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DISCUSSION PAPER SERIES

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Martin Biewen
University of Tübingen and IZA

Stefan Glaisner
University of Tübingen

Rolf Kleimann
IAW Tübingen

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ISSN: 2365-9793

IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

A Convenient Representation of the Wealth Distribution and More Evidence on Homeownership and Wealth Inequality in Euro Area Countries[1]

This note proposes a convenient graphical representation of the wealth distribution and illustrates it with data from the Eurosystem Household Finance and Consumption Survey (HFCS). We also present more evidence on the role of homeownership for wealth inequality in euro area countries.

JEL Classification: D31, C14, R3
Keywords: wealth inequality, transformation, homeownership

Corresponding author:
Martin Biewen
School of Business and Economics
University of Tübingen
Mohlstr. 36
72074 Tübingen
Germany
E-mail: martin.biewen@uni-tuebingen.de

[1] This paper uses data from the Household Finance and Consumption Surveys (HFCS) of the European Central Bank (ECB), 2010, 2014 and 2017.

1 Introduction

It is well-known that the wealth distribution exhibits a number of features that render its graphical representation difficult (Jenkins and Jäntii, 2005). Among them are the potential existence of negative values and excess zeros along with an 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). The purpose of this note is to propose a compact graphical exposition of the wealth distribution that addresses the above difficulties while retaining graphical interpretability across the whole range of wealth values. We demonstrate the usefulness of this graphical device by examining differences in the distribution of wealth across large euro countries based on the latest wave of the Eurosystem Household Finance and Consumption Survey (HFCS). Our graphical results are suggestive about the sources of cross-country differences in the wealth distribution which are corroborated by econometric decomposition analyses. In particular, we confirm the important role of homeownership for cross-country differences in wealth inequality using methods that rely on weaker assumptions than the previous literature (Mathä et al., 2017, Kaas et al., 2019).

2 Data

We use data from the Household Finance and Consumption Survey (HFCS) of the ECB for the years 2010, 2014 and 2017 (see HFCS, 2020). Our main variable 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 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]

[2]We obtain very 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.

[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.

We transform all monetary values into 2017 euros. Our illustration focusses on the following six large euro countries representing around 85 percent of the population of the euro zone: Germany (DE), Spain (ES), France (FR), Italy (IT), Greece (GR), and the Netherlands (NL). For our descriptive analyses, we make use of 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 six countries). 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
Number of observations	4,942	6,120	13,685	7,420	3,007	2,556
Proportion of households with						
Homeownership	.439	.803	.578	.684	.720	.574
Other real estate	.224	.398	.224	.206	.387	.061
Business wealth	.095	.140	.094	.143	.178	.041
Risky assets	.204	.146	.172	.084	.012	.156
Inheritance	.163	.282	.468	-	.012	.151
Debt/assets>.1	.334	.356	.298	.125	.133	.519
Age reference person						
<35 years	.192	.093	.160	.074	.095	.184
35-49 years	.244	.331	.267	.278	.263	.265
50-64 years	.281	.277	.272	.288	.295	.282
≥65 years	.282	.297	.299	.358	.346	.268
Education reference person						
No/primary/secondary	.101	.520	.303	.515	.381	.241
Upper secondary	.561	.162	.399	.351	.377	.380
Tertiary	.337	.316	.297	.133	.240	.377
Household structure and employment						
#children in hh	.358	.448	.496	.383	.422	.417
#employed/adult	.580	.428	.474	.453	.397	.529
Income position[b] in pooled DE/ES/FR/IT/GR/NL sample						
1st quartile	.175	.449	.196	.392	.640	.166
2nd quartile	.208	.253	.313	.271	.258	.150
3rd quartile	.245	.172	.307	.214	.080	.261
4th quartile	.370	.124	.183	.121	.020	.421

Source: HFCS, 2014, 2017. Weighted data. Average over 5 implicates. Notes: [a]2014, [b]Net equivalized income

3 Graphical representation of the wealth distribution

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 Ravaillon, 2017). To our best knowledge, these kind of transformations have not been used before for representing the wealth distribution graphically.

Our graphical representation is based on the simple transformation

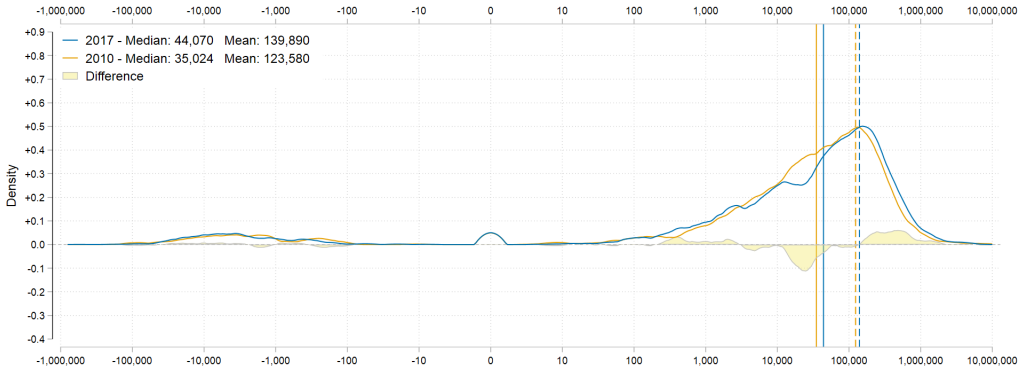
$$g(y) = \begin{cases} -\log_{10}(-y) & y < -1 \\ 0 & -1 \leq y \leq 1 \\ +\log_{10}(+y) & 1 < y \end{cases} \tag{1}$$

where y is wealth. Depending on the data, other logarithms may be used, but we found $\log_{10}$ convenient for our purposes. Figures 1 to 6 present the wealth distribution in the six countries considered by us based on kernel density estimates of the transformed wealth values according to the above transformation.

The representation of the wealth distribution as shown in figures 1 to 6 has the following useful features. First, 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. Second, the transformation in (1) is strictly monotonic.[4] As a consequence, the probability mass for a given range of wealth values in figures 1 to 6 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

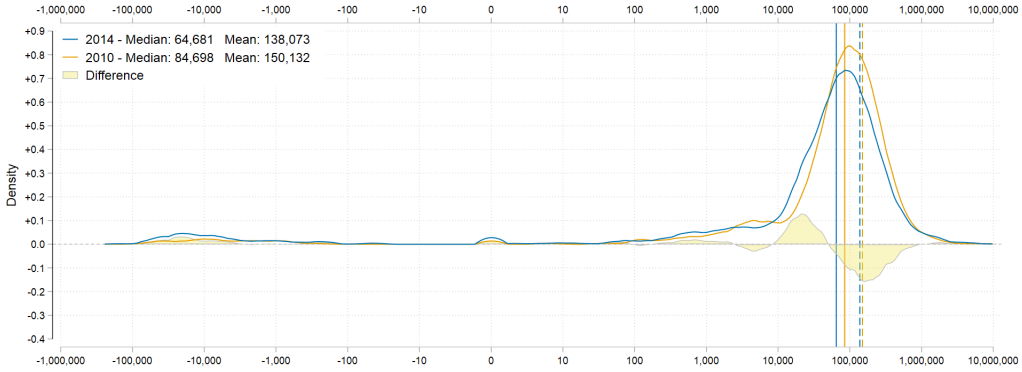
[4] Except for statements inside the narrow interval between the two thresholds which appear irrelevant.

Figure 1 – Distribution of net wealth in Germany, 2010 vs. 2017



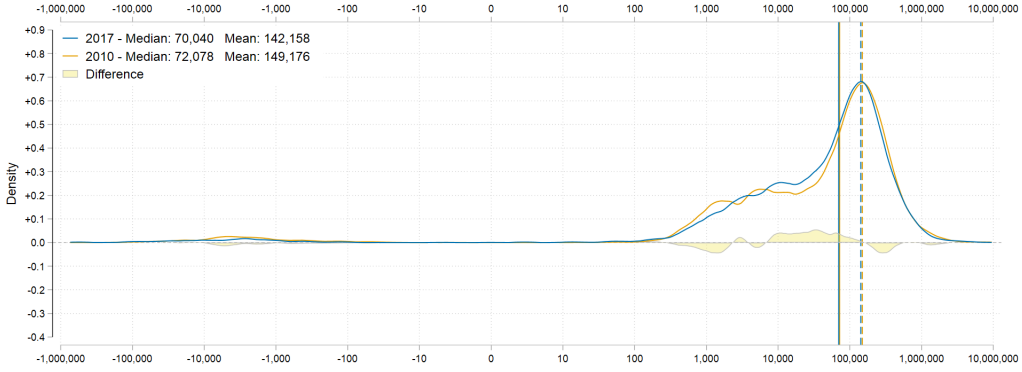
Source: HFCS, 2010, 2017. Density of transformed wealth values.

Figure 2 – Distribution of net wealth in Spain, 2010 vs. 2014



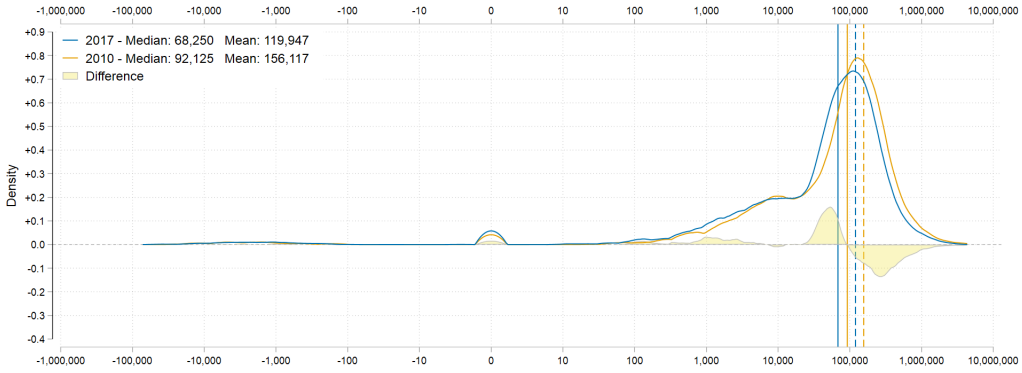
Source: HFCS, 2010, 2014. Density of transformed wealth values.

Figure 3 – Distribution of net wealth in France, 2010 vs. 2017



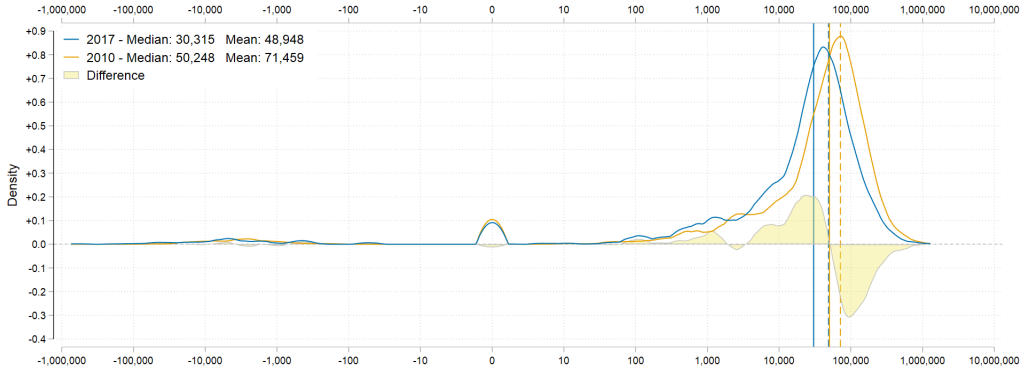
Source: HFCS, 2010, 2017. Density of transformed wealth values.

Figure 4 – Distribution of net wealth in Italy, 2010 vs. 2017



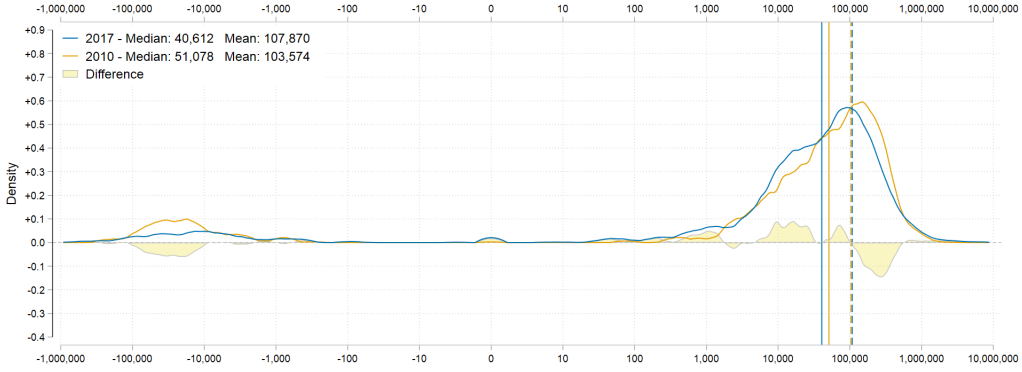
Source: HFCS, 2010, 2017. Density of transformed wealth values.

Figure 5 – Distribution of net wealth in Greece, 2010 vs. 2017



Source: HFCS, 2010, 2017. Density of transformed wealth values.

Figure 6 – Distribution of net wealth in the Netherlands, 2010 vs. 2017



Source: HFCS, 2010, 2017. Density of transformed wealth values.

the right hand side. Third, the graph presents a compact 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. Fourth, in the transformation chosen by us, the mean of the distribution coincides very well with the peak of the density plot, allowing the reader to form a quick visual estimate of mean per-capita wealth (of course, this property depends on the type of log chosen for the transformation). And fifth, the compact form of the plot makes it easy to identify country clusters sharing similar distributional shapes. In particular, the shape of the distribution appears to be strongly related to the proportion of households with homeownership as shown in the second row of table 1. More precisely, the graphs for countries with the highest proportion of homeowners (80.3 percent in Spain, 72.0 percent 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 (68.4 in Italy, 57.8 France and 57.4 percent in Netherlands). The shape for the country with the lowest proportion of homeowners (43.9 percent in Germany) is very distinct from those of the countries with many homeowners, displaying a much higher fraction of moderate wealth values below the mean.

4 Econometric analysis

In order to shed more light on these differences, we present in tables 2 and 3 basic decomposition analyses that relate features of the wealth distribution to the household characteristics shown in table 1. Table 2 displays the results of an Oaxaca-Blinder decomposition[5] which breaks down differences in mean wealth across countries into the contributions (in an accounting sense) of the *endowment* with certain household characteristics (characteristics effect) and those of the *wealth values* related to these characteristics (coefficients effect). The decomposition takes Germany as a point of reference as it stands out as a country with both a high level of wealth inequality (table 3) and – by far – the lowest proportion of homeowners (table 1).

[5] E.g., Jann (2008).

Table 2 – Oaxaca-Blinder decomposition of mean wealth differences (reference country: Germany), 2017

	ES[a]	FR	IT	GR	NL
Mean DE	130015.1***	139890.3***	139890.3***	139890.3***	139890.3***
	(6680.4)	(7200.8)	(7200.8)	(7200.8)	(7200.8)
Mean country	138072.6***	142158.1***	119947.4***	48948.0***	107869.5***
	(6998.9)	(2907.7)	(3008.5)	(1997.4)	(5982.7)
Difference	-8057.5	-2267.7	19942.8***	90942.3***	32020.8***
	(9425.1)	(7710.3)	(7924.4)	(7623.7)	(9212.3)
Characteristics	-7426.7	6429.0	16662.0***	53672.1	39290.1
	(15793.0)	(4934.6)	(5272.3)	(32665.0)	(17285.1)
Coefficients	-630.8	-8696.8	3280.7	37270.2	-7269.3
	(15782.2)	(7110.7)	(8542.1)	(33414.9)	(21047.9)
Household characteristics (characteristics effect)					
Homeownership[b]	-24058.0***	-14704.8***	-22629.9***	-11336.4***	-17547.4***
	(2726.4)	(1659.8)	(1611.0)	(1129.0)	(3145.4)
Other real estate[b]	-13575.3***	25.2	1631.8	-5958.3***	33214.4***
	(2889.1)	(1183.9)	(1048.5)	(870.8)	(9669.5)
Business wealth[b]	-3874.4***	149.1	-1909.4***	-1687.3***	12763.2
	(1060.4)	(992.5)	(625.7)	(552.3)	(5408.9)
Risky assets[b]	-8841.6*	2685.8***	6396.5***	27333.1	-6684.9**
	(4547.8)	(1093.0)	(1720.5)	(29787.5)	(2908.287)
Inheritance[b]	-83.8	-7898.2	-	-280.0	56.4
	(1767.6)	(1912.2)	(-)	(940.9)	(253.6)
Debt/assets>.1[b]	1961.9	-3479.6***	-10240.2***	7274.1***	19857.8***
	(1370.2)	(1260.55)	(1850.1)	(965.5)	(2522.7)
Age (ref. person)[c]	-570.1	-1127.4**	-1925.2*	118.9	455.2
	(1084.6)	(547.1)	(1201.8)	(559.9)	(803.3)
Education (ref. person)[c]	4919.4	5096.2***	18300.6***	2848.2***	-1049.9
	(5200.9)	(1051.6)	(2634.9)	(849.6)	(1550.6)
#children in hh	-944.6*	-520.7	-47.3	3.6	-102.5
	(548.4)	(381.9)	(143.7)	(149.8)	(373.4)
#employed/adult	-5843.5*	-924.8	-2337.5**	321.4	-177.4
	(3317.5)	(835.9)	(1166.1)	(1117.1)	(641.6)
Income[c]	43483.6***	27128.2***	29422.9***	49583.0***	-1494.7**
	(13653.0)	(2620.8)	(3647.4)	(12934.6)	(787.2)
Wealth values associated with household characteristics (coefficients effect)					
Homeownership[b]	28082.5***	14976.8***	20864.8***	43694.2***	4510.3
	(6531.6)	(5791.2)	(5422.4)	(5358.4)	(8391.3)
Other real estate[b]	15739.1***	12828.5***	18106.4***	30320.1***	-7342.8
	(4604.5)	(5385.1)	(5265.6)	(5171.9)	(13787.91)
Business wealth[b]	16363.0***	10262.3**	20341.9***	22218.4***	1523.8
	(4730.6)	(5025.6)	(5111.2)	(5090.0)	(9830.6)
Risky assets[b]	-1911.6	5597.9*	-372.0	-14706.5	5050.0**
	(7091.3)	(2587.9)	(2608.4)	(30075.7)	(1909.9)

Inheritance[b]	1642.2	-5643.5**	-	-987.1	-2187.0
	(4574.2)	(2592.9)	(-)	(2809.5)	(3585.5)
Debt/assets>.1[b]	-3472.8	3748.8	-12031.6**	-16471.7***	7325.6
	(6207.4)	(4701.7)	(4864.4)	(4506.8)	(5452.1)
Age (ref. person)[c]	-720.7	-952.7	472.6	1164.9	-2060.2
	(1565.3)	(1023.856)	(1130.7)	(1037.6)	(1473.2)
Education (ref. person)[c]	-3997.4	-3431.0	-4090.0	-213.4	1850.4
	(3732.4)	(2408.9)	(2380.3)	(2252.7)	(3258.8)
#children in hh	-2684.2	2105.3	2775.2	3476.9	2833.1
	(2979.0)	(2608.1)	(2811.7)	(2494.2)	(3205.6)
#employed/adult	30428.6	7486.6	13304.8	1376.8	4459.1
	(19666.1)	(10274.1)	(10487.1)	(9924.9)	(11694.6)
Income[c]	-14521.5**	-12786.3***	-7962.0***	-9604.7*	2693.0
	(7092.4)	(2701.9)	(2730.1)	(5118.3)	(2473.1)
Constant	-65577.9***	-42889.4***	-48129.3***	-22997.6***	-25924.9**
	(28775.2)	(9937.0)	(11693.9)	(12401.1)	(11336.6)

Source: HFCS, 2014, 2017. Bootstrap standard errors in parentheses account for multiply imputed data (Rubin, 1987).

[a]This column 2014, all other columns 2017, [b]Dummy variable indicating presence of asset class

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

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

It turns out that mean wealth in Germany is slightly lower than in Spain,[6] around as high as in France, somewhat higher than in Italy and the Netherlands, and much higher than in Greece. As to the sources of these differences, the upper panel of table 2 showing the characteristics effects suggests that mean wealth in Germany is relatively lower because homeownership and other real-estate property is not as widespread as in other countries (negative contributions), but that the high relative income positions of Germans in Europe more than make up for this disadvantage (positive contributions). By contrast, the lower panel of table 2 on the coefficients effects shows that, although Germans are less likely to own their home or other real estate, those who do own hold objects with a higher euro value than in other European countries (positive contributions). This also applies to the value of German business wealth (which is also less widespread but higher if present). In addition, the second but last row in table 2 suggests that, although Germans typically occupy higher relative positions in the European *income* distribution, the *wealth* effect of occupying a given income position is lower than in other countries (in other words, given their income level, Germans accumulate less wealth than in other countries). Finally, note the high positive contributions to German-Dutch differences in mean wealth due to the fact that not

[6]For reasons of data availability, the comparison Germany-Spain refers to the year 2014 rather than to 2017 as in all other cases.

owning other real estate and being highly indebted is much more widespread in the Netherlands than in Germany (compare table 1).

We now turn to the role of homeownership for cross-country differences in *wealth inequality* rather than in *mean wealth*. This question has been investigated by Mathä et al. (2017) and Kaas et al. (2019) using earlier waves of the same data base and decompositions based on Recentered-Influence Function (RIF-) regressions. The question we ask here is how far we can get in accounting for cross-country differences in wealth inequality focussing only on homeownership and a method that relies on considerably weaker assumptions.[7] We will show that counterfactually reducing the homeownership rate in a country increases wealth inequality, and that differences in wealth inequality between the country with the lowest homeownership rate – Germany – and other countries (except the Netherlands) can already be fully accounted for by reducing the homeownership rate in these countries to the low German level. Wealth inequality in the Netherlands is already higher than in Germany, but would be even higher if the Dutch had the extremely low German homeownership rate.

The method we use is reweighting (Fortin et al, 2011) in the following unconditional and conditional forms:

$$f_j^{cf,u}(y) = \int_h f_j(y|h)\, dF_{DE}(h) = \int_h f_j(y|h)\, \psi_h\, dF_j(h) \tag{2}$$

$$f_j^{cf,c}(y) = \int_h \int_x f_j(y|h,x)\, dF_{DE}(h|x)\, dF_j(x) = \int_h \int_x f_j(y|h,x)\, \psi_{h|x}\, dF_j(h|x) dF_j(x) \tag{3}$$

Here, y denotes wealth, h homeownership status and x the other household characteristics shown in table 1. The first line is the counterfactual distribution of wealth that would prevail in country j, if its *unconditional* homeownership rate ($=dF_j(h)$) was reduced to that in Germany ($=dF_{DE}(h)$), also reducing all other household characteristics that are associated with homeownership. In order to hold other household characteristics constant, one might prefer to form the counterfactual distribution of wealth that would prevail in country j, if its *conditional* homeownership rate ($=dF_j(h|x)$) was reduced to that in Germany ($=dF_{DE}(h|x)$). Considering the latter nets out the potential influence of other characteristics x on wealth. Put another way, the fraction of homeowners among households with certain characteristics described by x is changed to the low

[7] RIF regressions rely on linearity assumptions and local approximations which may be considered restrictive if differences in characteristics between countries are large (e.g., in homeownership rates).

German level (holding constant the distribution of these household characteristics as it is observed in the given country). The necessary reweighting factors are

$$\psi_h = \frac{dF(DE|DE \text{ or } j; h)}{dF(j|DE \text{ or } j; h)} \frac{dF(j|DE \text{ or } j)}{dF(DE|DE \text{ or } j)} \tag{4}$$

$$\psi_{h|x} = \frac{dF(DE|DE \text{ or } j; h, x)}{dF(j|DE \text{ or } j; h, x)} \frac{dF(j|DE \text{ or } j; x)}{dF(DE|DE \text{ or } j; x)} \tag{5}$$

whose components can be estimated by logit models and sample fractions (Fortin et al., 2011).

Table 3 presents the results of this exercise. For example, the difference in wealth inequality between Germany and Spain as measured by the Gini (.754 in Germany vs. .680 in Spain) can be fully accounted for by giving Spain the unconditional or conditional homeowner rate of Germany (leading to counterfactual Ginis for Spain of .787 and .770, close to the German Gini of .754). It turns out that using the German conditional or unconditional homeowner rate for other countries unambigously increases wealth inequality in these countries and in most cases fully (or even slightly more than fully) accounts for the original inequality difference. A notable exception are the Netherlands for which wealth inequality also increases if one assumes that unconditional or conditional homeownership is as in Germany, but whose wealth inequality level is higher than in Germany even before carrying out such a counterfactual exercise.

Table 3 – Counterfactual wealth inequality in different countries using distribution of homeownership as in Germany

	ES[a]	FR	IT	GR	NL
Gini country	.680	.672	.616	.615	.781
	(.012)	(.007)	(.008)	(.015)	(.017)
Gini country	.787	.723	.717	.742	.814
counterfactual (unconditional)[b]	(.012)	(.01)	(.008)	(.031)	(.016)
Gini country	.770	.727	.756	.800	814
counterfactual (conditional)[c]	(.061)	(.009)	(.009)	(.066)	(.017)
Gini Germany	.754	.737	.737	.737	.737
	(.011)	(.012)	(.012)	(.012)	(.012)

Source: HFCS, 2014, 2017. Bootstrap standard errors in parentheses account for multiply imputed data (Rubin, 1987), [a]This column 2014, all other columns 2017
[b]Counterfactual Gini using *unconditional* distribution of homeownerhip in Germany
[c]Counterfactual Gini using *conditional* distribution of homeownership in Germany

5 Conclusion

This note proposes a graphical representation of the wealth distribution with a number of useful features. We also confirm the important role of homeownership for cross-country differences in wealth inequality using methods that rely on weaker assumptions than the previous literature (Mathä et al., 2017, Kaas et al., 2019).

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