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WHY WEALTH INEQUALITY DIFFERS BETWEEN POST-SOCIALIST COUNTRIES?

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Why wealth inequality differs between post-socialist countries?

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Abstract: We provide the first attempt to understand how differences in households' socio-demographic and economic characteristics account for disparities in wealth inequality between five post-socialist countries of Central and Eastern Europe. We use 2013/2014 data from the second wave of the Household Finance and Consumption Survey (HFCS) and the reweighted Oaxaca-Blinder-like decompositions based on recentered influence function (RIF) regressions. Our results show that the differences in homeownership rates account for up to 42% of the difference in wealth inequality measured with the Gini index and for as much as 63-109% in case of the P50/P25 percentile ratio. Differences in homeownership rates are related to alternative designs of housing tax policies but could be also driven by other factors. We correct for the problem of the 'missing rich' in household surveys by calibrating the HFCS survey weights to top wealth shares adjusted using wealth data from national rich lists. Empirically, the correction procedure strengthens the importance of homeownership rates in accounting for cross-country wealth inequality differences, which suggests that our results are not sensitive to the significant underestimation of top wealth observations in the HFCS.

Keywords: wealth inequality, decomposition, recentered influence function (RIF) regressions, survey weight calibration, Household Finance and Consumption Survey (HFCS), post-socialist transition, Central and Eastern Europe (CEE), housing, homeownership, missing rich

JEL codes: D31, D63, P36

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1. Introduction

Recent literature has shown that cross-national differences in wealth inequality are strikingly large. A growing body of empirical literature attempts to understand why wealth disparities differ among countries (see, e.g., Bover 2010; Davies et al. 2017; Mathä et al. 2017; Cowell 2018a, b; Sierminska and Doorley 2018; Pfeffer and Waitkus 2019). Existing studies in this area, however, focus solely on the advanced countries such as the United States and Western European countries. In this paper, we shed light on the differences in wealth inequality among the selected Central and Eastern European (hereinafter: CEE) post-socialist countries. In a companion paper (Brzeziński et al. 2020), we have found that surprisingly there are huge differences in wealth inequality levels in emerging market economies of the CEE region, even after accounting for the phenomenon of the missing rich persons in household surveys.[1] While Slovakia is rather equal concerning wealth distribution, Poland and Hungary are at the average European levels, and the Baltic countries are among the most wealth-unequal countries in Europe. The question of what may account for this diversity of otherwise rather similar countries arises naturally.

In this paper, we use microeconomic decomposition techniques to study the contribution of socio-economic and demographic characteristics to cross-country differences in the distribution of wealth. In particular, we study how differences in the distributions of age, household structure, labour market status, housing status, educational attainment, household income, saving practices and received gifts and inheritances contribute to differences in inequality of net wealth distribution in five post-socialist CEE countries. Specifically, we use the reweighted Oaxaca-Blinder-type decompositions of wealth inequality measures based on recentered influence function (RIF) regressions (Firpo et al. 2009, 2018; Davies et al. 2017). We employ data from the Household Finance and Consumption Survey (HFCS) (wave 2 from 2013/2014) for Estonia, Latvia, Hungary, Poland, and Slovakia.

Our primary contribution is to present the first empirical investigation into the determinants of cross-country differences in wealth inequality between the post-socialist countries. Secondly, we make a methodological contribution to the literature on accounting for differences in wealth distribution by applying decomposition techniques to the top-corrected wealth distributions. As shown in the previous literature, raw survey-based estimates of wealth

[1] See Figure 1 below. The problem of the 'missing rich' arises both because of the sampling error (low probability of selecting the billionaires into the sample) and non-sampling errors (lower response rate among the wealthy and the tendency to higher under-reporting of their wealth).

inequality are significantly biased downwards due to survey non-response and under-reporting, which disproportionately concerns the richest households (Vermeulen 2016, 2018). Empirical studies have shown that due to this 'missing rich' phenomenon the top 1% wealth share in such countries as Austria or Germany is underestimated by as much as 8-10 percentage points (Bach et al. 2019; Vermeulen 2018). In our companion paper, we show that the size of analogous corrections for most of the CEE countries range from 7 to 15 percentage points in case of top 1% share, and from 4 to 11 percentage points in the case of Gini index (Brzeziński et al. 2020). The missing rich problem can seriously bias the outcome of decomposition analyses aiming at discovering determinants of over time changes or cross-country differences in wealth inequality. Therefore, we attempt to correct for this problem by calibrating the HFCS survey weights in a way that allows matching survey-based top wealth shares with the top-corrected top wealth shares derived using both survey wealth data and external wealth data coming from national rich lists. This approach allows us to decompose the top-corrected estimates of wealth inequality indices on the assumption that the distribution of covariates among the rich missing in household surveys is similar to that of the richest persons available in the HFCS data.

In the following section, we present a short review of the literature on wealth disparities in post-socialist countries. Section 3 describes data from the HFCS, while section 4 outlines the methodology. Section 5 presents and discusses our results on the determinants of cross-country differences in wealth disparities in the CEE region. Finally, section 6 concludes.

2. Wealth inequality in post-socialist transition countries

The literature on wealth inequality in post-socialist transition countries is rather scarce. The need for research in this area has been recognised, but the major obstacle that researchers faced was – until very recently – the lack of reliable data on households' wealth in these countries. Because of this, the analyses so far were based on non-representative or very incomplete data. For example, Guriev and Rachinsky (2008) argued that wealth inequality in post-socialist countries must have increased due to multiple factors, but they were unable to quantify the extent of wealth inequality rise. The factors they considered included decompressing wage inequality, different saving rates of the poor and the rich, privatization processes (especially the privatization of housing and socialist enterprises), and the growth of private entrepreneurship. They also noticed that in the CEE countries wealth disparities probably grew less than in the Post-Soviet states because the former hoped for the EU accession and were better motivated to introduce institutions supporting equality of opportunity.

Selected CEE countries were also analysed by Skopek et al. (2014) (along with many Western European countries). They found that the CEE countries differed a lot concerning the level of wealth inequality. They estimated that the most unequal country in the sample was Estonia. For Poland and Hungary, they found moderate levels of wealth disparities and placed Czechia among the most equal countries regarding wealth distribution. The major limitation of their study, however, was the use of the Survey of Health, Ageing and Retirement in Europe (SHARE) data, which covers only the population aged 50 and above.

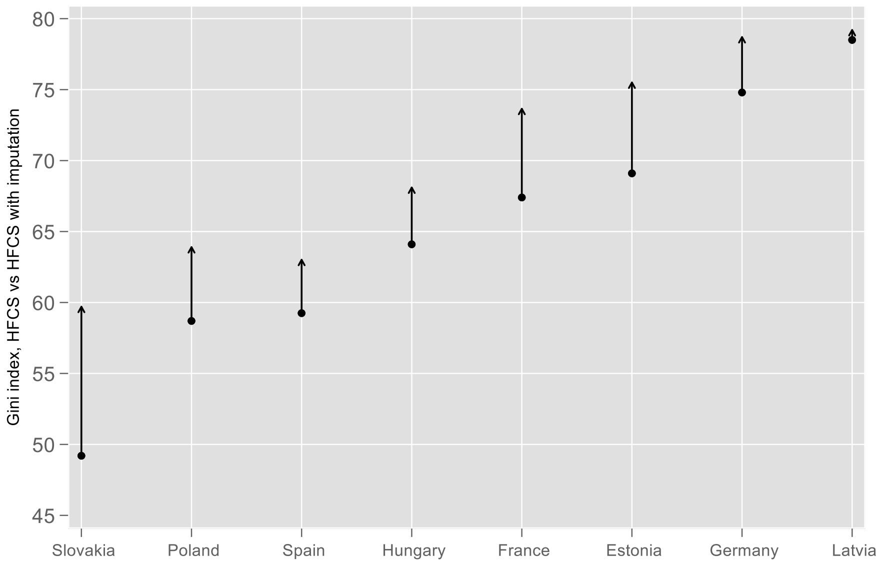
Skopek et al.'s (2014) results are in line with those of Brzeziński et al. (2020), who use the HFCS data for 2013/2014 and analyse entire populations of the selected CEE countries. After performing top-correction of the wealth data to capture the 'missing rich', they also find that some of the CEE countries such as Slovakia are characterized by rather low levels of wealth inequality (although much higher than was previously thought, e.g. with Gini index reaching 0.6), Poland and Hungary are at the intermediate level (Gini index equal to 0.64 and 0.68, respectively), while the Baltic states, including Estonia, are among the most unequal countries in Europe (Gini for Estonia: 0.76 and for Latvia: 0.79) and face the level of wealth inequality similar to that of Germany (Figure 1).[2] Brzeziński et al. (2019) correct for the 'missing rich' using data from the rich lists published by national magazines. This data source, although informative, likely does not provide fully reliable estimates. However, it is widely used in the literature on top-corrections of wealth disparities (e.g. Vermeulen 2016, 2018; Bach et al. 2019), because very often it is the only available data source on the wealth of the richest. The administrative data (e.g. wealth tax records, if such a tax exists, data from property registries, car registries, business registries etc.) are both hard to obtain from appropriate agencies, especially from agencies in countries other than researcher's country of origin, and hard to compile. One of the rare studies that use wealth administrative data for a CEE country is the one by Meriküll and Rõõm (2019), who find that, indeed, the Gini index for wealth in Estonia is underestimated by 6 percentage points. Interestingly, they find that the downward bias originates from item non-response (under-reporting of top wealth) and not from unit non-response (under-coverage of the rich in the surveys).

In general, out of all wealth components, the largest asset in household portfolios is housing (Causa et al., 2019). Housing debt is also the largest liability in household portfolios. These components are thus important drivers of wealth inequality and as such gain considerable attention from researchers. Yemtsov (2008) used household survey data to study the distribution

[2] Table A1 in the Appendix provides estimates of various inequality measures for net wealth distributions in the CEE countries.

of housing wealth in Poland, Russia and Serbia around 2001-2003. He found that housing privatization contributed significantly to increased housing inequality in all three countries. However, the effect was the lowest in Poland where privatized housing stock was quite evenly spread across the distribution of housing wealth. The universal importance of housing wealth for overall wealth inequality has been confirmed in several works. Mathä et al. (2017) argue that differences in homeownership rates and house price dynamics are important for explaining wealth differences across euro area countries. Causa et al. (2019), as well as Kaas et al. (2019), find a strong negative cross-country correlation between homeownership and wealth inequality: countries with low levels of homeownership face high wealth inequality, even if they happen to feature low levels of income inequality. Since housing is perceived as a fundamental driver of the accumulation and the distribution of wealth across the lifecycle and generations, we study in detail its role in shaping wealth inequality in the post-socialist countries.

Figure 1. Increase in the Gini index of household net wealth distribution due to imputation of the missing rich: CEE countries versus France, Germany and Spain



Note: countries sorted by the value of the unadjusted Gini index.
Source: For Estonia, Hungary, Latvia, Poland and Slovakia: Brzeziński et al. (2020). For Germany, France and Spain: Bach et al. (2019).

3. Data and descriptive statistics

We use data from the second wave of the Household Finance and Consumption Survey (HFCS) (HFCN 2016). The HFCS is a household wealth survey coordinated by the European Central Bank and conducted by national partners. An important feature of the study is that country wealth surveys that are part of the project follow an ex-ante harmonised methodology. As noticed by Cowell and van Kerm (2015), the HFCS provides harmonized, cross-country comparable data on household wealth and can be considered probably as the best quality survey data on wealth available for cross-country comparisons. The second wave of the survey conducted in 2014 and released in 2016 provided microdata for the eurozone countries, Poland and Hungary. Therefore, the group of the post-socialist CEE countries we focus in this paper includes Estonia, Latvia, Hungary, Poland, and Slovakia. In each of them, the HFCS has been the first comprehensive survey on household wealth ever conducted.

Table 1. Mean values of net wealth and socio-economic characteristics of households

	Estonia	Hungary	Latvia	Poland	Slovakia
Net wealth (euro)	96994	50817	40044	96350	66047
Age (HH head)	52	54	54	51	53
Share of female-headed HH	0.50	0.46	0.57	0.38	0.36
Number of HH members	2.25	2.35	2.38	2.82	2.81
Household type (shares)					
Single	0.36	0.33	0.32	0.24	0.26
Adults only (at least two)	0.33	0.37	0.36	0.37	0.34
Adults (at least one) with dependent children	0.31	0.29	0.32	0.39	0.40
Education of HH head (shares)					
Primary or lower-secondary	0.17	0.21	0.19	0.14	0.13
Upper-secondary or post-secondary	0.50	0.49	0.49	0.62	0.68
Tertiary	0.34	0.30	0.32	0.24	0.19
Labour market status of HH head (shares)					
Employed (also self-employed)	0.62	0.57	0.59	0.63	0.63
Unemployed (or other)	0.11	0.08	0.10	0.11	0.08
Retired	0.27	0.34	0.31	0.26	0.29
Number of HH members in employment	0.97	1.04	1.05	1.20	1.24
Income (Euro)	17095	10782	14240	14664	15425
Gifts and inheritances received (Euro)	1697	873	735	6326	1060
Homeownership (shares)					
Outright	0.58	0.65	0.63	0.65	0.70
Mortgage	0.19	0.19	0.13	0.12	0.15
Renter/Other	0.24	0.16	0.24	0.23	0.15
Share of HH with savings (last 12 month expenses were below income)	0.21	0.25	0.18	0.23	0.21
Financial assets share	0.17	0.22	0.16	0.20	0.09
Number of observations	2220	6205	1202	3455	2135

Note: Mean values across the five HFCS implicates. 'HH' stands for 'household'. Sampling weights used.
Source: Own calculations using data from the HFCS (2nd wave 2013/2014).

The HFCS survey is based on the concept of private marketable wealth. Our dependent variable, net household wealth, is defined as total household assets excluding public and occupational pension wealth minus total outstanding household's liabilities. The covariates for decomposition include household type and size, age, educational attainment and labour market status of the household head, household income and value of gifts and inheritances received, housing status, saving practices and financial assets share. Table 1 presents the mean values of these variables for countries in our sample.[3]

To account for the problem of survey non-response, the HFCS uses the multiple imputation approach (HFCN 2016). If the value of the variable was missing, five plausible values were imputed in the HFCS data. We perform our analyses separately on each of five data sets (implicates) with imputed values and combine the results according to Rubin's rules (Rubin 2004). The HFCS sampling weights are used in all our estimations.

4. Methods

4.1. Oaxaca-Blinder decomposition using RIF regressions

Decomposition techniques allow splitting the overall difference in wealth levels and wealth inequality between countries into the composition (characteristics) effect and coefficient (wealth structure) effect. The composition effect (also known as the 'explained' part of the decomposition) is related to the differences in the distribution of the covariates between the compared distributions. Coefficient effect (or the 'unexplained' part of the decomposition) is due to the changes in returns (prices) to the covariates. Several different decomposition methodologies were so far used in the literature on cross-country wealth inequalities. Cowell et al. (2018a) in their paper on wealth differences between Italy, the US, the UK, Sweden and Finland use semi-parametric decomposition method originally proposed by DiNardo, Fortin and Lemieux (1996). They find that the biggest share of cross-country differences reflects strong unexplained country effects, rather than differences in the distribution of household characteristics. Bover (2010) compares the effect of differences in household structures on wealth inequality in the US and Spain. Her results show that these differences account for most of the differences in the lower part of the distribution between the two countries, but mask even larger differences in the upper part of the distribution. Sierminska and Doorley (2018) analyse differences in the structure of wealth ownership between countries, taking into account participation rates in the components of wealth. They find that younger households' participation decisions in assets, compared to that of older households, are more responsive to income. They also show that family structure plays a significant role in explaining cross-country differences for both cohorts and that in more financially developed and economically open countries, households are less likely to own housing but more likely to be in debt.

[3] Table A2 in the Appendix presents the distribution of household net wealth by country.

In our view, the most useful approach is the recentered influence function (RIF)-based decomposition (Firpo et al. 2009, 2018) as it allows for computing the individual composition and coefficient effects for each covariate studied. It was used in several recent works to study various aspects of cross-country wealth differences in the rich eurozone countries. Lindner (2015) analyses 15 euro area countries; his work, however, focuses on contributions of and the elasticity with respect to components of the household's wealth, e.g. housing, real assets, financial assets etc. Mathä et al. (2017) concentrate on the intergenerational transfers, homeownership and house prices and group additional covariates into the 'demographics' category. Regarding methodology, they use the well-known Oaxaca-Blinder (OB) decomposition at the mean and at the 50th, 75th and 90th percentiles (OB-RIF decompositions). Their paper confirms that differences in homeownership rates and house price dynamics are important for explaining wealth differences across euro area countries. Kaas et al. (2019) used the OB-RIF decompositions to show that differences in homeownership status play an important role in accounting for wealth inequality differences across Euro area countries, especially in the lower part of the wealth distribution. Sierminska et al. (2019) used the methodology to explain changes in the gender wealth gap over time, while Davies et al. (2017) applied it to study changes in wealth inequality in Canada between 1999 and 2012.

The OB decomposition, since the issue of the seminal papers of Oaxaca (1973) and Blinder (1973), is widely used in labour economics. It allows researchers to analyse the difference in outcomes (e.g. wages) between two groups, one of which is usually thought to be discriminated against. The difference is decomposed into composition effect ('the explained part') that arises due to differences in characteristics, and coefficient effect ('the unexplained part') that arises due to rewards from the characteristics. In practice, it requires estimating two separate regressions (e.g. for men and women) and then creating a counterfactual distribution. Originally, the OB decomposition was designed to analyse differences in mean outcomes. Since then, several papers tried to extend it to other distributional statistics (for a review, see Fortin et al., 2011). This may be done with the use of RIF regressions (Firpo et al., 2009; 2018). Denoting household *i*'s wealth as y_i, we order households by their wealth, $y_1 \leq y_2 \dots \leq y_n$, and let $Y = (y_1, y_2 \dots, y_n)$. The influence function $\mathrm{IF}(y; v)$ of a distribution statistic *v* evaluated at $Y = y$ measures the influence of a particular point *y* of the distribution. In other words, it tells by how much statistic *v* changes when the fraction of distribution F_Y at $Y = y$ increases by an infinitesimal amount. RIF is then obtained by adding the distributional statistic, *v*, to the IF. By construction, IFs integrate to 0 and, hence, RIFs integrate to the distributional statistic *v*. Using the law of iterated expectations and denoting by X the set of covariates that can be used to perform a decomposition we can write: $v = \mathrm{E}_X\big[\mathrm{E}[\mathrm{RIF}(y; v)]\big]$. Assuming that the conditional expectation of the RIF is a linear function, $\mathrm{E}[\mathrm{RIF}(y; v)|X] = X\beta$, where β are the parameters obtained by running an OLS regression of $\mathrm{RIF}(y; v)$ on X, we obtain that: $v = E[X]\beta$. Using the sample estimates and the OLS estimates of β, we can perform the OB-RIF decompositions of the difference in estimates of distributional statistic v between groups (or time periods) t and r as follows:

$$\hat{v}_r - \hat{v}_t = (\hat{v}_r - \hat{v}_c) + (\hat{v}_c - \hat{v}_t) = \hat{\Delta}v_s + \hat{\Delta}v_x\,, \tag{1}$$

where

$$\begin{aligned} \hat{v}_t &= \mathrm{E}\big[RIF\big(y, v(F_Y^t)\big)\big] = \bar{X}^t\hat{\beta}^t, \\ \hat{v}_r &= \mathrm{E}\big[RIF\big(y, v(F_Y^r)\big)\big] = \bar{X}^r\hat{\beta}^r, \\ \hat{v}_c &= \mathrm{E}\big[RIF\big(y, v(F_Y^c)\big)\big] = \bar{X}^c\hat{\beta}^c, \end{aligned} \tag{2}$$

and subscript or superscript *c* stands for a ‘counterfactual’. F_Y is the distribution of outcome variable Y and $\bar{X}$ stands for average observed characteristics. By $\hat{\Delta}v_s$ we denote the estimated aggregate structural (‘unexplained’ or ‘coefficient’) effect, while $\hat{\Delta}v_x$ denotes estimated aggregate composition (‘explained’ or ‘characteristics’) effect. This approach provides both a decomposition into total (aggregate) effects for all covariates jointly, as well as a detailed decomposition in which the total explained and unexplained effects are divided into separate explained and unexplained contributions of each covariate. One interesting counterfactual F_Y^c is the distribution of *Y* that would prevail if the distribution of covariates in group (or time period) *r* was replaced by the distribution in *t*. The problem lies in determining counterfactual distribution F_Y^c, since we do not observe it in the data. Davies et al. (2017) notice, however, that:

$$F_Y^c(y) = \int F_{Y|X}^t(y|x)dF_X^r(x) = \int F_{Y|X}^t(y|x)dF_X^t(x)\,\psi_X(x),$$

where $\psi_X(x)$ is a reweighting factor. Since it satisfies Bayes’ law (DiNardo et al. 1996), it follows that:

$$\psi_X(x) = \frac{dF_{X_r}(x)}{dF_{X_t}(x)} = \frac{\mathrm{P}(X|T=r)}{\mathrm{P}(X|T=t)} = \frac{\mathrm{P}(T=r|X)}{\mathrm{P}(T=t|X)} * \frac{\mathrm{P}(T=t)}{\mathrm{P}(T=r)}.$$

Then $\hat{\mathrm{P}}(T = r|X)$ can be estimated using logit or probit model for the probability of being in a subsample r given X (in a pooled sample of r and t data) and $\hat{\mathrm{P}}(T = r)$ is the empirical fraction of observations in a subsample *r*. These two terms are then used to calculate reweighting factor $\psi_X(x)$. The counterfactual $\hat{v}_c$ can be then estimated as $\bar{X}^c\hat{\beta}^c$, where $\bar{X}^c$is the reweighted average of X obtained using the reweighting factor $\psi_X(x)$ and $\hat{\beta}^c$ is estimated using the OLS from a regression of RIF on X in the reweighted sample.[4]

The reweighted OB-RIF decomposition can be then rewritten as an extension of the OB-RIF decomposition (1) as follows:

$$\hat{v}_r - \hat{v}_t = \hat{\Delta}v_s + \hat{\Delta}v_x = \hat{\Delta}v_s^p + \hat{\Delta}v_s^e + \hat{\Delta}v_x^p + \hat{\Delta}v_x^e = \\ \bar{X}^r(\hat{\beta}^r - \hat{\beta}^c) + (\bar{X}^r - \bar{X}^c)\hat{\beta}^c + (\bar{X}^c - \bar{X}^t)\hat{\beta}^t + \bar{X}^c(\hat{\beta}^c - \hat{\beta}^t). \tag{3}$$

The estimated composition effect, $\hat{\Delta}v_x$, is now divided into a pure composition effect, $\hat{\Delta}v_x^p$, and a specification error $\hat{\Delta}v_x^e$, while the estimated structural effect is decomposed into a pure structural effect, $\hat{\Delta}v_s^p$, and a reweighting error, $\hat{\Delta}v_s^e$. The reweighting error can be used to assess the quality of the reweighting approach and should go to zero in large samples. Small specification error assures that the RIF regressions succeeded in computing the counterfactual distributions.

In this paper, we deal with decomposing wealth inequality differences between pairs of the CEE countries. Thus, v is a given inequality measure, e.g. the Gini coefficient (G), and the decomposition of the difference in wealth inequality estimates between, for instance, Poland (PL) and Slovakia (SK) following equation (3) can be written as:

$$\hat{G}_{PL} - \hat{G}_{SK} = \hat{\Delta}v_s^p + \hat{\Delta}v_s^e + \hat{\Delta}v_x^p + \hat{\Delta}v_x^e = \\ \bar{X}^{PL}(\hat{\beta}^{PL} - \hat{\beta}^c) + (\bar{X}^{PL} - \bar{X}^c)\hat{\beta}^c + (\bar{X}^c - \bar{X}^{SK})\hat{\beta}_{SK} + \bar{X}^c(\hat{\beta}^c - \hat{\beta}^{SK}). \tag{4}$$

Alternatively, the counterfactual distribution can be defined with the second country (i.e. Poland) being a reference one. In this case, the pure composition effect, $\hat{\Delta}v_x^p$, is valued at the coefficients of Poland, $\hat{\beta}_{PL}$, while the pure wealth structure effect, $\hat{\Delta}v_s^p$, is valued at the average characteristics of the second country, $\bar{X}_{SK}$. In our empirical analysis, we report results for both choices of the counterfactual.[5]

The advantages of OB-RIF methodology are that 1) it provides a detailed decomposition of inequality differences for a given distributional index, 2) it can be applied to decompose any distributional measure, 3) it accounts for specification and reweighting errors. The latter advantage means that a researcher can easily assess the importance of departure from the assumption that the RIF is represented by a linear function (indicated by specification error) and the quality of reweighting, since reweighting error should go to zero in large samples. The second advantage means that the RIF can be in practice be easily applied to decompose such

[4] See Fortin et al. (2011) and Firpo et al. (2018) for more details.
[5] We use the Stata implementation of OB-RIF decompositions by Rios-Avila (2019).

popular inequality measures as the Gini index and the top p% shares. The RIF for the Gini index, G, is given by (Davies et al., 2017):

$$\mathrm{RIF}(y;G) = 2\frac{y}{\mu}G + 1 - \frac{y}{\mu} + \frac{2}{\mu}\int_0^y F(z)dz$$

and for the p-th Lorenz ordinate $L(p)$ (notice that p% share is a simple function of the Lorenz curve[6]) the RIF is given by:

$$RIF\big(y;L(p)\big) = \begin{cases} \dfrac{y-(1-p)q_p}{\mu} + L(p)\left(1-\dfrac{y}{\mu}\right) & \quad if\, y < q_p \\ \dfrac{pq_p}{\mu} + L(p)\left(1-\dfrac{y}{\mu}\right) & \quad if\, y \geq q_p\,, \end{cases}$$

where μ represents the mean of the distribution F and q_p denotes its p-th quantile.

While the OB-RIF decomposition methodology has several attractive features, it does nonetheless suffer from some limitations. First, it does not allow to estimate the general equilibrium effects. Such effect could arise in our context, for example, when changing the distribution of covariates between countries affects returns to the covariates and by this have a secondary effect on the countries' wealth distribution. Second, the detailed decomposition assumes that the estimated effect of the covariates is not affected by the omitted variables. For this reason, we do not causally interpret our results even though we use a large number of observable covariates and the total estimated effects of unobserved variables are in general insignificant in our decompositions.[7] Finally, for categorical covariates, the detailed unexplained effects are sensitive to the choice of the base category (Oaxaca and Ransom 1999). This problem is less relevant for the explained part of the decomposition as the sum of detailed explained effects is unaffected by the choice of the reference category. On the other hand, for the unexplained part of the decomposition both the total unexplained effect associated with a given categorical variable and the detailed effects may change both the size and the sign depending on the choice of the base category.

4.2. Survey weights calibration to account for the missing rich in household surveys

Survey weights calibration techniques rely on adjusting original survey weights so that the estimates of given survey-based total amounts (i.e. average wealth, average wealth among the top 10%, etc.) match the total amounts taken from external sources (Deville and Särndal 1992;

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[6] For example, the top 10% share of the distribution *F(.)* is given by $1 - L(F; p_{90})$.

[7] Note, however, that the aggregate decomposition remains valid as long as the correlation between covariates and unobserved factors is the same across compared units (countries or time periods) (Fortin et al. 2011; Davies et al. 2017).

Törmälehto 2019). The procedure minimizes a distance measure between initial and adjusted weights subject to calibration equations. In our case, we calibrate the HFCS survey weights to match the top 5% wealth share estimated with original HFCS survey weights with the top-corrected top 5% wealth shares calculated in Brzeziński et al. (2020) for the CEE countries based on the joined HFCS data and data from the relevant national rich lists.[8] Using this approach, we do not add any direct information on wealth or socio-economic characteristics of the missing rich persons to the HFCS data. Instead, we only adjust the survey weights of the HFCS respondents so that the HFCS-based estimates of wealth inequality are inflated to their top-corrected counterparts that account for the problem of the missing rich in household survey data. The decompositions using data with calibrated weights correct for the problem of the missing rich in the appropriate way only when the distribution of covariates among the missing rich is not significantly different from the distribution of covariates among the richest persons available in the HFCS data. Admittedly, this is a strong assumption, which cannot be tested empirically due to the lack of relevant data on socio-economic characteristics of the richest persons.

5. Accounting for wealth inequality differences between post-socialist countries

5.1. Detailed decomposition of wealth inequality differences measured by Gini index

Table 2 presents the results of our decomposition analysis applied to pairs of CEE countries with Slovakia – a country with the lowest wealth inequality – being a reference country[9]. For each pair of countries, we present results using two counterfactuals (see section 4.1): (1) characteristics effect valued at the coefficients of Slovakia and coefficient effect valued at average characteristics of the other country, and 2) characteristics effect valued at the coefficients of the other country and coefficient effect valued at average characteristics of Slovakia. In the remainder of this paper, we report and interpret mainly those results which are statistically significant for both counterfactuals. The differences in the Gini index between the pairs of countries range from 10.2 to 29.4 percentage points and all are statistically significant. Total explained effects are usually smaller than the total unexplained effects (or wealth structure

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[8] See Table A3 in the Appendix for more information on the data from the national rich lists used.

[9] Inequality estimates from our decomposition analyses can slightly differ from those computed directly using HFCS data (see HFCN 2017 and Table A3 in the Appendix to this paper). The small differences are due to the fact that decomposition-based estimates are implied by RIF regressions with many covariates that suffer from the problem of missing values. The problem of missing values is addressed in the HFCS using multiple imputation, but this solution is applied only to some main variables (all components of household income, consumption and wealth). Decomposition results with other choices of a reference country are presented in the Appendix (Table A4). Detailed results of the underlying RIF regressions are available upon request.

effects) and are significant in half of the cases (PL vs SK, EE vs SK). Total unexplained effects account for at least 60% of the total difference in Ginis for each pair of countries. The specification and reweighting errors are in general small and insignificant, which suggests that we use appropriate model specifications and reweighting procedures. The exceptions are specification 2 for the comparison between Estonia and Slovakia and specification 1 in case of comparing Latvia and Slovakia. We treat results for these specifications as less reliable.

Turning to the detailed explained effects, we observe that for most of the specifications the differences in homeownership rates are jointly significant and account for up to 42% the difference in wealth inequality Ginis.[10] This effect is relatively the largest in case of the comparison between Poland and Slovakia as it accounts for 27-42% of the Gini difference depending on the counterfactual. It is rather insignificant for explaining wealth inequality differences between Hungary and Slovakia, but it accounts for 13-22% of the wealth differences when Slovakia is compared with Estonia or Latvia. These results reflect the fact that among the countries in our sample Slovakia and Hungary have the highest share of outright homeowners.[11] Previous research (e.g. Mathä et al. 2017; Kindermann and Kohls 2018; Kaas et al. 2019) has shown that high rates of homeownership are associated with lower wealth inequality. Kaas et al. (2019) found that the explained effect associated with homeownership accounts often for at least 50% of the overall difference in the Gini coefficient for wealth inequality across the Euro area advanced countries. However, their finding may be a consequence of choosing Germany as a reference country. As it is well known, Germany has a very low homeownership rate (44% according to the HFCS data), while most of the other Euro area countries have significantly higher homeownership rates (from about 55% to 80%). Therefore, even large differences in wealth inequality across Euro area countries can be accounted for by the vast disparities in homeownership rates. On the other hand, our post-socialist countries are characterized by notably lower inequality in homeownership rates (see Table 1). Hence, the explanatory potential for this factor in our analysis is somewhat more limited than in the case of the Western European countries. Still, it is worth noting that even for the CEE countries differences in homeownership rates produce the largest and the most significant detailed explained effects among all household characteristics that we study.

[10] The reference category for homeownership is outright homeownership.

[11] In fact, Slovakia and Hungary have the highest rates of homeownership in the OECD (Causa et al. 2019).

Table 2. Oaxaca-Blinder reweighted decomposition of wealth inequality (Gini index) using RIF regression: pairs of CEE countries (Slovakia as a reference country)

	PL vs SK		HU vs SK		EE vs SK		LV vs SK	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Gini (first country)	59.2***	59.2***	64.1***	64.1***	69.0***	69.0***	78.5***	78.5***
Gini (Slovakia)	49.0***	49.0***	49.0***	49.0***	49.0***	49.0***	49.0***	49.0***
Difference in Ginis	10.2***	10.2***	15.0***	15.0***	19.9***	19.9***	29.4***	29.4***
Total explained	2.7***	4.1**	-1.1	0.7	2.3*	4.2***	3.1	3.3
Total unexplained	7.5***	6.1***	16.1***	14.4***	17.6***	15.8***	26.4***	26.1***
Explained effect								
Total	2.7***	4.1**	-1.1	0.7	2.3*	4.2***	3.1	3.3
Pure	2.4***	5.2***	-0.3	1.2	2.8**	6.5***	2.8**	5.3***
Specification error	0.3	-1.1	-0.8	-0.6	-0.5	-2.4***	0.2	-2.0
Detailed explained effects								
Demographic	-0.1	-0.2	-1.1*	-0.9	-1.3***	-0.8	2.1*	-0.6
Household structure	-0.1	-0.0	0.6	0.4	0.6	0.3	-2.3*	0.2
Education	-0.5**	0.6	1.1***	2.2**	-0.6	1.6***	-0.4	1.9***
Employment	0.1	0.5	0.4	1.0	0.1	0.7*	-0.2	0.7
Income	0.0	-0.2	-1.8***	-4.6	0.2	0.4	-0.3	-1.3
Gifts and inheritances	-0.0	0.0	0.0	0.0	0.0	-0.0	0.3	-0.0
Homeownership (mortgage)	-0.6**	-0.4	0.3*	0.2	0.6	0.3	-0.4	-0.0
Homeownership (renter)	3.4***	4.7***	0.3	2.8	3.1***	4.1***	4.1***	4.4***
Financial assets share	0.1	0.0	0.0	-0.0	-0.0	0.0	-0.0	0.0
Saving	0.0	0.0	-0.0	0.1	-0.0	-0.0	-0.0	-0.1
Unexplained effect								
Total	7.5***	6.1***	16.1***	14.4***	17.6***	15.8***	26.4***	26.1***
Reweighting error	0.0	-0.3	-1.5	-0.2	-1.6	0.7	3.9*	-0.4
Pure	7.5***	6.4***	17.6***	14.5***	19.2***	15.0***	22.4***	26.5***
Detailed unexplained effects								
Demographic	-4.0	-4.5	-14.1	-5.1	20.2	6.7	-40.0**	-22.0
Household structure	-0.4	-0.8	-6.5	-4.9	-3.7	-4.1	15.5	16.3**
Education	12.7***	7.0*	6.5	-0.2	8.0	1.0	8.3	2.4
Employment	10.1*	10.3*	-2.9	-9.1	7.5	2.8	18.0	-1.3
Income	-6.5	-9.8	30.1***	10.4**	-5.4	-13.1	-12.4	-1.1
Gifts and inheritances	0.0	-0.1	0.0	-0.0	0.0	-0.3	-0.9	-0.4
Homeownership (mortgage)	0.5	0.9	-1.3	0.8	2.4	1.5	1.4	1.3
Homeownership (renter)	-1.1**	-1.1	-3.4***	-2.1***	-1.2	-1.5	0.4	-0.2
Financial assets share	0.1	0.0	0.1	-0.3	-0.6	-0.4	-0.3	-0.2
Saving	0.5	-0.4	-0.7	-0.5	-1.4	-1.6	-1.4	-0.2
Constant	-4.3	4.7	9.9	25.5*	-6.6	24.1	33.9	31.9

Note: $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The HFCS sampling weights are used. Standard errors (not shown for brevity) were obtained using the bootstrapping (with 200 replications) the whole estimation procedure including the reweighting and accounting for the multiple imputation. See main text for definitions of effects (section 4.1) and covariates (section 3). All values in the table are multiplied by 100. Specification (1) shows explained effects valued at the coefficients of the reference country (SK) and unexplained effects values at the characteristics of the other country, while specification (2) presents explained effects valued at the coefficients of the other country and unexplained effects at characteristics of the reference country (SK). The reweighting procedure includes all covariates listed in the table and interactions between housing and education variables, housing and household type, housing and employment, housing and saving, and others. Income enters the decomposition analysis as the logarithm of equivalized (square root scale) household income. To save space, some individual effects are aggregated into grouped effects: demographic effect (age, female, number of household members), household structure (single, at least two adults, adults with dependent children), education (primary or lower secondary, upper secondary or post-secondary, tertiary), and employment (employed or self-employed, unemployed or inactive, retired).

Source: Own calculations using data from the HFCS.

The cross-sectional nature of the data set used in this paper does not allow to investigate why homeownership rates differ between the post-socialist countries. The existing literature offers several hypotheses. Kindermann and Kohls (2018) show that rental market inefficiencies can account for the large variation in homeownership rates between euro-area countries and explain about 50% of the cross-country variation in wealth inequality. Fehr and Hofmann (2020) derive a model implying that differences in homeownership rates between Germany and Mediterranean countries can be largely explained by higher generosity of public long-term care insurance system in Germany. On the other hand, Huber and Schmidt (2019) argue that cross-country differences in homeownership rates are driven by cultural preferences for homeownership, which are persistent and transmitted between generations. It could be also that country-specific housing policies such as regulations of mortgage markets or subsidies to owing the house differentiate the incentives to invest into housing. Kaas et al. (2019) explore this possibility empirically using a variety of housing policy indicators such as mortgage loan-to-value ratios (LTV), the presence of imputed rent taxation, the possibility of mortgage interest rate tax deductions and the VAT rates on new home purchases. Given that they analyse only nine (euro-area) countries in two points in time, their exercise does not have significant statistical power but is shows that tax policies (but not other housing market policies) are correlated with differences in homeownership rates between countries and, with the opposite sign, with Gini coefficient for wealth inequality. There is some suggestive evidence that housing taxation policies may play some role in explaining why homeownership rates differ among the post-socialist countries. Barrios et al. (2019) estimate the user costs of owner-occupied housing (UCOH) indicator for the European countries, which measures the distortions exerted by the tax system on individual housing investment decisions.[12] Their results show that over 2001-2014 the UCOH indicator has been relatively low and stable over time in Slovakia, while it was significantly higher for most of the period in Latvia and Poland.[13] The differences in homeownership rates between some countries that we study could be therefore related to the alternative housing tax policy solutions. However, this issue should be studied further using more detailed data on policies and their changes over time, as well as using richer and, in particular, longitudinal datasets on household wealth.

[12] The indicator takes into account the recurrent property taxes, taxes on the flow of services from ownership (imputed rents), tax reliefs on debt financed housing, transfer taxes on house sale and capital gains taxes.

[13] On the other hand, the UCOH indicator for Estonia and Slovakia is rather similar with respect to the level and changes over time. It seems therefore that heterogeneity in housing tax policy cannot account for all significant between-country differences in homeownership rates across the CEE countries.

Specifically for the post-socialist countries, the differences in homeownership rates could also be a result of different distributions of housing assets under socialism, different trajectories of housing privatization after 1989 and varying development of the rental markets for housing. As shown by Wind et al. (2017), already under socialism there were significant cross-country differences in the homeownership rate. In 1980, the rate was as high as 71% in Hungary and 53% in Czechia, but only 26% in Estonia and 36% in Poland. There were also important differences in the speed and privatization strategies concerning the housing stock, as well as regarding the development of housing policies (Pichler-Milanović 1999; Stephens et al. 2015).

Other detailed explained effects in Table 2 are usually small and not significant for both choices of the counterfactual. One exception is the effect of education in case of comparison between Hungary and Slovakia, which accounts for 7-15% of the 15 percentage point difference in Gini for wealth inequality between the countries. This effect is driven by the fact that a sizable fraction of the Hungarian population (21%) attained an only primary or lower-secondary level of education (compared to just 13% in Slovakia). We also find that in some cases the detailed explained effects for demographic variables, income or education are significant, but these effects are usually rather negligible in size and not robust to the choice of the counterfactual. Our finding that explained demographic effects do not play an important role in explaining cross-country wealth differences is consistent with previous literature (Bover 2010; Fessler et al. 2014). We find that the role of gifts and inheritances is negligible, which is consistent with research for advanced countries suggesting that inheritances have an either insignificant or small impact on household wealth inequality (Karagiannaki 2017; Elinder et al. 2018). We do not find any role for financial assets share or saving practices as factors explaining cross-country wealth inequality in our sample of countries. This is somewhat surprising as there are significant cross-country differences in households' saving practices and, especially, in the shares of wealth held in the form of financial assets (see Table 1). However, it could be that these differences did not yet translate into significant disparities in cross-country wealth inequality across post-socialist countries because of the relatively short period of wealth accumulation after the fall of communism.

There is some heterogeneity concerning the contribution of detailed wealth structure effects (i.e. differences in the returns to the covariates) to the overall cross-country differences in wealth inequality across the pairs of post-socialist countries.[14] We interpret these results with

[14] It is worth noting here that the unexplained effect due to the constant (capturing the effects of omitted variables) is in general insignificant in our decompositions.

caution as the contribution (detailed and total) of each categorical covariate to the wealth structure effect depends on the choice of the base category (see section 4.1 for a discussion). Differences in returns to education and employment seem to play a large role in explaining the fact that the Gini coefficient of wealth inequality in Poland is 10 percentage points higher than in Slovakia. These effects account for as much as 69%-125% of the total wealth inequality difference between the countries. More detailed decompositions for education (results available upon request) show that the large positive unexplained effect for education is due to the relatively low returns to wealth that are associated with having higher education in Poland and the relatively low wealth returns to low levels of education in Slovakia. The positive unexplained effect for employment results from the fact that being retired in Slovakia has a much bigger wealth equalizing effect than in Poland. These results can probably be explained by regulatory and institutional differences in the educational and pension systems in Poland and Slovakia.

The unexplained detailed effect associated with income is large and significant when Hungary is compared to Slovakia. It accounts for 69-200% of the wealth inequality difference between the countries. This effect stems from the fact that the positive correlation between household income and wealth is significantly stronger for Hungary than for Slovakia.[15] The RIF regressions show that household income is strongly and significantly associated with wealth inequality for Hungary, but not for other countries. A more detailed analysis shows that being income poor is more strongly associated in Hungary with wealth inequality than in other countries (full results available upon request). This effect could work through the interaction between households' income and liabilities. While for Slovakia income-poor households are on average less relatively indebted than all households, it is the opposite for Hungary.[16]

The wealth structure effect for being a home renter plays an inequality-decreasing role in case of a comparison between Hungary and Slovakia. In other words, if not for this effect wealth inequality in Hungary would be even 14-23% higher than in Slovakia. This is a consequence of the fact that being a home renter is much more inequality-increasing in Slovakia than in Hungary. Related to this, Gini for wealth distribution among home renters in Slovakia in 91% higher than the overall Gini, while the corresponding number for Hungary is only 52%.

[15] The Pearson correlation coefficient between log wealth and log income for Hungary is 0.39, while for Slovakia it is 0.27.
[16] For Slovakia, the ratio of household liabilities to household net wealth is on average 22.2% and just 14.8% for the income-poor household. The corresponding statistics are, respectively, 24.9% and 35.9% for Hungary.

5.2. Decomposing wealth inequality differences: alternative measures

Table 3 presents results for decomposing wealth inequality differences using alternative inequality measures.[17] Our findings for these inequality indices (ratios of the 90th, 50th and 25th percentiles, and the top 10%, 5% and 1% wealth shares) are generally in line with those for the Gini index but reveal some important subtleties. For most of the other inequality measures used, the total explained effects (as a percent the total difference in inequality) are smaller or similar to those for the Gini index. The only exception is the ratio of the 50th to the 25th percentile, P50/P25, which is sensitive to wealth differences in the bottom and the middle of the distribution and insensitive to wealth differences in the upper part of the distribution. For this measure, the total explained effect accounts for as much as 58-84% of the total inequality difference when Poland, Estonia and Latvia are compared with Slovakia and for 35% in case of comparison between Hungary and Slovakia. Among the detailed explained effects, the homeownership rates play the biggest role as they explain 63-109% of the cross-country differences measured by the P50/P25 index.[18]

Overall, our results for alternative inequality indices suggest that cross-country differences in the distribution of homeownership rates account for the most of differences in disparities in the bottom part of the wealth distribution in the CEE countries. However, they play a moderate role when we use an inequality measure that is most sensitive to wealth differences around the middle of the distribution, the Gini index, or inequality indices that are affected mainly by disparities between the highest wealth values (top wealth shares). These facts can be linked to the varying inequalities in homeownership status in different parts of wealth distributions in our sample countries. While the Gini index of outright homeownership rates for households in the bottom half of wealth distribution is on average 0.50 in our group of countries, it is only 0.21 for the households in the upper part of the distribution. A similar conclusion was obtained by Kaas et al. (2019) in case of Euro area countries.

To sum up, our findings show that in general the differences in homeownership rates among the post-socialist CEE countries account for the majority of cross-country wealth inequality disparities when they are measured using the bottom-sensitive inequality indices, but only for 13-42% (Table 2) of wealth inequality differences when using the Gini index. In the

[17] In order to save space, we present results only for selected effects (total explained and total unexplained effects as well as detailed explained effects for homeownership rates). Full results are available upon request. Results for other choices of a reference country are given in the Appendix (Table A5).

[18] The effect is smaller only in case of Hungary-Slovakia comparison as it reaches just 18%. Notice that the joint explained effect of housing variables for the comparison of Latvia and Slovakia is marginally insignificant (*p*-value of 0.12)

case of the Gini index, several country-specific wealth structure effects are also important when explaining wealth inequality differences between certain pairs of countries.

Table 3. Oaxaca-Blinder reweighted decomposition of various wealth inequality measures using RIF regression: pairs of CEE countries (Slovakia as a reference country)

	Gini	P90/P50	P50/P25	Top 10% share	Top 5% share	Top 1% share
PL vs SK						
Difference in inequality	10.2***	116.4***	69.7***	8.3***	7.0***	3.0*
Total explained	2.7***	20.9**	58.5***	1.1*	0.7	0.3
Homeownership (mortgage)	-0.6**	-4.6*	-6.2**	-0.6*	-0.6*	-0.3
Homeownership (renter)	3.4***	31.9***	81.8***	2.0***	1.5***	0.7***
Total unexplained	7.5***	95.5***	11.2	7.2***	6.2***	2.6
HU vs SK						
Difference in inequality	15.0***	160.3***	69.7***	14.1***	12.8***	7.7***
Total explained	-1.1	-16.5	24.2**	-3.0*	-3.3*	-0.5
Homeownership (mortgage)	0.3*	1.1	5.0***	0.1	0.0	-0.1
Homeownership (renter)	0.3	3.6	7.4	0.2	0.1	0.1
Total unexplained	16.1***	176.8***	45.5***	17.1***	16.0***	8.2***
EE vs SK						
Difference in inequality	19.9***	185.4***	156.0***	21.6***	20.8***	12.3***
Total explained	2.3*	60.9***	97.9***	1.2	0.3	-1.3
Homeownership (mortgage)	0.6	7.0*	5.8*	0.8	0.8	0.8
Homeownership (renter)	3.1***	39.0***	91.7***	3.0***	3.1***	2.5*
Total unexplained	17.6***	124.5***	58.1***	20.4***	20.5***	13.5**
LV vs SK						
Difference in inequality	29.4***	318.5***	238.9***	29.0***	26.5***	14.3***
Total explained	3.1	-37.8	139.5**	4.5	5.3	1.9
Homeownership (mortgage)	-0.4	-8.5	-26.4	-0.0	0.2	-0.0
Homeownership (renter)	4.1**	70.8***	234.2	3.3***	3.0**	1.7**
Total unexplained	26.4***	356.3***	99.4***	24.5***	21.2***	12.4***

Note: see note to Table 2. We present results for specification (1) showing explained effects valued at the coefficients of the reference country (SK) and unexplained effects values at the characteristics of the other country. Results for other choices of a reference country are available in Table A5 in the Appendix. Full decomposition results for various inequality measures are available upon request.
Source: Own calculations using data from the HFCS.

5.3. *Decomposing wealth inequality differences with survey weight calibration*

In Table 4, we present our results using survey weight calibration which corrects wealth inequality estimates to account for the problem of the missing rich in the HFCS.[19] The weight calibration approach allows to adjust the raw estimates of wealth inequality indices that are underestimated due to the missing highest wealth observations in household survey data to the corrected estimates (see Figure 1) obtained using Pareto imputation techniques applied to the joined survey data and data from the rich lists (Brzeziński et al. 2019). Our analysis assumes that the distribution of covariates among the missing rich is similar to that of the richest persons

[19] We have also experimented with survey weight calibration based on matching survey-based and top-corrected estimates of other measures as top 1% or top 10% wealth shares. These alternatives led to similar decomposition results.

captured in the HFCS. This is a strong assumption, but in the absence of reliable and comprehensive non-survey data on socio-economic characteristics of the rich, we think that our approach is an informative experiment.[20]

The approach based on calibrated weights (Table 4) leads to smaller cross-country differences in wealth inequality Ginis as the corrections are in general larger for countries with a lower unadjusted value of the Gini (see Figure 1). Similarly, differences in top wealth shares are also substantially reduced. For these measures, estimates of inequality differences based on calibrated survey weights often lose statistical significance. On the other hand, the percentile ratios are much less affected by our adjustment procedure.[21]

Table 4. Oaxaca-Blinder reweighted decomposition of various wealth inequality measures using RIF regression with calibrated weights: pairs of CEE countries (Slovakia as a reference country)

	Gini	P90/P50	P50/P25	Top 10% share	Top 5% share	Top 1% share
PL vs SK						
Difference in inequality	4.8	117.4***	65.6***	2.3	0.2	-7.1
Total explained	2.5**	20.2**	58.9***	1.2	1.0	0.5
Homeownership (mortgage)	-0.7*	-5.0	-5.8**	-0.8	-0.8	-0.4
Homeownership (renter)	3.0***	31.4***	80.1***	1.9***	1.5***	0.9***
Total unexplained	2.3	97.2***	6.7	1.0	-0.7	-7.6
HU vs SK						
Difference in inequality	8.4	148.8***	70.7***	6.2	3.8	-2.9
Total explained	-2.1	-34.8	23.8**	-4.4*	-4.8*	-1.4
Homeownership (mortgage)	0.1	1.5	5.0***	-0.2	-0.3	-0.4
Homeownership (renter)	0.3	3.5	7.0	0.1	0.1	0.0
Total unexplained	10.5	183.6***	46.9***	10.6	8.6	-1.5
EE vs SK						
Difference in inequality	16.3**	186.1***	176.6***	18.0*	17.4	8.4
Total explained	1.2	68.4***	118.2***	-0.2	-1.4	-3.7
Homeownership (mortgage)	0.9	6.1	6.0	1.2	1.4	1.7
Homeownership (renter)	4.4***	53.8***	126.7***	4.9***	5.4***	5.6**
Total unexplained	15.1*	117.8***	58.4***	18.2	18.8	12.1
LV vs SK						
Difference in inequality	23.0***	295.1***	264.9**	18.5**	14.1	-2.4
Total explained	3.0	30.0	184.8	3.9	4.9	2.3
Homeownership (mortgage)	-0.7	-3.9	-35.5	-0.2	0.0	-0.2
Homeownership (renter)	5.8**	83.9**	333.3	4.3***	4.1***	2.4**
Total unexplained	20.0***	265.1***	80.1*	14.6*	9.2	-4.7

Note: see note to Table 2 and section 4.2 for details of the weight calibration procedure. We present results for specification (1) showing explained effects valued at the coefficients of the reference country (SK) and unexplained effects values at the characteristics of the other country. Full decomposition results are available upon request.
Source: Own calculations using data from the HFCS.

[20] While some information on the socio-economic characteristics of the richest persons in the post-socialist countries can be collected using publicly available sources (e.g. data on gender, age, or education), the data on homeownership, housing value, saving, income, financial vs real assets distribution are missing.
[21] This is, of course, in general expected as the wealth calibration procedure adjusts mainly survey weights of households belonging to the top 5% of country's net wealth distribution.

The top-corrected decomposition results are broadly consistent with the unadjusted ones from Table 3. One striking difference is that for the approach based on calibrated weights the explained effects for homeownership rates are often relatively (as compared to total inequality differences) larger across all inequality indices used. This is best visible when we focus on the pairs of countries with the biggest wealth inequality differences (i.e. Estonia vs Slovakia and Latvia vs Slovakia). In these cases, the joint explained effect of homeownership rates in terms of the Gini index is 13-15% using the unadjusted approach (Table 3) and 22-33% using calibrated survey weights (Table 4). The increase seems to be even higher in case of the P50/P25 index as the corresponding numbers for the approach based on the raw weights are 63-87% (Table 3), while those for the calibrated weights approach are within 75-113% range.[22] It is worth noting here that the increased importance of explained effects for homeownership rates is also preserved when inequality is measured using top wealth shares. Overall, the decomposition results using calibrated survey weights suggest that our main findings regarding the role of homeownership in explaining cross-country wealth inequality differences are robust to the underestimation of top wealth values in the HFCS.

6. Conclusions

Thirty years after the fall of communism and the emergence of the market economy in Central and Eastern Europe there are vast cross-country differences in household wealth inequality in the region. In this paper, we provide the first attempt to understand how differences in households' socio-demographic and economic characteristic can account for disparities in wealth inequality between these countries. We used the reweighted Oaxaca-Blinder-type decompositions based on recentered influence function (RIF) regressions to study microeconomic differences in net wealth distribution among Estonia, Latvia, Hungary, Poland, and Slovakia. We found that for almost all pairs of countries (except Hungary vs Slovakia) the differences in homeownership rates are highly significant and account for up to 42% of the difference in wealth inequality measured with the Gini index. It seems that the cross-country differences in homeownership rates between countries that we study can be partly accounted for by alternative designs of the housing tax policy as the countries with high homeownership rates have tax policies that relatively do not distort households' investment into housing. However, future research should try to disentangle precisely how current levels of homeownership rates were shaped by other factors such as different trajectories of housing

[22] Note, however, that the joint effect of housing variables in case of comparison between Latvia and Slovakia is marginally insignificant (*p*-value of 0.12).

privatization after the fall of socialism, varying development of the rental markets for housing, and different distribution of housing assets under socialism. Interestingly, we also found that the differences in homeownership rates explain most, and in some cases all, of the cross-country disparities in wealth inequality in the bottom part of the wealth distribution, where inequality in own housing wealth is the highest. We did not find any role for financial assets share, saving practices or gifts and inheritances in explaining cross-country wealth inequality in our post-socialist countries. In some cases, especially when comparing countries with relatively small cross-country wealth differences, we found that some wealth structure effects are large and significant, but these effects are less reliable and harder to interpret.

Apart from making an empirical contribution, we also attempted to account for the problem of the 'missing rich' in household surveys by calibrating the HFCS survey weights to top wealth shares adjusted using wealth data from national rich lists. This correction procedure preserves and even strengthens the role of homeownership rate as a factor accounting for cross-country wealth inequality differences. This suggests that our results are not sensitive to the underestimation of top wealth observations in household survey data.

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Appendix. Supplementary tables

Table A1. Inequality measures for household net wealth distributions in CEE countries (HFCS-based estimates vs estimates based on HFCS and imputed top wealth values)

	Estonia		Hungary		Latvia		Poland		Slovakia	
	HFCS	HFCS+ rich list	HFCS	HFCS+ rich list	HFCS	HFCS+ rich list	HFCS	HFCS+ rich list	HFCS	HFCS+ rich list
Top 0.1%	9.0	17.7	5.4	10.8	5.6	16.5	2.9	8.3	3.3	11.1
Top 1%	21.4	36.0	17.3	24.3	23.6	33.0	12.1	20.3	9.5	22.5
Top 5%	43.3	54.8	35.7	42.8	49.2	52.6	29.1	37.9	23	38.3
Top 10%	55.7	65.1	48.5	54.5	63.4	64	41.9	49.6	34.6	48.4
Gini	0.691	0.755	0.641	0.681	0.785	0.792	0.587	0.639	0.492	0.597
Theil	1.093	1.724	0.793	1.164	1.141	1.597	0.613	0.973	0.448	1.066
GE(2)	6.823	43.09	2.853	64.309	4.715	135.639	1.365	77.015	1.552	99.772

Note: 'HFCS + rich list' denotes HFCS data with top values imputed using data from the relevant rich list.
Source: Brzeziński et al. (2020) using data from the HFCS, Äripäev (2013), Napi.hu (2014), Kapitals (2014), Forbes Polska (2014) and Forbes Slovensko (2015).

Table A2. Distribution of household net wealth by country (in Euros)

Country	Mean	P10	P25	P50	P75	P90	N
Estonia	97.0	0.4	11.0	43.5	90.9	194.9	2220
Hungary	50.8	0.9	9.8	26.2	55.9	108.0	6205
Latvia	40.0	0.0	3.1	14.2	35.0	82.6	1202
Poland	96.4	0.5	21.5	57.1	121.1	209.6	3454
Slovakia	66.0	3.5	25.2	50.3	82.4	131.7	2135

Source: own calculation using HFCS data.

Table A3. Descriptive statistics for wealth distributions in CEE countries from the HFCS and national rich lists

Sample	Data set	N	Oversampling top 10 %	Mean	Standard Deviation	Minimum	Maximum
Estonia (2013)	HFCS	2220	31 %	97	353	- 65	14 000
	Äripäev	503		20 500	30 100	5 600	298 000
Hungary (2014)	HFCS	6205	2 %	51	12	-355	4 104
	Napi.hu	100		79 600	99 400	17 300	490 000
Latvia (2014)	HFCS	1202	53 %	40	121	-170	4 065
	Kapitals	100		28 800	49 200	7 000	299 000
Poland (2014)	HFCS	3455	10 %	96	159	-31	4 606
	Forbes PL	103		235 000	424 000	50 200	2 700 000
Slovakia (2014)	HFCS	2135	5 %	66	111	-43	8 796
	Forbes SK	10		675 000	603 300	390 000	2 370 000

Note: Oversampling rate of the top 10% is equal to (S90 – 0.1)/0.1, where S90 is the share of sample households in the wealthiest 10%(HFCN 2016). All monetary values are given in thousands of euro.
Source: Brzeziński et al. (2020) using data from the HFCS, Äripäev (2013), Napi.hu (2014), Kapitals (2014), Forbes Polska (2014) and Forbes Slovensko (2015).

Table A4. Oaxaca-Blinder reweighted decomposition of wealth inequality (Gini index) using RIF regression: pairs of CEE countries (Poland, Hungary and Estonia as reference countries)

	HU vs PL		EE vs PL		LV vs PL		EE vs HU		LV vs HU		LV vs EE	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Gini (first country)	64.1***	64.1***	69.0***	69.0***	78.5***	78.5***	69.0***	69.0***	78.5***	78.5***	78.5***	78.5***
Gini (second country)	59.2***	59.2***	59.2***	59.2***	59.2***	59.2***	64.1***	64.1***	64.1***	64.1***	69.0***	69.0***
Difference in Ginis	4.8***	4.8***	9.7***	9.7***	19.2***	19.2***	4.9**	4.9**	14.4***	14.4***	9.5***	9.5***
Total explained	-3.8***	-9.1*	1.3	-0.2	0.8	-0.8	4.5***	4.4***	2.8	2.9***	0.3	-1.1
Total unexplained	8.7***	13.9***	8.4***	10.0***	18.5***	20.0***	0.4	0.5	11.6***	11.5***	9.1***	10.6***
Explained effect												
Total	-3.8***	-9.1*	1.3	-0.2	0.8	-0.8	4.5***	4.4***	2.8	2.9***	0.3	-1.1
Pure	-3.5***	-4.1	1.2*	-0.0	-0.1	-0.5	4.7*	4.7***	3.3**	2.9***	0.2	-1.1
Specification error	-0.4	-5.0	0.1	-0.2	0.9	-0.3	-0.2	-0.3	-0.5	-0.0	0.1	-0.0
Detailed explained effects												
Demographic	-1.2*	-0.2	-0.9**	-0.2	2.5	-0.0	-0.1	-0.0	-0.5	0.4	0.1	0.4
Household structure	0.7	0.8	0.8*	0.4	-2.4	0.2	0.1	0.3*	0.6	-0.2	0.4	-0.5*
Education	0.9***	-1.9**	-0.4	-1.0***	-0.1	-0.9***	0.0	-0.5***	-0.3	-0.3	0.4	0.0
Employment	-0.2	-0.3	0.0	-0.1	-0.6	-0.3	0.1	0.1	0.4	0.1	-0.0	-0.1
Income	-1.8***	1.3	0.3	-0.1	-0.3	0.1	1.5	2.6***	0.3	0.7**	-0.5	-0.6
Gifts and inheritances	0.0	0.0	-0.0	0.0	0.2	0.0	0.0	0.0	-0.0	0.0	0.2	0.0
Homeownership (mortgage)	0.6**	0.5	1.2*	1.0***	0.2	0.3	0.5	-0.1	-0.6	-0.4*	-0.9*	-0.8
Homeownership (renter)	-2.4***	-4.1***	0.1	-0.1	0.5	0.1	2.2***	2.3***	3.4***	2.4***	0.5	0.4
Financial assets share	-0.0	-0.1*	-0.0	0.0	0.0	-0.0	-0.0	0.0	0.0	0.0	0.0	-0.0
Saving	-0.0	-0.0	0.1	-0.0	-0.0	-0.1	0.3	0.0	-0.0	0.1	-0.0	0.1
Unexplained effect												
Total	8.7***	13.9***	8.4***	10.0***	18.5***	20.0***	0.4	0.5	11.6***	11.5***	9.1***	10.6***
Reweighting error	-1.0	6.5	-1.2	0.2	4.3	0.2	-2.5	1.3*	2.5	-0.1	3.7	0.2
Pure	9.7***	7.4***	9.6***	9.7***	14.1***	19.8***	2.9	-0.8	9.1***	11.6***	5.4	10.4***
Detailed unexplained effects												
Demographic	-6.4	-13.6	16.1*	10.9	-29.9**	-23.3**	14.6	17.7	-12.9	-20.8	-40.1**	-31.1**
Household structure	-3.0	-2.5	-2.8	-3.4	20.8*	16.0**	-0.8	1.0	15.8**	23.0***	15.2**	18.3**
Education	-2.4	-1.6	-4.3	-2.5	-4.5	0.1	0.8	-2.4	1.0	3.1	2.6	2.9
Employment	-13.5***	-11.7**	-5.1*	-1.9	-0.6	-5.4	8.5	9.3**	15.1	6.2	-6.0	-4.0
Income	-6.2***	-4.2**	-1.3	-0.9	0.1	-1.0	4.0**	3.4**	6.3	4.3	-0.5	-0.6
Gifts and inheritances	0.0	0.0	0.0	-0.1	-1.2	-0.4	-0.0	-0.0	-2.0	-0.4	-4.7	-0.4
Homeownership (mortgage)	-1.8**	-1.7	0.7	0.4	0.2	-0.3	1.9	3.0*	1.8	1.7	-0.4	-0.1
Homeownership (renter)	-3.4***	-2.4***	-0.6	-1.0	2.1	0.4	1.2	2.8**	2.5	3.3	1.0	2.8
Financial assets share	-0.2	-0.2	-0.6	-0.5	-0.3	-0.4	-0.1	-0.1	-0.1	-0.1	0.0	-0.6
Saving	-0.7	-1.4	-1.4	-1.5*	-1.3	-0.2	-0.8	-0.4	0.8	0.5	0.7	0.6
Constant	47.3***	46.7***	8.9	10.2	28.7	34.2	-26.4*	-35.0**	-19.3	-9.3	37.7*	22.5

Note: $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The HFCS sampling weights are used. Standard errors (not shown for brevity) were obtained using the bootstrapping (with 200 replications) the whole estimation procedure including the reweighting and accounting for the multiple imputation. See main text for definitions of effects (section 4.1) and covariates (section 3). All values in the table are multiplied by 100. Specification (1) shows explained effects valued at the coefficients of the reference country (SK) and unexplained effects values at the characteristics of the other country, while specification (2) presents explained effects valued at the coefficients of the other country and unexplained effects at characteristics of the reference country (SK). The reweighting procedure includes all covariates listed in the table and interactions between housing and education variables, housing and household type, housing and employment, housing and saving, and others. Income enters the decomposition analysis as the logarithm of equivalized (square root scale) household income. To save space, some individual effects are aggregated into grouped effects: demographic effect (age, female, number of household members), household structure (single, at least two adults, adults with dependent children), education (primary or lower secondary, upper secondary or post-secondary, tertiary), and employment (employed or self-employed, unemployed or inactive, retired).

Source: Own calculations using data from the HFCS.

Table A5. Oaxaca-Blinder reweighted decomposition of various wealth inequality measures using RIF regression: pairs of CEE countries (Poland, Hungary and Estonia as reference countries)

	Gini	P90/P50	P50/P25	Top 10% share	Top 5% share	Top 1% share
HU vs PL						
Difference in inequality	4.8***	43.9**	-0.0	5.8***	5.8***	4.7**
Total explained	-3.8***	-59.7**	-57.8***	-4.7**	-4.6**	-0.5
Homeownership (mortgage)	0.6***	2.1	9.3***	0.1	0.0	-0.2
Homeownership (renter)	-2.4***	-25.1***	-52.0***	-1.2***	-0.8***	-0.4***
Total unexplained	8.7***	103.6***	57.8***	10.4***	10.4***	5.3*
EE vs PL						
Difference in inequality	9.7***	69.0***	86.3**	13.3***	13.8***	9.3**
Total explained	1.3	32.2*	15.0	1.4	1.3	1.0
Homeownership (mortgage)	1.2*	13.9**	11.4**	1.5	1.5	1.6
Homeownership (renter)	0.1	1.2	2.9	0.1	0.1	0.1
Total unexplained	8.4***	36.8	71.3**	11.9***	12.5***	8.3**
LV vs PL						
Difference in inequality	19.2***	202.1***	169.2***	20.7***	19.5***	11.3***
Total explained	0.8	-80.6	53.7	2.1	2.4	1.0
Homeownership (mortgage)	0.2	3.4	10.5	0.0	-0.1	0.0
Homeownership (renter)	0.5	8.0	26.5	0.4	0.3	0.2
Total unexplained	18.5***	282.6***	115.5**	18.6***	17.1***	10.4***
EE vs HU						
Difference in inequality	4.9**	25.1	86.3***	7.5**	8.0**	4.5
Total explained	4.5**	46.3	90.2**	4.8***	5.0**	2.8
Homeownership (mortgage)	0.5	5.4	4.4	0.6	0.6	0.6
Homeownership (renter)	2.2***	27.3**	64.3**	2.1**	2.1**	1.7*
Total unexplained	0.4	-21.2	-3.9	2.7	3.1	1.8
LV vs HU						
Difference in inequality	14.4***	158.2**	169.2**	14.9***	13.7***	6.6**
Total explained	2.8	76.9	97.4	2.9	2.8	2.0
Homeownership (mortgage)	-0.6	-11.5	-35.6	-0.0	0.3	-0.0
Homeownership (renter)	3.4***	58.9**	194.8	2.7***	2.5**	1.4*
Total unexplained	11.6***	81.3	71.8	12.0***	11.0***	4.6
LV vs EE						
Difference in inequality	9.5***	133.1*	82.9	7.4	5.7	2.0
Total explained	0.3	-136.7**	14.4	1.3	1.4	0.5
Homeownership (mortgage)	-0.9	-17.9	-55.4	-0.0	0.5	-0.1
Homeownership (renter)	0.5	8.5	28.0	0.4	0.4	0.2
Total unexplained	9.1***	269.8***	68.5	6.1	4.2	1.5

Note: see notes to Table 2 (main text) and Table A4. We present results for specification (1) showing explained effects valued at the coefficients of the reference country (SK) and unexplained effects values at the characteristics of the other country. Full decomposition results for various inequality measures are available upon request.
Source: Own calculations using data from the HFCS.

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