (2018) recognizes the fact that the original RIF-decomposition introduced by Fortin et al. (2011) heavily relies on local approximations and linearity assumptions which may be questionable if two very different populations are compared. This appears particularly relevant for cross-country comparisons in which the countries compared typically differ considerably with respect to their covariate distributions (see table 1).

The basic idea of the hybrid RIF-decomposition is to create an artificial intermediate case 01 which represents country 0 but with its distribution of covariates X reweighted to that of reference country 1. For this step, reweighting is used for the whole covariate distribution of country 0 based on DiNardo et al. (1996) (see below). In a second step, two separate Oaxaca-Blinder decompositions are carried out on the recentered influence functions of all three three entities 0, 01 and 1 in order to decompose the overall difference in wealth inequality $\nu(F_{Y,1}) - \nu(F_{Y,0})$ between country 1 and country 0 into four components:

$$\nu(F_{Y,1}) - \nu(F_{Y,0}) = \underbrace{\left(\bar{X}_{01} - \bar{X}_0\right)\hat{\gamma}_0^{\nu}}_{\Delta_{X,p}^{\nu}} + \underbrace{\bar{X}_{01}\left(\hat{\gamma}_{01}^{\nu} - \hat{\gamma}_0^{\nu}\right)}_{\Delta_{X,c}^{\nu}} + \underbrace{\bar{X}_1\left(\hat{\gamma}_1^{\nu} - \hat{\gamma}_{01}^{\nu}\right)}_{\Delta_{S,p}^{\nu}} + \underbrace{\left(\bar{X}_1 - \bar{X}_{01}\right)\hat{\gamma}_{01}^{\nu}}_{\Delta_{S,c}^{\nu}} \quad (2)$$

In this equation, the detailed *pure characteristics effects* $\Delta^{\nu}_{X,p}$ reflects the contribution of differences in the distribution of particular covariates (or groups of covariates) to the difference in wealth inequality between country 1 and country 0. The *specification error* $\Delta^{\nu}_{X,c}$ describes the differences in estimated RIF coefficients in the sample of country 0 and the coefficients estimated in the sample of country 0 whose distribution was reweighted to that of country 1. If the specification error is significantly different from zero, this means that covariate distributions in countries 0 and 1 are too different to be represented by a common linear RIF-approximation. The *pure coefficients effect* $\Delta^{\nu}_{S,p}$ describes the contribution of how different countries 0 and 1 are in how they translate household characteristics into wealth inequality. Finally, the *reweighting error* $\Delta^{\nu}_{S,c}$ reflects differences in the means of covariates in countries 1 and 0 whose distribution was reweighted to that of reference country 1. The reweighting error will be close to zero if reweighting is successful in changing the distribution of covariates in country 0 to that of country 1 (which is usually no problem).

The hybrid RIF-decomposition (2) (which is called hybrid because it combines RIF with reweighting) has the virtue of containing an aggregate decomposition of the inequality difference $\nu\left(F_{Y,1}\right) - \nu\left(F_{Y,0}\right)$ into an aggregate characteristics effect Δ^{ν}_{X} and an aggregate coefficients effect Δ^{ν}_{S}:

$$
\begin{aligned}
\nu\left(F_{Y,1}\right) - \nu\left(F_{Y,0}\right) &= \left[\underbrace{\left(\bar{X}_{01} - \bar{X}_{0}\right)\hat{\gamma}^{\nu}_{0}}_{\Delta^{\nu}_{X,p}} + \underbrace{\bar{X}_{01}\left(\hat{\gamma}^{\nu}_{01} - \hat{\gamma}^{\nu}_{0}\right)}_{\Delta^{\nu}_{X,c}}\right] + \left[\underbrace{\bar{X}_{1}\left(\hat{\gamma}^{\nu}_{1} - \hat{\gamma}^{\nu}_{01}\right)}_{\Delta^{\nu}_{S,p}} + \underbrace{\left(\bar{X}_{1} - \bar{X}_{01}\right)\hat{\gamma}^{\nu}_{01}}_{\Delta^{\nu}_{S,c}}\right] \\
&= \left[\underbrace{\left(\bar{X}_{01}\hat{\gamma}^{\nu}_{01} - \bar{X}_{0}\hat{\gamma}^{\nu}_{0}\right)}_{\Delta^{\nu}_{X}}\right] + \left[\underbrace{\left(\bar{X}_{1}\hat{\gamma}^{\nu}_{1} - \bar{X}_{01}\hat{\gamma}^{\nu}_{01}\right)}_{\Delta^{\nu}_{S}}\right] \qquad (3) \\
&= \left[\nu\left(F_{Y,01}\right) - \nu\left(F_{Y,0}\right)\right] + \left[\nu\left(F_{Y,1}\right) - \nu\left(F_{Y,01}\right)\right] \qquad (4)
\end{aligned}
$$

In (4), $F_{Y,01}$ is the wealth distribution of country 0 with the characteristics distribution reweighted to that of country 1. This distribution is given by

$$F_{Y,01} = \int F_{Y,0}(y|x)\, dF_{X,1}(x) = \int F_{Y,0}(y|x)\, \psi_x\, dF_{X,0}(x) \qquad (5)$$

with the reweighting factor ψ_x being defined by

$$\psi_x = \frac{dF(\text{country} = 1|\text{country} = 0 \text{ or } 1; x)}{dF(\text{country} = 0|\text{country} = 0 \text{ or } 1; x)} \frac{dF(\text{country} = 0|\text{country} = 0 \text{ or } 1)}{dF(\text{country} = 1|\text{country} = 0 \text{ or } 1)} \tag{6}$$

(in which all quantities can be estimated by logit models and sample fractions). Equation (3) verifies that the hybrid RIF-decomposition (2) decomposes the aggregate characteristics effect Δ_X^ν into the pure characteristics effect and the specification error ($= \Delta_{X,p}^\nu + \Delta_{X,c}^\nu$), and the coefficients effect $\Delta_{S,p}^\nu$ into the pure coefficients effect and the reweighting error ($= \Delta_{S,p}^\nu + \Delta_{S,c}^\nu$).

Table 2 presents the result of the hybrid RIF-decomposition for our set of countries. Given our special interest in the role of homeownership, we chose the country with the lowest level of homeownership ($=$ DE) as the reference country in order to study what happens to wealth inequality when homeownership is changed towards a lower level.[6] The first row of table 2 shows the wealth inequality in each country as measured by the Gini coefficient, while second row displays the Gini for the given country when all its characteristics are reweighted towards the German case. The third row presents wealth inequality in the reference country Germany. As indicated above, wealth inequality is lower than in Germany in all of the countries, except for the Netherlands where wealth inequality is higher than in any other country considered by us.

Panel (b) of table 2 presents the aggregate decomposition of inequality differences into characteristics and coefficients effects as defined in equation (3). It turns out that differences in wealth inequality are more or less fully accounted for by differences in household characteristics (except for the Netherlands, which is the only country with a significant coefficients effect, Portugal, for which effects are very imprecisely estimated, and Austria, for which differences in characteristics are statistically significant, but whose inequality difference with the reference country is close to zero in the first place). The fact that most cross-country differences in wealth inequality are explained by differences in household characteristics raises the question *which* household

[6] In all of the following tables, estimates and standard errors accounting for multiple imputation were computed as follows: let $(\hat{\theta}_i, \hat{\sigma}_i^2)$ denote the point estimates and estimated sampling variances from $i = 1, \dots, M$ imputed implicates, then final point estimates and sample variances are calculated as $\bar{\theta} = M^{-1} \sum_{i=1}^M \hat{\theta}_i$ and $\bar{\sigma}^2 = M^{-1} \sum_{i=1}^M \hat{\sigma}_i^2 + (M-1)^{-1} \sum_{i=1}^M (\hat{\theta}_i - \bar{\theta})^2$ (Rubin 1987). Point estimates of the hybrid RIF-decomposition can be computed using Rios-Avila (2020). Sampling variance were computed using bootstrap in which we resample simultaneously from all countries together (500 replications).

characteristics explain cross-country differences.

Table 2 – Hybrid RIF-decomposition of wealth inequality differences, 2017

	ES[a]	FR	IT	GR	NL	BE	PT	AT	FI	SK
(a) Wealth inequality $\nu\left(F_{Y,0}\right)$, $\nu\left(F_{Y,01}\right)$, $\nu\left(F_{Y,1}\right)$										
Gini country	.680	.672	.616	.615	.781	.618	.674	.722	.654	.544
	(.014)	(.007)	(.007)	(.016)	(.017)	(.015)	(.011)	(.026)	(.006)	(.018)
Gini reweighted	.782	.744	.726	.733	.824	.714	.710	.763	.755	.753
	(.022)	(.014)	(.013)	(.047)	(.042)	(.017)	(.042)	(.023)	(.013)	(.071)
Gini target (DE)	.754	.737	.737	.737	.737	.737	.737	.737	.737	.737
	(.011)	(.012)	(.012)	(.012)	(.012)	(.012)	(.012)	(.012)	(.012)	(.012)
(b) Aggregate decomposition $\nu\left(F_{Y,1}\right)-\nu\left(F_{Y,0}\right)=\Delta_X^\nu+\Delta_S^\nu$										
Difference	.074***	.065***	.122***	.122***	-.044**	.119***	.063***	.015	.083***	.193***
	(.017)	(.014)	(.014)	(.044)	(.021)	(.018)	(.016)	(.028)	(.014)	(.022)
Characteristics	.102***	.071***	.110***	.117***	.042	.095***	.036	.041***	.100***	.209***
	(.023)	(.011)	(.012)	(.044)	(.037)	(.014)	(.040)	(.014)	(.012)	(.072)
Coefficients	-.028	-.006	.012	.005	-.086*	.024	.027	-.025	-.017	-.015
	(.023)	(.018)	(.017)	(.049)	(.044)	(.020)	(.044)	(.025)	(.017)	(.070)
(c) Characteristics effect $\Delta_X^\nu=\Delta_{X,p}^\nu+\Delta_{X,c}^\nu$										
Total	.102***	.071***	.110***	.117***	.042	.095***	.036	.041***	.100***	.209***
	(.023)	(.011)	(.012)	(.044)	(.037)	(.014)	(.040)	(.014)	(.012)	(.072)
Pure	.163***	.094***	.161***	.379***	.062	.113***	.326***	.057***	.108***	.658*
	(.031)	(.009)	(.015)	(.077)	(.042)	(.014)	(.048)	(.012)	(.011)	(.358)
Spec. error	-.061*	-.023***	-.051***	-.262***	-.020	-.017***	-.290***	-.016	-.008	-.449
	(.034)	(.005)	(.010)	(.084)	(.030)	(.007)	(.054)	(.012)	(.006)	(.318)
(d) Detailed pure characteristics effects $\Delta_{X,p}^\nu$										
Homeownership[b]	.113***	.060***	.103***	.160***	.076***	.101***	.143***	.015**	.105***	.207***
	(.014)	(.006)	(.010)	(.037)	(.013)	(.012)	(.015)	(.007)	(.009)	(.053)
Other real estate[b]	.010*	.000	.005**	.002	.029	.000	-.001	.017**	.009***	-.001
	(.006)	(.000)	(.002)	(.004)	(.022)	(.003)	(.001)	(.008)	(.002)	(.004)
Business wealth[b]	-.002	.000	.001	.001	.012	-.005	-.008	.011	-.002	.001
	(.002)	(.000)	(.001)	(.003)	(.015)	(.004)	(.006)	(.007)	(.002)	(.012)
Risky assets[b]	.013*	.001*	.014**	.043	-.004	.006*	.054**	-.013	.002	.006
	(.007)	(.001)	(.006)	(.045)	(.003)	(.004)	(.025)	(.008)	(.002)	(.025)
Inheritance[b]	.002	.013***	-[c]	-.008	-.001	.007	.001	.001	.006	.004
	(.004)	(.004)	(-)	(.009)	(.003)	(.005)	(.004)	(.005)	(.004)	(.009)
Debt/assets>.1[b]	-.002	.005***	.021***	.031*	-.052***	-.001	-.002	.010*	-.008***	.022
	(.003)	(.002)	(.006)	(.017)	(.011)	(.002)	(.003)	(.005)	(.003)	(.016)
Age[d]	.015**	.003**	.004	.004	.005	.005	.005	.002	.006*	-.003
	(.006)	(.001)	(.002)	(.007)	(.004)	(.003)	(.006)	(.002)	(.003)	(.013)
Education[d]	-.013	.000	.016**	-.006	-.013*	.005	-.043**	.006	.002	.013
	(.014)	(.002)	(.007)	(.009)	(.007)	(.009)	(.021)	(.005)	(.002)	(.014)
#children in hh	.000	.001	.000	.001	.001	.001	-.002	(.005)	.000	.001
	(.002)	(.001)	(.000)	(.003)	(.002)	(.001)	(.003)	(.002)	(.000)	(.004)

#employed/adult	-.008	-.003	-.009**	-.014	.003	-.008	-.005	.002	-.011***	.000
	(.007)	(.003)	(.004)	(.012)	(.004)	(.005)	(.005)	(.003)	(.004)	(.005)
Income^d	.036	.015***	.006	.165**	.006	.002	.185***	.008**	.000	.408
	(.025)	(.003)	(.009)	(.071)	(.005)	(.004)	(.056)	(.004)	(.002)	(.326)
(e) Coefficients effect $\Delta_S^\nu = \Delta_{S,p}^\nu + \Delta_{S,c}^\nu$										
Total	-.028	-.006	.012	.005	-.086*	.024	.027	-.025	-.017	-.015
	(.023)	(.018)	(.017)	(.049)	(.044)	(.023)	(.044)	(.025)	(.017)	(.070)
Pure	-.023	.008	.007	.026	-.062*	.036*	.019	-.018	.001	.025
	(.019)	(.017)	(.006)	(.035)	(.037)	(.019)	(.029)	(.027)	(.015)	(.075)
Reweighting error	-.005	-.014***	.007	-.021	-.024**	-.012*	.009	-.007	-.019**	-.040
	(.015)	(.004)	(.006)	(.048)	(.012)	(.007)	(.027)	(.006)	(.009)	(.078)
(f) Detailed pure coefficients effects $\Delta_{S,p}^\nu$										
Homeownership^b	-.046**	.010	.027*	.005	.021	-.018	-.062	.025	.049***	.016
	(.024)	(.016)	(.015)	(.037)	(.034)	(.017)	(.048)	(.031)	(.013)	(.053)
Other real estate^b	.019	.017*	.006	-.006	.016	.026	-.003	-.005	.041***	.009
	(.012)	(.0091)	(.008)	(.029)	(.017)	(.011)	(.022)	(.012)	(.009)	(.039)
Business wealth^b	.019**	.022***	.025***	.029***	.008	.001	.013	-.010	.010	.012
	(.009)	(.007)	(.007)	(.011)	(.014)	(.010)	(.012)	(.014)	(.009)	(.021)
Risky assets^b	-.019	-.012	-.017	-.002	-.030**	.016	.006	.0120	-.023***	.000
	(.013)	(.008)	(.008)	(.025)	(.014)	(.010)	(.021)	(.019)	(.008)	(.043)
Inheritance^b	-.012	-.009	-^{c}	.029	.022*	-.001	-.051**	-.015	-.010*	.009
	(.012)	(.006)	(-)	(.018)	(.012)	(.009)	(.021)	(.017)	(.005)	(.034)
Debt/assets>.1^b	.010	-.003	-.001	-.042	-.020	.018	.033*	.012	-.017	-.010
	(.015)	(.017)	(.011)	(.031)	(.015)	(.012)	(.020)	(.018)	(.011)	(.042)
Age^d	-.004	.001	.001	.000	-.004	.002	.002	.000	.000	-.025*
	(.006)	(.002)	(.003)	(.005)	(.005)	(.003)	(.005)	(.003)	(.003)	(.014)
Education^d	-.013	-.006	.001	.007	.007	-.011	.001	.001	-.008	.003
	(.008)	(.009)	(.008)	(.015)	(.022)	(.012)	(.016)	(.01)	(.008)	(.017)
#children in hh	.005	.008	-.014	.001	.007	-.001	.003	.008	.000	-.008
	(.011)	(.01)	(.010)	(.015)	-.007	(.007)	(.013)	(.013)	(.005)	(.017)
#employed/adult	-.095*	.011	.026	-.024	-.009	.061**	.015	-.019	.022	-.143
	(.053)	(.023)	(.028)	(.058)	(.033)	(.028)	(.049)	(.038)	(.025)	(.136)
Income^d	.015*	-.001	-.003	.012	-.014*	-.003	.000	-.003	-.013**	-.008
	(.008)	(.005)	(.004)	(.011)	(.008)	(.007)	(.009)	(.006)	(.005)	(.017)
Constant	.104*	-.023	-.040*	.023	-.052*	-.053*	.060	-.024	-.050**	.170
	(.06)	(.022)	(.024)	(.073)	(.029)	(.031)	(.070)	(.038)	(.026)	(.184)

Source: HFCS, 2014, 2017. Reference country: Germany. Bootstrap standard errors in parentheses account for multiply imputed data.

[a]This column 2014, all other columns 2017, [b]Dummy variable indicating presence of asset class, [c]Variable not available for Italy

[d]Combined contribution of respective group of variables shown in table 1

***/**/* = statistically significant at 1%/5%/10%-level

The strength of the RIF-decomposition is that provides such a breakdown of effects characteristic by characteristic (= detailed decomposition). However, this holds only if there are no specification problems, which is called into question by panel (c) of table 2 displaying the aggregate pure characteristics effect and specification error of the decomposition (defined by $\Delta^{\nu}_{X,p}$ and $\Delta^{\nu}_{X,c}$ in equation (2)). It turns out that specification errors are generally statistically significant and often sizable in magnitude. They are the larger the more different the country is from Germany in terms of household characteristics. They are particularly large for Greece, Portugal and Slovakia which were countries singled-out for being the most different from the European average in section 2.

Panel (d) of table 2 shows the detailed pure effects of each characteristic ($\Delta^{\nu}_{X,p}$ in equation (2)). Apart from some minor exceptions, only two characteristics are identified as the main determinants of wealth inequality differences: differences in homeownership and differences in income. However, effects do not add up to the overall characteristics effects because of the large specification error. This is especially true for the countries Greece, Portugal and Slovakia which (in addition to large differences in homeownership) feature large deviations in terms of income from the comparison country Germany. For example, in the Greek case compositional effects in homeownership and income add up to .160 + .165 =.325 Gini points which is almost three times the total characteristics effects of .122. Table A.1 in the appendix provides a detailed breakdown of the specification errors. It shows particularly strong contributions from the constant term, pointing towards general approximation errors of the RIF-function, especially for the three countries Greece, Portugal and Slovakia (but also for Spain).

The decomposition results for the coefficients effect are given in panels (e) and (f) of table 2 ($\Delta^{\nu}_{S,p}$ and $\Delta^{\nu}_{S,c}$; a detailed breakdown of $\Delta^{\nu}_{S,c}$ is provided in table A.1 in the appendix). There are no significant aggregate coefficients effects, except for the Netherlands (with total effect of -.086 Gini points of which -.024 points may be due to reweighting error). The detailed breakdown of coefficient effects in panel (f) indicates a few interesting effects which, however, appear small when compared to the substantial compositional effects in panels (c) and (d). For example, there appear to be differences compared to the German case in how the population homeownership translates into wealth inequality in Spain and in Austria. In Spain, a given homeownership rate translates *more* into wealth inequality than in Germany (-.046), whereas it translates *less* into wealth inequality in Austria (.049). Similar statements apply to business wealth, which would lead to slightly higher wealth inequality in Spain, France, Italy and Greece, if its distributional impact on wealth inequality was as strong as in Germany. In some cases, there are small but statistically significant reweighting errors which, however, do not have the potential to destroy the interpretation of the coefficients effect. A detailed breakdown of reweighting errors is provided in the lower panel of table A.1 in the appendix, indicating effects close to zero and mostly statistically insignificant.

Taken together, the conclusion from the RIF-decomposition is that differences in wealth inequality between euro area countries can be explained by differences in household characteristics (= characteristics effects) but not by how household characteristics translate into wealth inequality (= coefficients effects). The detailed results of the RIF-decomposition suggest a leading role for differences in homeownership rates and income differences, but the results are technically invalid due the large amounts of specification error.

4.2 Reweighting analysis

Given the inconclusive findings in the previous section, our strategy in this section is to look for alternative evidence on how given household characteristics contribute to cross-country differences in wealth inequality. For this purpose, we use conditional reweighting introduced by DiNardo et al. (1996).[7] Reweighting is a method that predates RIF-analysis but that is based on much less restrictive assumptions (it only requires mild ignorability assumptions, see Firpo et al. 2011). A virtue of reweighting is that it is capable of providing graphical results for which we use our graphical device as developed in section 3.[8]

Reweighting with respect to conditional homeownership

In particular,

$$F^{cf}_{Y,0,h} = \int_{x'} \int_{h} F_{Y|H,X',0}(y|h,x')\, dF_{H|X',1}(h|x')\, dF_{X',0}(x') \tag{7}$$

$$= \int_{x'} \int_{h} F_{Y|H,X',0}(y|h,x')\, \psi_{h|x'}\, dF_{H|X',0}(h|x')\, dF_{X',0}(x') \tag{8}$$

[7] In the context of wealth distributions, reweighting was also used by Bover (2010) and Cowell et al. (2018).

[8] A disadvantage of conditional reweighting is that decompositions may depend on the ordering of the decomposition. This is not an issue in our application as cross-country differences can be more or less completely explained by one factor (homeownership), or two factors (homeownership and income), see below.

is the counterfactual wealth distribution that would prevail in country 0, if its conditional homeownership rate $dF_{H|X',0}(h|x')$ (i.e., the fraction of homeowners in narrow population subgroups x', where x' denotes all other household characteristics except homeownership) was changed to the German one ($=dF_{H|X',1}(h|x')$). The corresponding reweighting factor $\psi_{h|x'}$ is defined by

$$\psi_{h|x'} = \frac{dF(\text{country} = 1|\text{country} = 0 \text{ or } 1; h, x')}{dF(\text{country} = 0|\text{country} = 0 \text{ or } 1; h, x')} \frac{dF(\text{country} = 0|\text{country} = 0 \text{ or } 1, x')}{dF(\text{country} = 1|\text{country} = 0 \text{ or } 1, x')}. \quad (9)$$

Reweighting with respect to conditional homeownership and income

Alternatively, we can change both conditional homeownership *and income* to that of the reference country, i.e.

$$F^{cf}_{Y,0,h,i} = \int_{x''} \int_{h,i} F_{Y|H,I,X'',0}(y|h,i,x'')\, dF_{H,I|X'',1}(h,i|x'')\, dF_{X'',0}(x'') \quad (10)$$

$$= \int_{x''} \int_{h,i} F_{Y|H,I,X'',0}(y|h,i,x'')\, \psi_{h,i|x''}\, dF_{H,I|X'',0}(h,i|x'')\, dF_{X'',0}(x'') \quad (11)$$

is the counterfactual wealth distribution that would prevail in country 0, if its distribution of homeownership h and income i conditional on other characteristics x'' ($=dF_{H,I|X'',0}(h,i|x'')$) was changed to the German one ($=dF_{H,I|X'',1}(h,i|x'')$). The reweighting factor in this case is

$$\psi_{h,i|x''} = \frac{dF(\text{country} = 1|\text{country} = 0 \text{ or } 1; h, i, x'')}{dF(\text{country} = 0|\text{country} = 0 \text{ or } 1; h, i, x'')} \frac{dF(\text{country} = 0|\text{country} = 0 \text{ or } 1, x'')}{dF(\text{country} = 1|\text{country} = 0 \text{ or } 1, x'')}. \quad (12)$$

DiNardo et al. (1996) have shown that the counterfactual densities of $F^{cf}_{Y,0,h}$ and $F^{cf}_{Y,0,h,i}$ can be computed by employing the reweighting factors (9) and (12) together with the sample weights in kernel density estimation, which we do for the following graphical results.

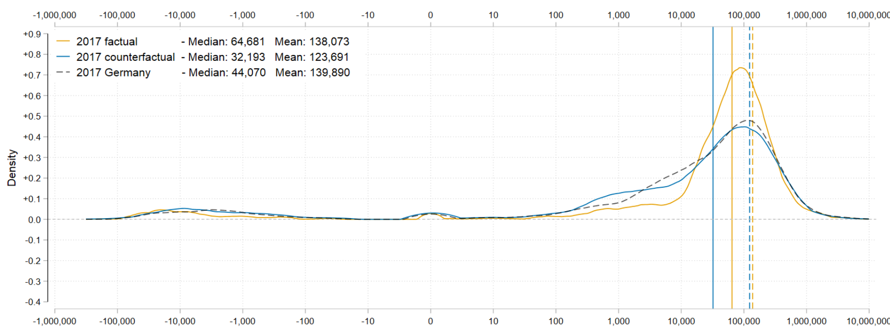
The results of the reweighting analysis are shown in figures 4 to 13. Implanting the low German conditional homeownership into other countries[9] transforms their wealth distribution towards the one observed in Germany. For a number of countries, this works strikingly well (Spain, France, Belgium, Finland). For other countries, we achieve a very good match only after reweighting

[9]More precisely, in each country the fraction of homeowners among households with certain characteristics described by x' is changed to the low German level, preserving the distribution of these characteristics as well the relationship between characteristics and wealth as it is observed in the country considered. In this sense, this identifies the isolated effect of homeownership, leaving everything else as it is in the given country.

in addition with respect to income differences (Italy, Greece, Portugal, Slovakia).[10] For the Netherlands, reweighting with respect to the German homeownership rate also shifts mass to the left-hand side of the mean, but this does not make its wealth distribution more similar to the German one (as already seen above, the wealth distribution of the Netherlands looks quite different from those of other countries). Austria's wealth distribution is similar to the German one from the start and reweighting does not induce much change given the two countries are also very similar in terms of homeownership.

Figure 4 – Spain: counterfactual wealth distribution

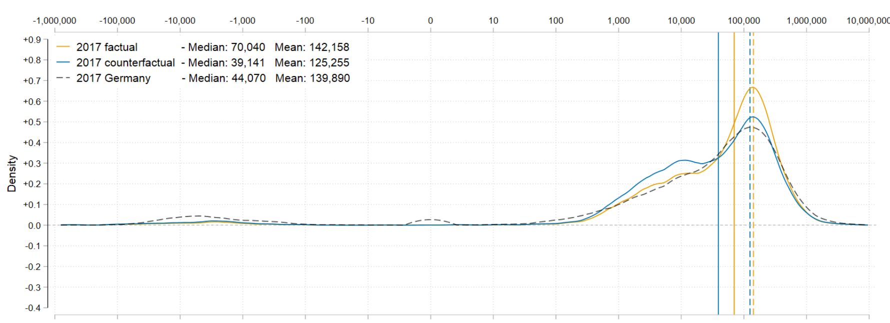
(reweighted w.r.t German conditional homeownership)



Source: HFCS, 2014. Density of transformed wealth values. Vertical lines: mean (dashed), median (solid)

Figure 5 – France: counterfactual wealth distribution

(reweighted w.r.t German conditional homeownership)

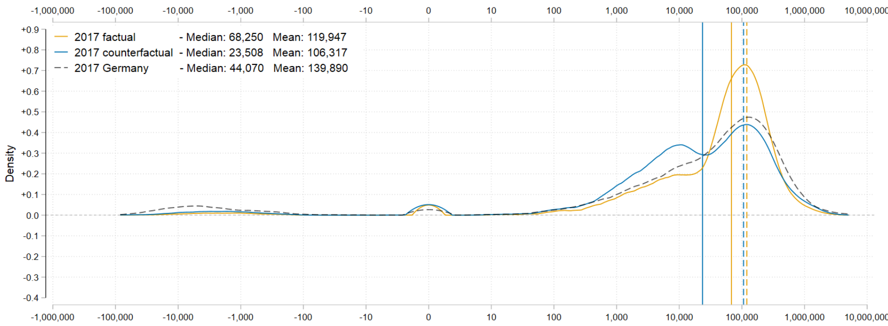


Source: HFCS, 2017. Density of transformed wealth values. Vertical lines: mean (dashed), median (solid)

[10]For the countries for which we only show reweighting results with respect to homeownership, the graphs remain virtually unchanged if we additionally reweight with respect to income differences.

Figure 6 – Italy: counterfactual wealth distribution

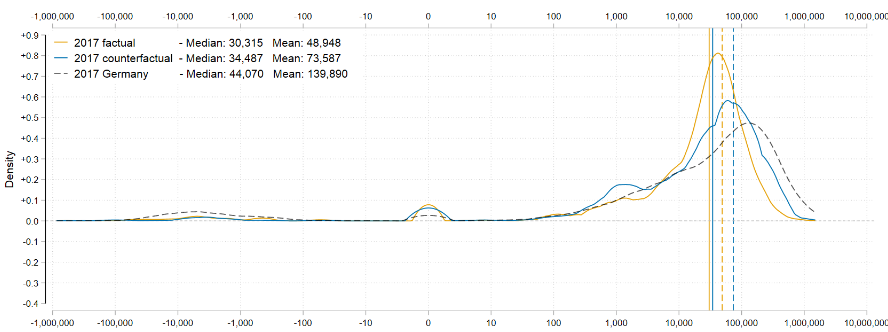
(reweighted w.r.t German conditional *homeownership and income*)



Source: HFCS, 2017. Density of transformed wealth values. Vertical lines: mean (dashed), median (solid)

Figure 7 – Greece: counterfactual wealth distribution

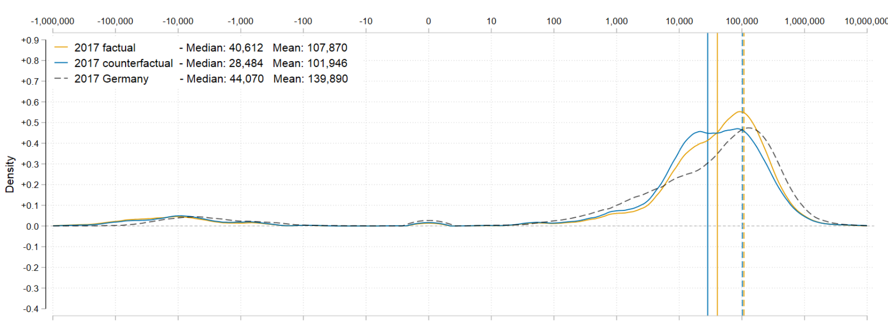
(reweighted w.r.t German conditional *homeownership and income*)



Source: HFCS, 2017. Density of transformed wealth values. Vertical lines: mean (dashed), median (solid)

Figure 8 – Netherlands: counterfactual wealth distribution

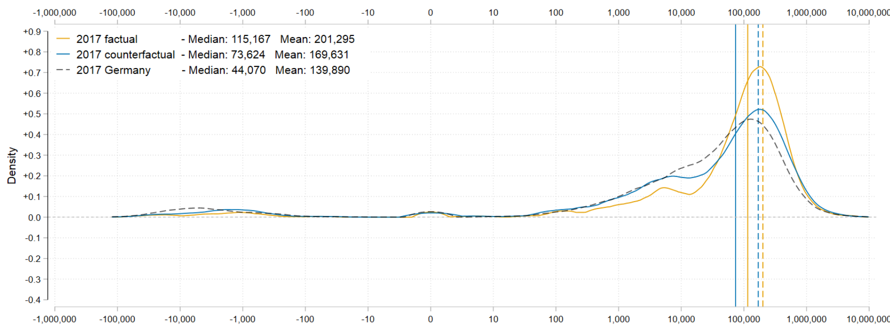
(reweighted w.r.t German conditional homeownership)



Source: HFCS, 2017. Density of transformed wealth values. Vertical lines: mean (dashed), median (solid)

Figure 9 – Belgium: counterfactual wealth distribution

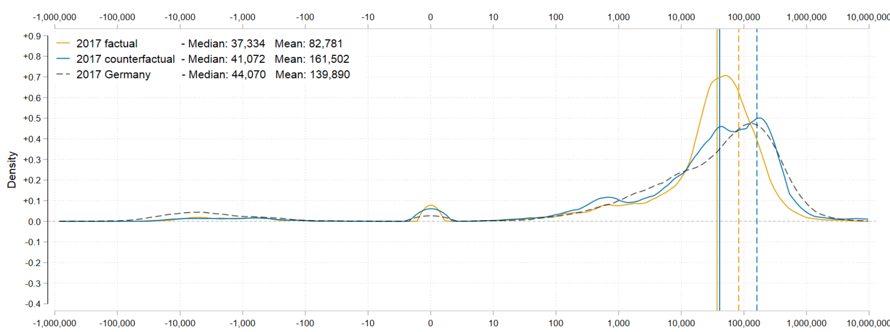
(reweighted w.r.t German conditional homeownership)



Source: HFCS, 2017. Density of transformed wealth values. Vertical lines: mean (dashed), median (solid)

Figure 10 – Portugal: counterfactual wealth distribution

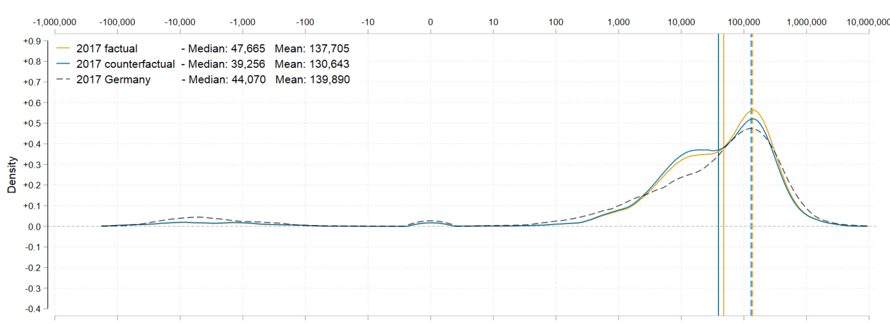
(reweighted w.r.t German conditional *homeownership and income*)



Source: HFCS, 2017. Density of transformed wealth values. Vertical lines: mean (dashed), median (solid)

Figure 11 – Austria: counterfactual wealth distribution

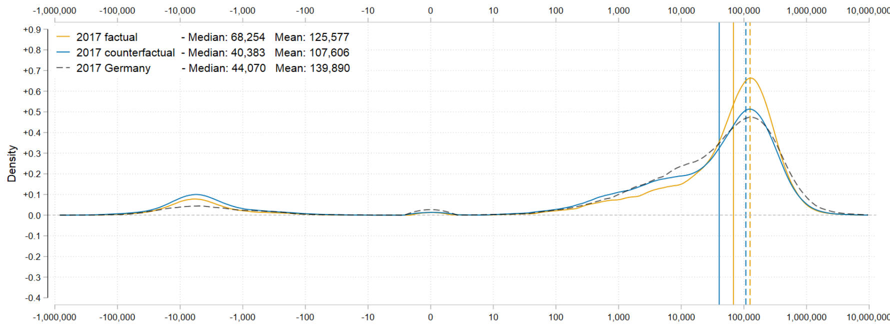
(reweighted w.r.t German conditional homeownership)



Source: HFCS, 2017. Density of transformed wealth values. Vertical lines: mean (dashed), median (solid)

Figure 12 – Finland: counterfactual wealth distribution

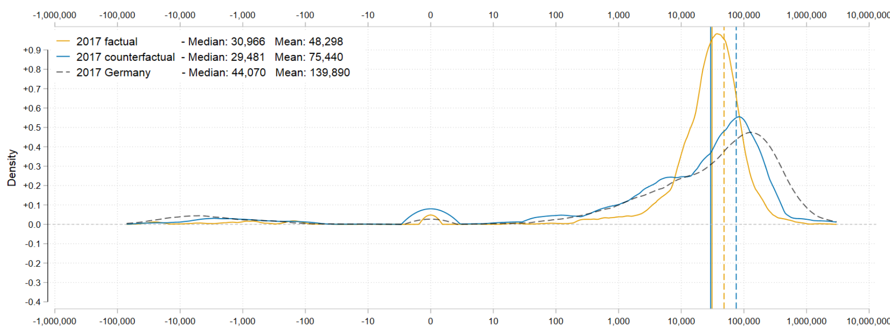
(reweighted w.r.t German conditional homeownership)



Source: HFCS, 2017. Density of transformed wealth values. Vertical lines: mean (dashed), median (solid)

Figure 13 – Slovakia: counterfactual wealth distribution

(reweighted w.r.t German conditional *homeownership and income*)



Source: HFCS, 2017. Density of transformed wealth values. Vertical lines: mean (dashed), median (solid)

Our graphical findings are reflected in the results for inequality measures provided in table 3. It turns out that reducing homeownership to the low German level unambiguously increases wealth inequality in all countries (panel (b) of table 3). This lends validity to the proposition that low homeownership is connected to higher levels of wealth inequality, holding other things constant. However, although reweighting homeownership reduces and in many cases eliminates the inequality difference to the reference country, it 'overshoots' for a number of countries (row five of table 3). Reweighting in addition with respect to income levels lowers inequality again, with the exception of the Netherlands and Belgium (row seven of table 3). The explanation is that for most countries, reweighting to German income levels means increasing incomes (allowing more wealth poor households to accumulate wealth), while for the Netherlands and Belgium, it means reducing them (see last panel of table 1). As the last row of table 3 shows, reweighting with respect to both homeownership *and* income generally renders inequality differences statistically insignificant (the only exceptions are Belgium, for which the original inequality difference is reduced from .119 to .036, and the Netherlands for which differences – again – remain persistent).

Table 3 – Wealth inequality differences between countries, reweighting results, 2017

	ES[a]	FR	IT	GR	NL	BE	PT	AT	FI	SK
(a) Wealth inequality										
Gini Germany	.754	.737	.737	.737	.737	.737	.737	.737	.737	.737
	(.011)	(.012)	(.012)	(.012)	(.012)	(.012)	(.012)	(.012)	(.012)	(.012)
Gini country	.680	.672	.616	.615	.781	.618	.674	.722	.654	.544
	(.014)	(.007)	(.007)	(.016)	(.017)	(.015)	(.011)	(.026)	(.006)	(.018)
Difference to	.074***	.065***	.122***	.122***	-.044**	.119***	.063***	.015	.083***	.193***
Gini Germany	(.017)	(.014)	(.014)	(.044)	(.021)	(.018)	(.016)	(.028)	(.014)	(.022)
(b) Reweighted: homeownership as in Germany[b]										
Gini country	.773	.727	.756	.815	.811	.690	.802	.737	.721	.780
(reweighted)	(.017)	(.009)	(.008)	(.071)	(.018)	(.014)	(.021)	(.025)	(.008)	(.041)
Difference[d] to	-.019	.010	-.018	-.078	-.074***	.047***	-.065***	.000	.016	-.043
Gini Germany	(.02)	(.015)	(.015)	(.072)	(.022)	(.018)	(.024)	(.027)	(.014)	(.043)
(c) Reweighted: homeownership and income as in Germany[c]										
Gini country	.751	.721	.740	.655	.826	.701	.776	.755	.720	.719
(reweighted)	(.021)	(.007)	(.009)	(.049)	(.020)	(.014)	(.046)	(.026)	(.009)	(.059)
Difference[d] to	.003	.016	-.002	.082	-.088***	.036**	-.039	-.017	.018	.018
Gini Germany	(.023)	(.014)	(.015)	(.051)	(.023)	(.017)	(.048)	(.029)	(.015)	(.060)

Source: HFCS, 2014, 2017. Reference country: Germany. Bootstrap standard errors in parentheses account for multiply imputed data. [a]This column 2014, all other columns 2017, [b]Homeownership conditional on the other characteristics in table 1 [c]Homeownership and income conditional on the other characteristics in table 1, [d]Gini Germany minus reweighted Gini of country ***/**/* = statistically significant at 1%/5%/10%-level

Taken together, both our graphical and our numerical results suggest that differences in wealth inequality between countries can be largely accounted for by differences in homeownership rates, but that for some country comparisons differences in household incomes also matter. The only country not covered by these explanations are the Netherlands. Wealth inequality in the Netherlands is exceptionally high in the first place and lowering its homeownership to the German level would make it even higher. Rather, the high level of wealth inequality in the Netherlands appears to be related to the exceptionally high level of household leverage (.519 of the population has a debt/asset ratio over .1, see table 1), leading to a sizable characteristics effect of -.052 in the hybrid decomposition (panel (d) of table 2). However, there also appear to be coefficients effects related to risky asset holdings (-.030, panel (f) of table 2) as well as some large, completely unexplained coefficients effects (-.052 for the constant, panel (f) of table 2), making the Dutch case hard to understand.

5 Conclusion

Based on data from the Household Finance and Consumption Surveys (HFCS), this paper revisits the question of how differences in homeownership and other household characteristics shape cross-country differences in wealth inequality. We first show that commonly used RIF-decompositions are typically tested positive for misspecification due to the large differences in the distribution of household characteristics between countries. We then present an alternative analysis for which we introduce a convenient graphical representation of the wealth distribution with a number of useful properties, which allows us to study cross-country differences not only numerically but also visually. Our results suggest a strong relationship of the *shape of the wealth distribution* with the proportion of homeowners in the population. We show that not only differences in wealth inequality but differences in distributional shape can be accounted for to a very large extent by differences in homeownership across countries. However, for some countries – especially those whose incomes range low compared to the European average – taking account of income differences also matters. As to the general applicability of RIF-decompositions, our conclusion is that these may still be very helpful in identifying the main determinants of cross-country differences, although detailed quantitative results may break down due to specification error.

A limitation of our analysis is the well-known undercoverage of extreme wealth in sample surveys (e.g., Bach et al. 2019). While we certainly acknowledge this limitation, we find it unlikely that our main conclusions would be changed with more comprehensive data as our graphical analysis and our inequality measures focus on the main part of the distribution rather than on the top ('the 99 percent rather than the 1 percent'). Moreover, the countries considered appear to be affected by an undercoverage of top wealth values in a similar way (Bach et al. 2019), implying that this aspect will not drive cross-country differences. Finally, the differences in homeownership identified by us as one of the main drivers of cross-country differences are unlikely to be of high importance at the very top of the distribution.

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7 Declarations

7.1 Competing interests

The authors have no relevant financial or non-financial interests to disclose. The authors did not receive support from any organization for the submitted work.

7.2 Data availability statement

The data that support the findings of this study are available upon application from the Household Finance and Consumption Network (HFCN) at the European Central Bank (ECB).

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9 Appendix

Table A.1 – Detailed breakdown of specification and reweighting errors

	ES[a]	FR	IT	GR	NL	BE	PT	AT	FI	SK
Detailed characteristics specification errors $\Delta^{\nu}_{X,c}$										
Homeownership[b]	.057***	.0288***	.055***	.057**	.005	.036***	.065**	.008	.000	.038
	(.017)	(.008)	(.011)	(.029)	(.023)	(.009)	(.028)	(.017)	(.007)	(.040)
Other real estate[b]	-.007	-.01*	-.030	.016	.054*	-.025***	.002	-.037**	-.015***	-.010
	(.013)	(.006)	(.007)	(.031)	(.0295)	(.009)	(.022)	(.016)	(.006)	(.036)
Business wealth[b]	.001	-.008**	-.001	-.004	.001	-.002	-.013	-.019**	-.003	-.013
	(.008)	(.003)	(.003)	(.014)	(.020)	(.005)	(.012)	(.009)	(.005)	(.03)
Risky assets[b]	-.023	-.011**	-.020**	-.054	.036***	-.013**	-.096**	.006	.009***	-.026
	(.018)	(.004)	(.008)	(.052)	(.012)	(.006)	(.040)	(.007)	(.003)	(.046)
Inheritance[b]	.009	.006**	-[c]	-.023	-.007	-.001	.038**	.007	.003	-.010
	(.010)	(.003)	(-)	(.020)	(.011)	(.004)	(.017)	(.011)	(.003)	(.020)
Debt/assets>.1[b]	-.009	.010	-.001	-.021	-.017***	-.005	-.006	-.004	.021***	.019
	(.012)	(.011)	(.008)	(.019)	(.011)	(.010)	(.012)	(.011)	(.006)	(.069)
Age[d]	.006	.000	-.002	.001	.004	.001	-.001	-.001	-.002	-.050
	(.009)	(.001)	(.002)	(.008)	(.004)	(.002)	(.007)	(.002)	(.002)	(.085)
Education[d]	.011	.003	-.002	-.005	.004	.002	.004	.000	-.004	.038
	(.007)	(.003)	(.004)	(.013)	(.019)	(.006)	(.019)	(.004)	(.003)	(.056)
#children in hh	-.005	-.008	.011*	.000	.010	.005	-.021	.002	-.002	.006
	(.009)	(.007)	(.007)	(.011)	(.010)	(.005)	(.013)	(.007)	(.002)	(.012)
#employed/adult	.107	-.001	.006	.066	-.021	-.020	.032	.012	.013	.157
	(.048)	(.013)	(.021)	(.044)	(.031)	(.023)	(.042)	(.021)	(.020)	(.151)
Income[d]	-.043**	-.015***	-.015***	-.049	.004	-.006	-.114***	-.002	-.007	-.112
	(.020)	(.004)	(.005)	(.053)	(.005)	(.005)	(.036)	(.004)	(.004)	(.232)
Constant	-.165***	-.017	-.052**	-.246***	.017	.010	-.180***	.034	-.022	-.486**
	(.063)	(.011)	(.021)	(.084)	(.026)	(.023)	(.058)	(.021)	(.016)	(.240)
Detailed coefficients reweighting errors $\Delta^{\nu}_{S,c}$										
Homeownership[b]	-.006	-.008***	.005	-.023	-.030***	-.013***	-.016	-.008**	-.019***	-.018
	(.005)	(.002)	(.005)	(.019)	(.008)	(.004)	(.014)	(.004)	(.007)	(.04)
Other real estate[b]	.002	.000	.001	-.003	.001	.001	-.001	.000	.001	.001
	(.003)	(.001)	(.001)	(.011)	(.003)	(.002)	(.004)	(.001)	(.002)	(.019)
Business wealth[b]	-.002	.000	.000	.003	-.005	.001	-.001	.001	.001	-.006
	(.002)	.000	(.001)	(.007)	(.005)	(.003)	(.004)	(.003)	(.002)	(.013)
Risky assets[b]	-.002	.000	.000	-.006	.001	.000	.008	.000	.001	.004
	(.004)	(.000)	(.000)	(.015)	(.001)	(.002)	(.011)	(.001)	(.001)	(.029)
Inheritance[b]	.000	.000	-[c]	-.004	-.001	-.001	.004	.000	.000	-.008
	(.001)	(.000)	(-)	(.015)	(.002)	(.001)	(.010)	(.002)	(.000)	(.018)
Debt/assets>.1[b]	.000	-.003*	-.001	.021*	.009***	.001	-.001	.000	-.004	-.018
	(.002)	(.002)	(.002)	(.012)	(.003)	(.001)	(.006)	(.001)	(.003)	(.039)
Age[d]	.000	-.003	.000	.002	.000	-.002	.002	-.001	-.001	.073
	(.007)	(.002)	(.002)	(.009)	(.004)	(.002)	(.008)	(.002)	(.004)	(.098)
Education[d]	0	.000	.000	-.002	.000	.000	.006	.000	-.001	-.034

	(.002)	(.000)	(.001)	(.007)	(.001)	(.001)	(.010)	(.001)	(.001)	(.063)
#children in hh	0.000	.001	.000	.000	.000	.000	.000	.001	.000	.001
	(.001)	(.001)	(.001)	(.004)	(.001)	(.001)	(.003)	(.002)	(.000)	(.007)
#employed/adult	.002	.001	.001	.000	.000	.001	-.001	.000	.003	-.017
	(.006)	(.001)	(.001)	(.006)	(.001)	(.002)	(.004)	(.001)	(.002)	(.029)
Income^d	.000	-.003**	.001	-.009	.000	.000	.008	.000	.000	-.019
	(.006)	(.001)	(.001)	(.013)	(.003)	(.002)	(.009)	(.001)	(.001)	(.052)

Source: HFCS, 2014, 2017. Reference country: Germany. Bootstrap standard errors in parentheses account for multiply imputed data.

^{a}This column 2014, all other columns 2017, ^{b}Dummy variable indicating presence of asset class, ^{c}Variable not available for Italy

^{d}Combined contribution of respective group of variables shown in table 1

***/**/* = statistically significant at 1%/5%/10%-level