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Differences in Wealth and Wealth Inequality among the CEE Countries

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Differences in wealth and wealth inequality among the CEE countries*

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Abstract:

In this paper, we use Oaxaca-Blinder-like decompositions based on RIF regressions to study differences in net wealth distribution among the selected CEE countries: Estonia, Latvia, Hungary, Poland, and Slovakia. We also investigate differences in wealth inequality between the CEE countries and Germany. Overall, we find that differences in the distribution of observable characteristics play small or negligible role in explaining diversity of wealth inequality in the CEE region. However, we also find that when accounting for large differences in wealth inequality between Germany and most of the CEE countries (except Latvia), a major role is played by large differences in the distribution of households' housing status.

Keywords: household wealth, wealth inequality, decomposition, Household Finance and Consumption Survey (HFCS), Central and Eastern Europe (CEE)

JEL Codes: D31, D63, P36

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1. Introduction

There is a disproportion in the field between the study of income inequality and of wealth inequality. While we better and better understand the sources of income inequality, both within and between countries, the determinants of wealth inequality are still under-researched. This is especially true for the Central and Eastern European (CEE) countries, and the main reason for this state of the art until recently was lack of reliable data on household wealth.

Wealth is of prime importance as a determinant of individual economic well-being and its distribution in the society. It provides security by smoothing income shocks and enabling individuals to maintain consumption during retirement. Wealth itself generates income, thus shaping the distribution of current income and of current consumption. It is positively correlated with power and social recognition and some of its elements, e.g. real estates and vehicles, are a straightforward source of utility for its owners.

It is widely agreed, however, that wealth is more unequally distributed than income and it potentially plays a role in increasing within-country social tensions. The distribution of household wealth also differs substantially across countries (Cowell et al., 2016; Mathä et al., 2017). Existing studies in this matter, however, focus on the U.S. and Western European countries. In this paper we aim at shedding light at the differences in wealth and wealth inequality among the selected Central and Eastern European countries, additionally compared to an example of a rich developed country such as France.

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 age, household type, labour market status, housing status, educational attainment, household income and received gifts and inheritances contribute to differences in the Gini coefficient for wealth among the selected CEE countries.

Decomposition techniques allow us to split the overall difference in wealth levels and wealth inequality between countries into endowments (characteristics) effects and coefficients effects. The endowments effects are related to the changes in the distribution of the above-mentioned covariates. Coefficients effects are due to the changes in returns (prices) to these covariates. Decomposition analyses of this type allow to assess the importance of individual factors in explaining cross-country differences in wealth and wealth inequality. Several different decomposition methodologies were so far used in the literature on wealth inequality. Cowell et al. (2016) 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; the method is referred to as "DFL" in the literature, after the initials of the authors). They find that the biggest share of cross-country differences reflects strong unexplained country effects, rather than differences in distribution of household characteristics and economic 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 (2014) 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.

In our view, the most useful approach is the Recentered Influence Function (RIF)-based decomposition (Firpo et al. 2009) as it allows for computing the individual endowment and coefficient effect for each covariate studied. It was used by e.g. Lindner (2015) and Mathä et al. (2017) 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 "demographics" category. Regarding methodology, they use Oaxaca-Blinder (OB) decomposition at the mean (comparing each country to Germany) and OB-RIF decompositions at 50th, 75th and 90th percentile. Their paper confirms that differences in homeownership rates and house price dynamics are important for explaining wealth differences across euro area countries. Sierminska et al. (2019) focus on the role of households' socio-economic characteristics in explaining the differences in wealth inequality over time. They also analyse gender wealth gap. Using RIF-based regressions, they identify the explanatory factors of wealth gaps. They focus on the role of changes in labour supply, permanent income, portfolio composition, and marital status and find that increasing labour market participation of women and the resulting changes in occupational structure had a positive effect on women's wealth accumulation.

In this paper, we use OB-RIF decompositions of the Gini coefficient for wealth, as proposed by Davies, Fortin, and Lemieux (2017). We employ the Household Finance and Consumption Survey (HFCS) to analyse differences in wealth and wealth inequality among the selected CEE countries, present in the survey: Estonia, Latvia, Hungary, Poland, and Slovakia. We find that differences in the distribution of observable characteristics play small or negligible role in explaining diversity of wealth inequality in the CEE region. However, when compared to Germany, a major role in large differences in wealth inequality between Germany and most of the CEE countries is played by the differences in the distribution of households' housing status.

The remainder of the paper is as follows. Section 2 describes the HFCS data, followed by the methods in Section 3. Section 4 presents and discusses our findings. Section 5 concludes.

2. Data

We use data from the second wave of Eurosystem Household Finance and Consumption Survey (HFCS). 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 CEE countries we focus in this study includes Estonia, Latvia, Hungary, Poland, and Slovakia. In each of them, the HFCS has been the first comprehensive survey on household wealth ever conducted.

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, education 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 mean values of these variables for the selected CEE countries and Germany.

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

	Estonia	Hungary	Latvia	Poland	Slovakia	Germany
Net wealth (euro)	96994	50817	40044	96350	66047	214359
Age (HH head)	52	54	54	51	53	53
Share of female-headed HH	0.50	0.46	0.57	0.38	0.36	0.36
Household type (shares)						
Single	0.36	0.33	0.32	0.24	0.26	0.40
Adults only (at least two)	0.33	0.37	0.36	0.37	0.34	0.37
Adults (at least one) with dependent child/ children	0.31	0.29	0.32	0.39	0.40	0.22
Education of HH head (shares)						
Primary or lower-secondary	0.17	0.21	0.19	0.14	0.13	0.11
Upper-secondary or post-secondary	0.50	0.49	0.49	0.62	0.68	0.58
Tertiary	0.34	0.30	0.32	0.24	0.19	0.31
Number of HH members in employment	0.97	1.04	1.05	1.20	1.24	0.99
Labour market status of HH head (shares)						
Employed (also self-employed)	0.62	0.57	0.59	0.63	0.63	0.64
Unemployed (or other)	0.11	0.08	0.10	0.11	0.08	0.07
Retired	0.27	0.34	0.31	0.26	0.29	0.29
Income (euro)	17095	10782	14240	14664	15425	48487
Gifts and inheritances received (euro)	5551	2039	2035	20506	3901	14984
Housing (shares)						
Owner	0.58	0.65	0.63	0.65	0.70	0.28
Mortgage	0.19	0.19	0.13	0.12	0.15	0.17
Renter/Other	0.24	0.16	0.24	0.23	0.15	0.55
Share of HH with savings (last 12 month expenses were below income)	0.21	0.25	0.18	0.23	0.21	0.47
Financial assets share	0.17	0.22	0.16	0.20	0.09	0.42
Number of HH members	2.25	2.35	2.38	2.82	2.81	2.02

Note: Mean values across the implicates. 'HH' stands for 'household'.

Due to a common problem of item-non response in household income and wealth data, the HFCS database provides multiply imputed values for each missing value. This is done via stochastic imputation which estimates missing observations conditional upon observed variables that can plausibly explain missingness (ECB, 2016). The procedure results in five parallel datasets that should be taken into account during model estimation[1].

3. Methods

The Gini coefficient, despite its drawbacks, remains a widely used measure of inequality. One of the drawbacks is its non-decomposability when subgroup distributions (of income or wealth, for instance) are overlapping (Davies, Fortin, & Lemieux, 2017). There are three types of decomposition that could be of interest. First, decomposing inequality measure between groups, e.g. different households types: "how much" of inequality takes place within groups, for example within the group of lone parents, and how much between groups, e.g. to what extend lone parents' situation differs from the one of couples with dependent children and which group faces the biggest inequality. Second, we can attempt to decompose inequality into its components, e.g. different income or wealth sources. For instance, we could be interested in answering the question: "How much of wealth inequality stems from inequality in housing, how much from financial assets and how meaningful is debt?". Third, supposing that there is a bunch of factors contributing to inequality, we could be interested in asking about their relative importance. "How much of an increase in inequality over a given period of time stems from the changing composition of family types, how much – if any – from the raising share of highly-educated workers and how much remains unexplained?".

In this paper we focus on the third of the abovementioned types of decomposition. We base on the work by Davies, Fortin, and Lemieux (2017), who introduce Oaxaca-Blinder-type (OB) decomposition using Recentered Influence Functions (RIF). We utilize the Stata implementation of OB-RIF decomposition proposed by Rios-Avila (2019). In the remainder of this section, we briefly summarize OB decomposition, then we describe RIF and finally we present how these two methodological concepts work together in a handy tool that can be used for decomposing changes in inequality.

[1] This may be done in Stata using the family of *mi* commands. All results presented in this paper made use of this command.

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 counterfactual distribution (for example: "how much would women earn if their characteristics remained factual but they were rewarded as if they were men?").

Originally, 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, Lemieux, and Firpo (2011)). Other focused on computing counterfactuals linked to specific covariates of interest. This may be done with the use of RIF regressions (Firpo et al., 2009). Influence function $IF(y; v)$ 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 to the IF, so as the change in the average value of RIF over time would be equal to the change in distributional statistic. As Davies et al. (2017) note, since added component is constant, the estimated coefficients from both IF and RIF regressions will be the same, except for the constant.

The starting point for the OB-RIF decomposition of a change in the statistic v between groups or periods t and r is the sequence of equations:

$$v_r - v_t = (v_t - v_c) + (v_c - v_t) = \Delta v_s + \Delta v_x = \Delta v_s^p + \Delta v_s^e + \Delta v_x^p + \Delta v_x^e,$$

where

$$v_t = \mathrm{E}\left[RIF\left(y, v(F_Y^t)\right)\right] = \bar{X}^t \hat{\beta}^t,$$

$$v_r = \mathrm{E}\left[RIF\left(y, v(F_Y^r)\right)\right] = \bar{X}^r \hat{\beta}^r,$$

$$v_c = \mathrm{E}\left[RIF\left(y, v(F_Y^c)\right)\right] = \bar{X}^c \hat{\beta}^c,$$

and subscript or superscript c stands for 'counterfactual'. F_Y is the distribution of outcome variable Y, $\bar{X}$ stands for average observed characteristics and $\hat{\beta}$ are the coefficients from the OLS regression. By Δv_s we denote structural ("unexplained") effect, while Δv_x denotes compositional ("explained") effect. The former may be further decomposed into pure structural effect Δv_s^p and reweighting error Δv_s^e and the latter into pure compositional effect Δv_x^p and specification error Δv_x^e.

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:

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

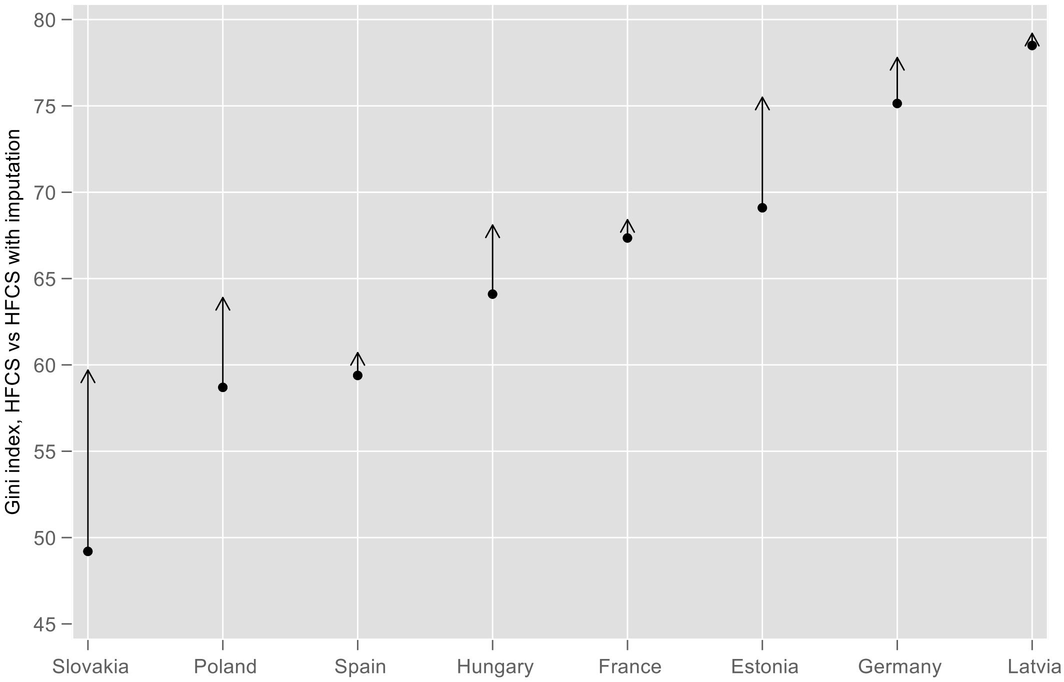
Then $\hat{\mathrm{P}}(T=r|X)$ can be estimated using logit or probit model for the probability of being in a subsample r given X (in a pooled sample of r and t data) and $\hat{\mathrm{P}}(T=r)$ is the empirical fraction of observations in a subsample r. These two terms are then used to calculate reweighting factor $\psi_X(x)$, which in turn allows to obtain counterfactual statistic of interest v_c.

4. Results

Inequality of household net wealth is quite diverse in the CEE region. Figure 1 from Brzezinski et al. (2019) shows that, after accounting for the phenomenon of the missing rich in household surveys, some of the CEE countries such as Slovakia and Poland are characterized by rather low levels of wealth inequality, Hungary is at the intermediate level, while the Baltic states are among the most unequal countries in Europe (such as Germany).

Table 2 presents results of our decomposition analysis applied to the CEE countries with Slovakia (the least wealth unequal country) as the reference point. The differences in the Gini index between the compared countries range from 9 to 29 percentage points and all are statistically significant.

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: Brzezinski et al. (2019).

However, only for Poland and Hungary the contribution of the observed characteristics (the total composition effect) is significant. On the other hand, for all pairs of compared countries the total unexplained effect (or wealth structure effect) is significant and much larger quantitatively. In case of inequality difference between Poland and Slovakia, about one third of the difference is accounted for by differences in housing status distribution. Differences in housing status seem to be inequality-increasing factor for each pair of countries we study, but their contribution to the overall wealth difference in most of the cases is negligible. The detailed decomposition shows that returns to education are inequality-increasing across all comparisons in Table 2, while returns on renting a house are inequality-decreasing.

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

	PL vs SK	HU vs SK	EE vs SK	LV vs SK
Total effects				
First country	0.594***	0.640***	0.696***	0.792***
	(0.010)	(0.010)	(0.016)	(0.023)
SK	0.502***	0.502***	0.502***	0.502***
	(0.014)	(0.014)	(0.014)	(0.014)
Total difference	0.092***	0.138***	0.195***	0.290***
	(0.017)	(0.017)	(0.022)	(0.027)
Explained	0.026***	-0.087***	0.024	0.037
	(0.008)	(0.027)	(0.017)	(0.023)
Unexplained	0.066***	0.225***	0.171***	0.253***
	(0.017)	(0.035)	(0.033)	(0.031)
Detailed explained effects				
Demographic	-0.001	-0.003	-0.015	0.040
	(0.001)	(0.007)	(0.010)	(0.027)
Household structure	-0.001	0.010**	0.005	-0.015
	(0.001)	(0.004)	(0.004)	(0.013)
Education	-0.005**	0.001	-0.009	-0.009
	(0.002)	(0.006)	(0.006)	(0.008)
Employment	0.001	0.015***	0.007	-0.002
	(0.001)	(0.005)	(0.007)	(0.007)
Income	0.000	-0.106***	0.003	0.000
	(0.001)	(0.031)	(0.002)	(0.002)
Gifts and inheritances	0.000	-0.012	0.001	-0.007
	(0.002)	(0.009)	(0.001)	(0.014)
Housing (owner)	0.009***	0.007***	0.018***	0.011***
	(0.003)	(0.002)	(0.005)	(0.004)
Housing (mortgage)	0.002	-0.001*	-0.001	0.001
	(0.001)	(0.001)	(0.002)	(0.001)
Housing (renter/other)	0.020***	0.004	0.016***	0.018**
	(0.004)	(0.003)	(0.003)	(0.007)
Saving	0.000	-0.002	0.000	0.000
	(0.000)	(0.001)	(0.001)	(0.002)
Financial assets share	0.000	-0.000	-0.001	-0.000
	(0.001)	(0.001)	(0.004)	(0.002)
Detailed unexplained effects				
Demographic	0.039	-0.023	0.137	-0.209*
	(0.110)	(0.117)	(0.159)	(0.124)
Household structure	-0.000	-0.007*	-0.002	0.016
	(0.003)	(0.004)	(0.004)	(0.012)
Education	0.043***	0.018*	0.033**	0.029**
	(0.009)	(0.010)	(0.013)	(0.014)
Employment	0.079*	-0.033	0.053	0.093
	(0.043)	(0.048)	(0.049)	(0.062)
Income	-0.076	0.266**	-0.049	-0.082
	(0.086)	(0.125)	(0.086)	(0.089)
Gifts and inheritances	-0.007*	0.018	-0.005	0.008
	(0.003)	(0.017)	(0.004)	(0.028)

Housing (owner)	0.006	0.033**	0.031	0.023
	(0.016)	(0.014)	(0.031)	(0.022)
Housing (mortgage)	0.009	0.009*	0.011	0.009
	(0.005)	(0.005)	(0.009)	(0.008)
Housing (renter/other)	-0.009***	-0.015***	-0.017***	-0.013
	(0.004)	(0.004)	(0.006)	(0.010)
Saving	0.003	-0.011	-0.008	0.001
	(0.009)	(0.010)	(0.009)	(0.013)
Financial assets share	0.001	-0.000	-0.000	-0.000
	(0.002)	(0.002)	(0.003)	(0.003)
_cons	-0.022	-0.029	-0.012	0.380***
	(0.092)	(0.106)	(0.128)	(0.109)

Note: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. See main text for definitions of covariates.

Table 3 presents the results of our decompositions in case of comparing wealth inequality between CEE countries and Germany. In this setting, the compositional effect is always significant (except LV vs DE) case, while the unexplained effect is insignificant. The distribution of housing status is the major factor contributing to the observed difference in wealth inequality, accounting for more than 75% of the difference in Gini coefficient for wealth inequality between Poland and Germany. Much smaller, but significant, role is played by differences in the distribution of educational attainment. Other covariates play much smaller role in most of the cases.

Table 3. Oaxaca-Blinder decomposition of wealth inequality (Gini index) using RIF regression: CEE countries vs Germany

	PL vs DE	HU vs DE	EE vs DE	LV vs DE
Total effects				
First country	0.594***	0.640***	0.696***	0.792***
	(0.010)	(0.010)	(0.016)	(0.023)
SK	0.784***	0.784***	0.784***	0.784***
	(0.007)	(0.007)	(0.007)	(0.007)
Total difference	-0.190***	-0.144***	-0.087***	0.008
	(0.013)	(0.013)	(0.017)	(0.024)
Explained	-0.140***	-1.026***	-0.148***	-0.131
	(0.050)	(0.226)	(0.043)	(0.102)
Unexplained	-0.050	0.882***	0.060	0.139
	(0.054)	(0.230)	(0.044)	(0.111)
Detailed explained effects				
Demographic	0.002	0.010*	0.001	-0.007
	(0.011)	(0.006)	(0.006)	(0.011)
Household structure	-0.005	-0.009***	-0.001	0.020
	(0.005)	(0.003)	(0.004)	(0.017)
Education	0.007***	0.018***	0.000	0.004

	(0.002)	(0.003)	(0.003)	(0.004)
Employment	0.001	-0.006*	0.001	0.006
	(0.004)	(0.003)	(0.001)	(0.006)
Income	0.002	-0.839***	-0.051	0.017
	(0.045)	(0.230)	(0.043)	(0.072)
Gifts and inheritances	0.000	-0.081	-0.005	-0.048
	(0.001)	(0.055)	(0.003)	(0.092)
Housing (owner)	-0.071***	-0.057***	-0.047***	-0.059***
	(0.007)	(0.004)	(0.013)	(0.010)
Housing (mortgage)	0.002*	-0.001	-0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.002)
Housing (renter/other)	-0.076***	-0.076***	-0.059***	-0.067***
	(0.005)	(0.006)	(0.010)	(0.020)
Saving	-0.001	0.014**	0.012	0.002
	(0.005)	(0.007)	(0.007)	(0.014)
Financial assets share	-0.001	0.000	0.001	0.001
	(0.002)	(0.002)	(0.005)	(0.006)
Detailed unexplained effects				
Demographic	0.132**	0.060	0.216*	-0.066
	(0.061)	(0.073)	(0.127)	(0.086)
Household structure	0.004	0.012**	0.004	-0.019
	(0.004)	(0.005)	(0.006)	(0.018)
Education	0.015***	-0.015**	0.007	0.000
	(0.005)	(0.006)	(0.008)	(0.008)
Employment	0.030	-0.062**	0.009	0.036
	(0.020)	(0.027)	(0.028)	(0.042)
Income	-0.041	1.037***	0.041	-0.062
	(0.067)	(0.294)	(0.069)	(0.105)
Gifts and inheritances	-0.008**	0.085	-0.001	0.047
	(0.004)	(0.063)	(0.006)	(0.106)
Housing (owner)	-0.020***	-0.009	-0.010	-0.014
	(0.007)	(0.006)	(0.012)	(0.009)
Housing (mortgage)	0.003	0.003	0.005	0.003
	(0.006)	(0.005)	(0.010)	(0.009)
Housing (renter/other)	0.032***	0.010	0.004	0.017
	(0.009)	(0.010)	(0.019)	(0.034)
Saving	0.031**	-0.001	0.008	0.026
	(0.012)	(0.016)	(0.015)	(0.025)
Financial assets share	0.006*	0.003	0.000	0.002
	(0.003)	(0.004)	(0.012)	(0.010)
_cons	-0.233***	-0.239***	-0.223**	0.169*
	(0.066)	(0.086)	(0.109)	(0.089)

Note: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. See main text for definitions of covariates.

5. Conclusions

In this paper, we use Oaxaca-Blinder-like decompositions based on RIF regressions to study differences in net wealth distribution among the CEE countries. We also investigate differences in wealth inequality between the CEE countries and Germany. Overall, we have found that differences in the distribution of observable characteristics play small or negligible role in explaining diversity of wealth inequality in the CEE region. However, we have found that when accounting for large differences in wealth inequality between Germany and most of the CEE countries (except Latvia), a major role is played by large differences in the distribution of households' housing status.

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