



Quality of life
**Wealth distribution and
social mobility:
Supplementary analyses**

[Wealth distribution and social mobility](#)

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This report presents the results of research conducted largely prior to the outbreak of COVID-19 in Europe in February 2020. For this reason, the results do not fully take account of the outbreak.

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Introduction

This working paper provides methodological background, more detailed results and other additional information as a background to Eurofound's report *Wealth distribution and social mobility* (2021).

The Chapters of this working paper are organised in the order the related materials appear in Eurofound (2021). The paper first presents summary indicators of wealth income inequality and compares their estimates in relation to whether the net wealth is measured at household or individual level (Chapter 1), followed by formal tests of significance in the change of wealth inequality (Chapter 2). Chapter 3 studies wealth inequality in the pooled sample of those 14 countries which were included in all three waves of the European Central Banks's Household Finance and Consumption Survey (HFCS). This is followed by the analysis of Lorenz-curves, which provide a more detailed assessment of inequality changes than summary indicators of inequality (Chapter 4). Chapter 5 presents the wealth portfolio (value of the main assets and liabilities) by wealth quintile for a selected number of countries.

Chapter 6 explains the econometric method, the cross-sectional ordered probit model, in detail, and presents some examples on interpreting the estimates. The impact of grandparents on educational mobility is analysed in Chapter 7, while the last chapter (8) presents estimates related to wealth persistence.

Please note that this report focuses on reporting household wealth per capita (net household wealth divided by the number of people living in the household) and assigns the same wealth for each individual in the household (for example, in a four-person household, each is assumed to possess one-quarter of the household wealth and this household represents four observations in the sample). Most analyses in this report are conducted at the level of the individual, unless indicated otherwise.

1 – Estimates of net household wealth inequality at household and individual level

This chapter quantifies the impact of alternative measurement units of wealth for summary indicators of wealth inequality.

When wealth data are available for households, research can choose to take into account one of three alternative units: households, households per capita and ‘equivalised household size’ (whereby household members are given different weights, a frequent measure in household income calculations). In reporting wealth distribution, using the household as a unit is not uncommon (European Central Bank, 2020a; OECD, forthcoming).

This study focuses on household wealth per capita (total household wealth divided by the number of people living in the household), under the assumption that benefits (not purely financial) are shared, both with partners and with dependants. For households with more than one person, an equal share of household wealth is assigned.

Regardless of the conceptual differences explained in Box 1 in Eurofound (2021, p.15), the impact of the approach on the summary characteristics of wealth inequality is minor, as shown Table 1 below. For example, the difference between the Gini index of net wealth inequality for each country does not exceed 0.028 when the aforementioned three approaches are compared, and the correlation between the measures is high (at least 0.969).

Table 1: Wealth inequality indicators based on three alternative units of measurement, 2017 HFCS

	GINI				THEIL			
	HH	IND	EQ	range	HH	IND	EQ	Range
21 HFCS country aggregate	0.700	0.708	0.701	0.008	0.961	0.996	0.955	0.041
AT	0.730	0.702	0.719	0.028	1.202	1.119	1.199	0.083
BE	0.632	0.648	0.624	0.024	0.786	0.795	0.733	0.062
CY	0.749	0.731	0.739	0.018	1.171	1.107	1.110	0.064
DE	0.739	0.733	0.735	0.006	1.023	1.012	1.005	0.018
EE	0.709	0.684	0.687	0.025	1.160	1.066	1.072	0.095
FI	0.662	0.661	0.656	0.006	0.746	0.751	0.721	0.030
FR	0.674	0.685	0.672	0.013	0.942	0.976	0.931	0.045
GR	0.602	0.609	0.602	0.008	0.580	0.606	0.583	0.026
HR	0.606	0.625	0.610	0.019	0.808	0.881	0.833	0.073
HU	0.650	0.659	0.640	0.019	0.915	0.934	0.888	0.046
IE	0.670	0.696	0.670	0.025	0.836	0.925	0.847	0.089

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IT	0.606	0.624	0.607	0.017	0.680	0.727	0.675	0.052
LT	0.589	0.607	0.588	0.019	0.709	0.770	0.713	0.061
LU	0.652	0.676	0.656	0.024	1.048	1.126	1.059	0.078
LV	0.679	0.663	0.661	0.019	0.907	0.866	0.858	0.049
MT	0.602	0.623	0.626	0.024	0.794	0.910	0.893	0.116
NL	0.782	0.775	0.778	0.006	1.002	0.977	0.972	0.030
PL	0.567	0.549	0.550	0.018	0.623	0.590	0.575	0.048
PT	0.679	0.688	0.669	0.018	1.068	1.063	0.983	0.085
SI	0.594	0.597	0.573	0.024	0.708	0.671	0.607	0.100
SK	0.540	0.552	0.538	0.014	0.560	0.603	0.572	0.043
<i>cor(HH,IND)</i>	<i>0.969</i>				<i>0.958</i>			
<i>cor(IND,EQ)</i>	<i>0.984</i>				<i>0.982</i>			
<i>cor(HH,EQ)</i>	<i>0.987</i>				<i>0.973</i>			
<i>max</i>				<i>0.028</i>				<i>0.116</i>
<i>min</i>				<i>0.006</i>				<i>0.018</i>
<i>average</i>				<i>0.017</i>				<i>0.061</i>

Source: Calculations based on 2017 HFCS.

Note: regarding measurement unit, HH= net household wealth, IND=net household wealth per capita, EQ= net household wealth in terms of equivalised household size.

2 – Testing for equality of the inequality indices

This chapter assesses the statistical significance of changes in Gini and Theil coefficients of wealth inequality.

Inequality indices, such as the Theil and the Gini, are extremely sensitive to the exact nature of the upper tail of income distributions. Even without underreporting of wealth or income, the practice of sampling instead of collecting information on the full population can lead to considerable underestimation of the true inequality index. Keeping one extremely wealthy individual out of the sample can be enough for substantial underestimation.

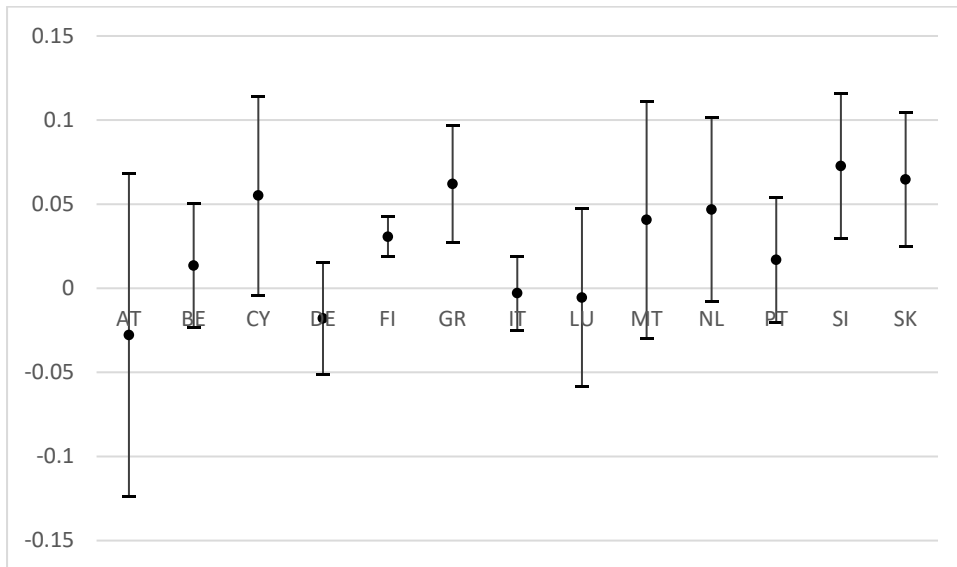
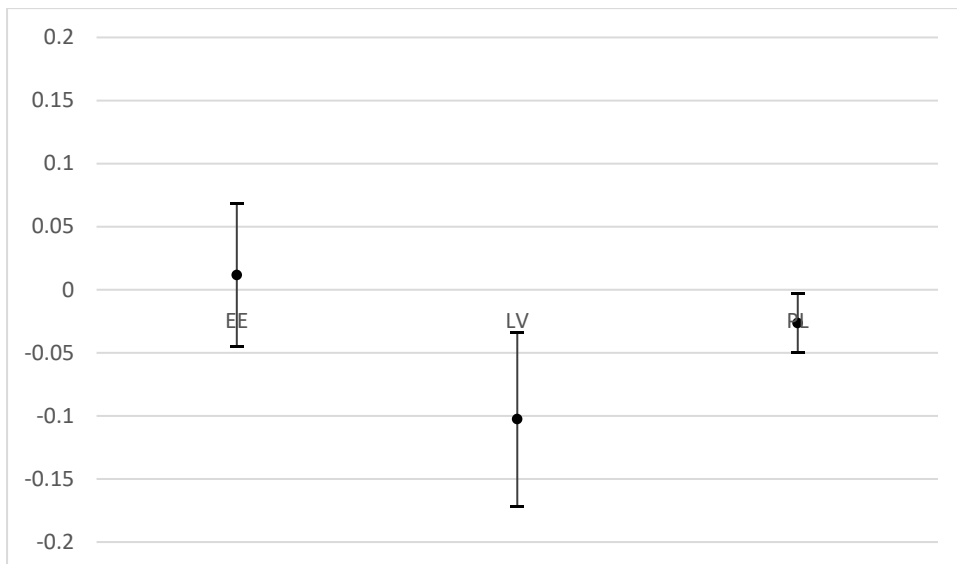
In the case of testing differences between inequality indices, asymptotic tests, but also bootstrap modifications, too often find statistically significant differences where there are none. This is due to sampling. If two countries have the same wealth distribution and only one sample happened to capture an extremely wealthy individual, the distributions will look substantially different without being so.

Neves Costa and Pérez-Duarte (2019) report confidence intervals for absolute changes in the Gini, Atkinson and Theil indicators. Although they do not specify exactly the estimation method for the variance of each index, they state e.g., in the note of Table 3, ‘Standard errors computed taking into account the multiple imputation and bootstrap weights’. This leads us to believe they follow the strategy put forward in the methodological report of the HFCS (European Central Bank (2020b), chapter 7 ‘Variance estimation’), which is based on variance estimates obtained through within-implicate variance (based on bootstrap replicate weights) and between-implicate variance.

The HFCS methodological report (European Central Bank (2020b)) suggests testing for differences in an indicator between waves by assuming a zero-covariance between the indicator in one wave and in another. While they do not specify, we presume that Neves Costa and Pérez-Duarte (2019) follow this approach to construct confidence intervals around the differences between inequality indices from wave 1 to wave 2. They find that only Slovakia and Greece show a statistically significant difference in the Gini from wave 1 to wave 2 of the HFCS; for the Theil Index, they find no statistically significant differences.¹

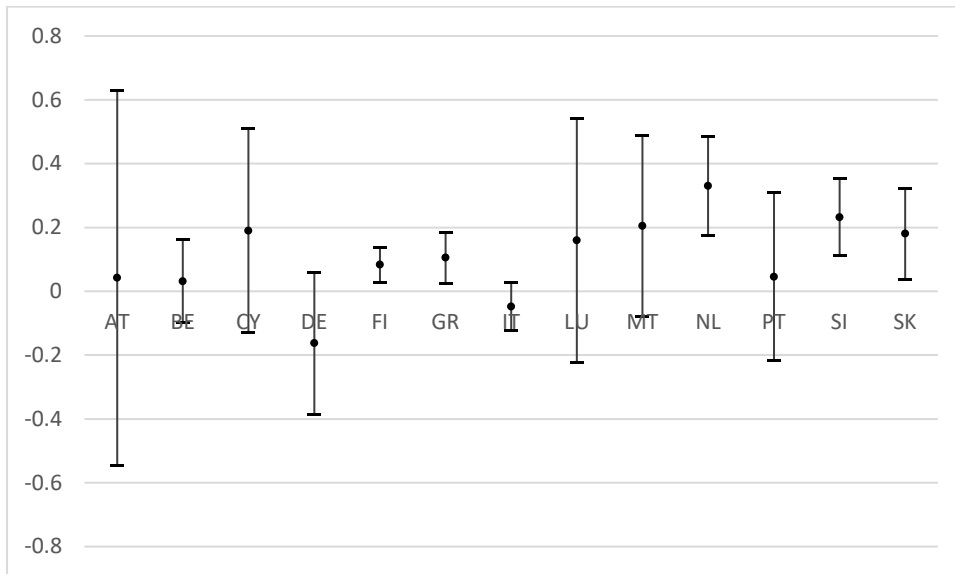
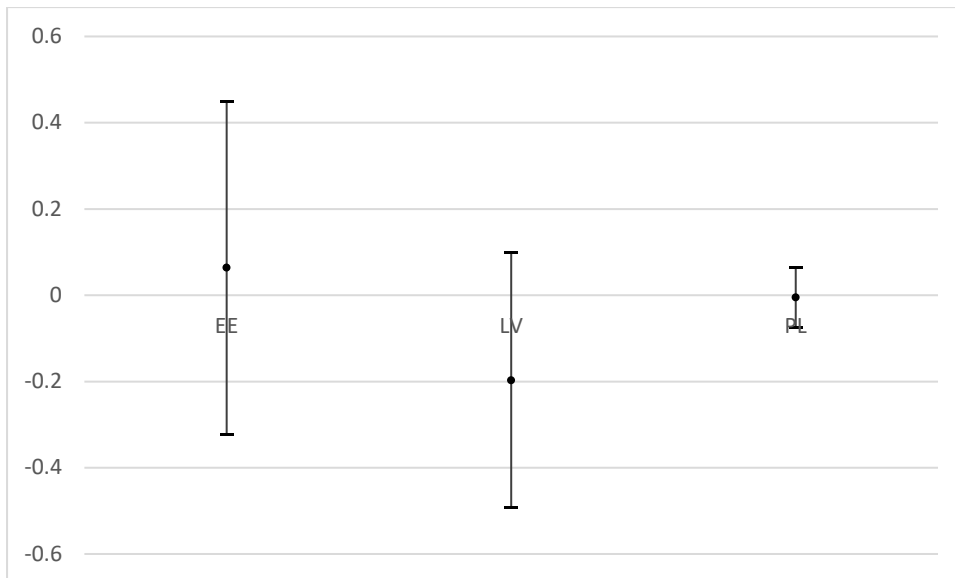
Using the same methodology, the Figures below show 95% confidence intervals for the difference between the Gini and the Theil, from wave 1 to wave 3 when available, and from wave 2 to 3 or 1 to 2 when constrained by data availability.

¹ Following this same approach, from wave 1 to wave 2, statistically significant differences were found only in Slovenia, with a meaningful increase. In tests of the Gini Index, statistically significant increases were found in Greece, Slovakia, Finland and Slovenia. Note that the analysis was carried out at the individual level, with the focus on net wealth per capita, instead of at the household level as in Costa and Pérez-Duarte (2019). Costa and Pérez-Duarte (2019) report no statistically significant differences in the Theil Index, and statistically significant increases in Greece and Slovakia, from wave 1 to wave 2.

Figure 1: Difference in Gini index with 95% confidence intervals**A. Wave 3 – Wave 1****B. Wave 3 – Wave 2**

Source: Calculations based on the HFCS - waves 2010 and 2017.

Note: Some countries are not depicted due to missing values of wealth per capita or of bootstrap replicate weights. In wave 2, there are missing values of wealth for Hungary (10) and France (485) and of bootstrap replicate weights for Germany and Ireland. In wave 1, there are missing values for bootstrap replicate weights for France.

Figure 2: Difference in Theil index with 95% confidence intervals**A. Wave 3 – Wave 1****B. Wave 3 – Wave 2**

Source: Calculations based on the HFCS - waves 2010 and 2017.

There were statistically significant increases in wealth inequality as measured by the Gini index in Finland, Greece, Slovenia and Slovakia and statistically significant decreases in Latvia and Poland (Figure 1). For the Theil Index, there were statistically significant increases in concentration in the same countries and also in the Netherlands (Figure 2). In the case of the Theil index, no statistically significant decreases from earlier waves to more recent waves were found.

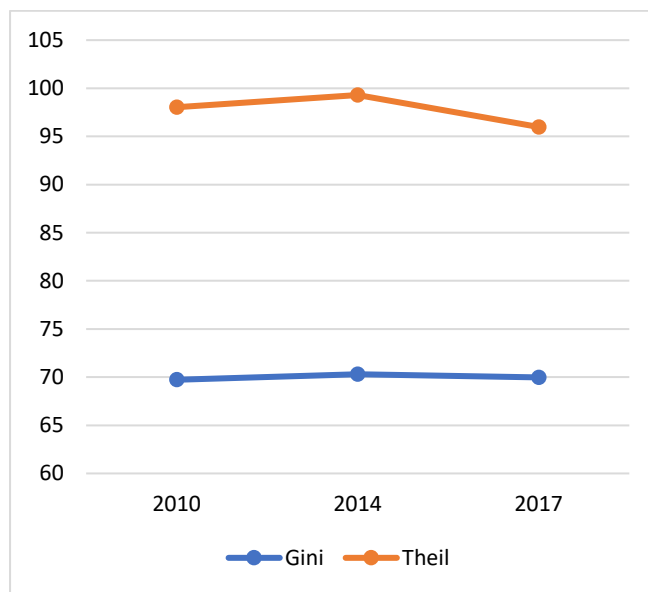
However, this procedure for calculating the confidence interval for the change in the Gini and Theil indices based on bootstrap within-implicate variation can be problematic, because they often find differences when there are none, as showed by Davidson and Flachaire (2007) and Midoes Correia (2016). Further research should explore alternative ways of testing.

3 – Wealth inequality in the pooled group of 14 HFCS countries

This chapter calculates wealth inequality indicators for the combined group (an aggregate based on a pooled sample) of these 14 countries for which data is available in all three waves of HFCS.

It is notable that in the aggregate of those 14 countries that included in all three waves of HFCS, wealth inequality hardly changed over 2010, 2014, and 2017 (Figure 3): the Gini, respectively, was: 69.7, 70.3, and 69.9. The Theil index indicates a small increase from 2010 to 2014 and a small decline from 2014 to 2017.

Figure 3: Evolution of Gini and Theil net wealth inequality indicators (aggregate of 14 countries)

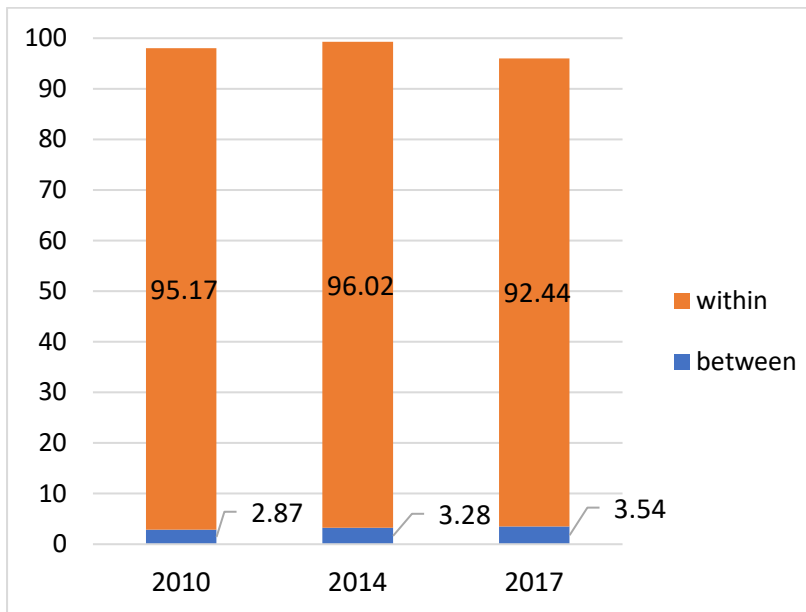


Source: Calculations based on 2010, 2014 and 2017 HFCS.

Note: those 14 countries considered which were included in all three waves: Austria, Belgium, Cyprus, Germany, Finland, France, Greece, Italy, Luxembourg, Malta, Netherlands, Portugal, Slovenia and Slovakia. The Gini coefficient and the Theil index are multiplied by 100. Theil Index can only take positive values of wealth. Gini index calculated with zero and negative values as well. See the definitions of the Gini and Theil indicators in Box 2 of the main report.

The decomposition of the Theil index of wealth inequality of the combined group of the 14 countries into within-country and between-country inequality components shows that it is predominantly determined by within-country inequality (Figure 4). Therefore, the reasons for the small change in the aggregate wealth inequality has to be looked for in the developments of within-country inequality.

Figure 4: Decomposition of the Theil index of net wealth inequality (aggregate of 14 HFCS countries)



Source: Calculations based on the 2010, 2014 and 2017 HFCS.

Note: those 14 countries considered which were included in all three waves: Austria, Belgium, Cyprus, Germany, Finland, France, Greece, Italy, Luxembourg, Malta, Netherlands, Portugal, Slovenia and Slovakia.

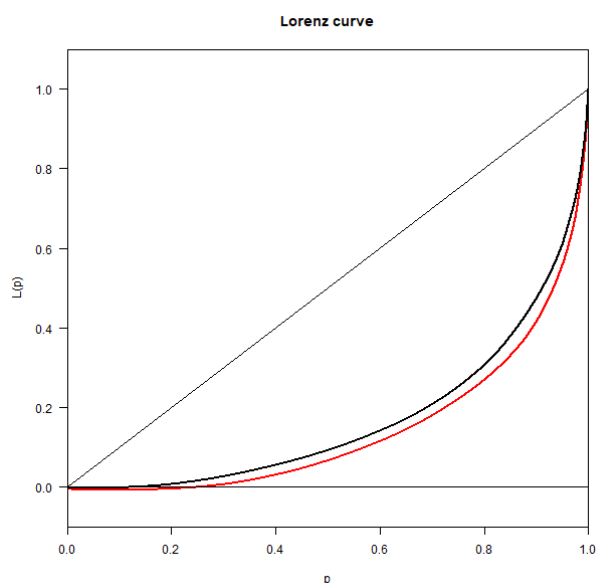
4– Evolution of the wealth distribution through the lens of Lorenz curves

This chapter studies changes in the wealth distribution with the help of Lorenz-curves for selected countries and thus complements the analysis of the main report, which included Gini coefficients and income shares.

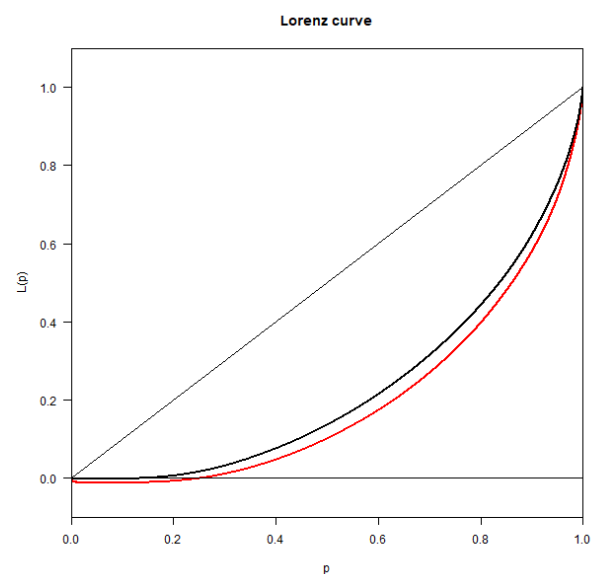
The Lorenz curve is a graphical representation of the distribution. First, people are ordered by wealth (from the poorest to the richest) and then share of the poorest $x\%$ of people in total wealth is plotted in the y axis. For example, 20% on the horizontal axis represents the poorest 20% of the society and the corresponding value plotted on the vertical axis shows the share of the poorest 20% of the society in total wealth. A 45-degree line would correspond to perfect equality: the share of the poorest 10% of the society would be 10% in total wealth, the share of the poorest 20% of the society would be 20% in total wealth, and so on. Thereby, the difference between the 45-degree line and the Lorenz curve is an indication of inequality.

Figure 5: Lorenz Curves: Noticeable increases in Gini index (2010 vs. 2017)

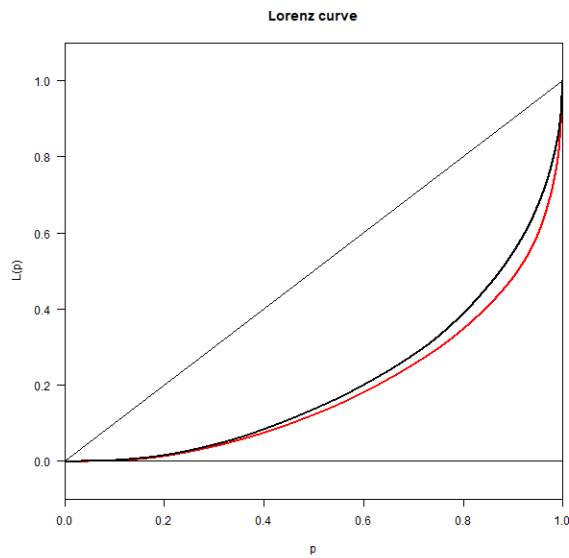
Cyprus



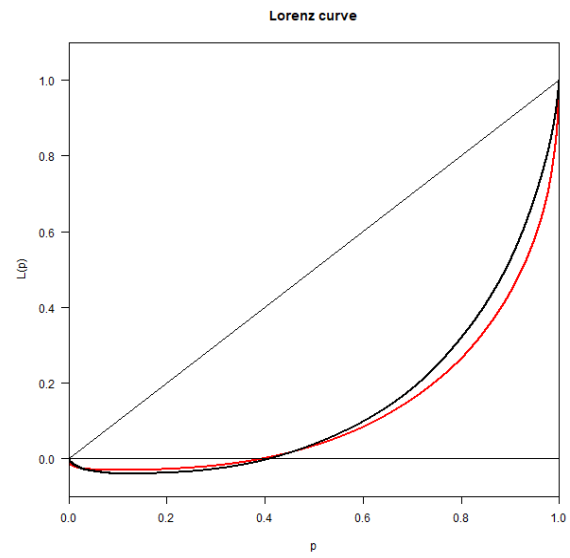
Greece



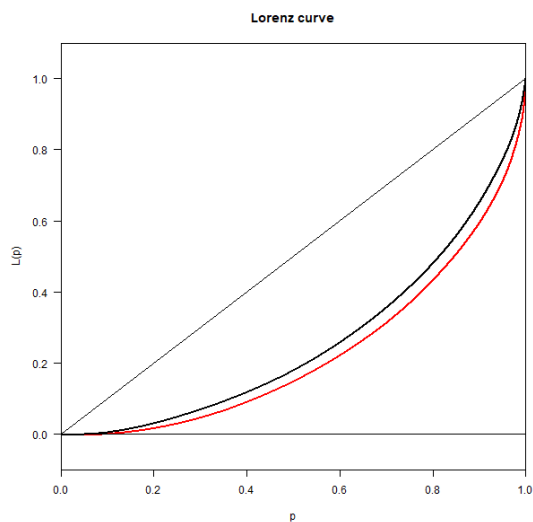
Malta



Netherlands



Slovakia



Source: Calculations based on the HFCS - waves 2010 and 2017.

Note: the 2010 wave is in black, the 2017 wave is in red.

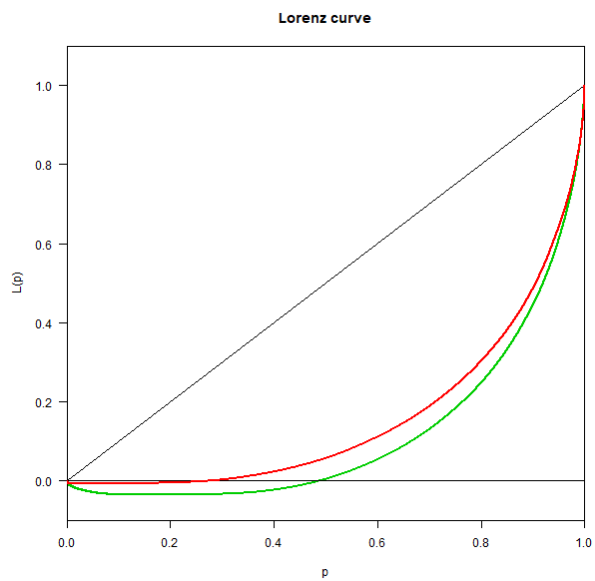
In most cases the Lorenz curves for 2010 and 2017 do not cross each other, but there is a notable exception, the Netherlands (Figure 5). The 2017 Lorenz curve is above the 2010 Lorenz curve for people in the 5-45% bracket in terms of net wealth in the society, while it is below for the poorest 5% and for the richest 55%. The intersection is related to negative net wealth holdings, suggesting that some of the net-wealth poor segments of the society held less negative net wealth in 2017 than in 2010.

In Malta, the 2010 and 2017 curves overlap for the poorest 10%, suggesting that the increase in inequality is due to higher wealth accumulation in the top percentiles at detriment of the middle-class, but not the lowest-wealth group.

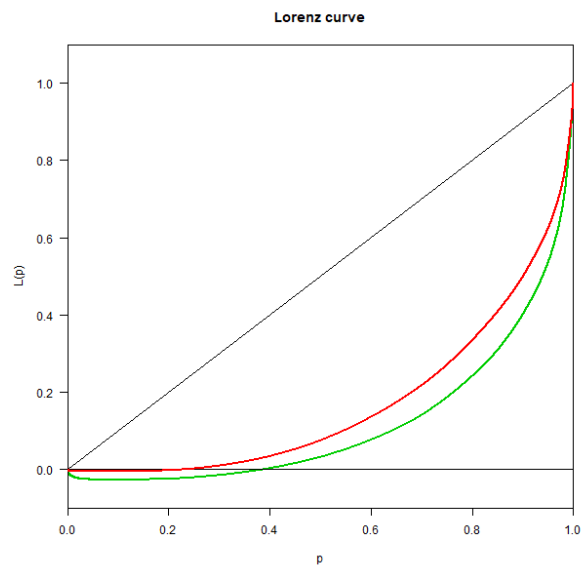
In Greece and Cyprus, the lowest-wealth groups have been more negatively affected, holding more negative wealth in 2017 than in 2010. This could relate to the particularly harsh macroeconomic adjustment that the two countries went through, as well as corresponding house prices declines: in Greece, house prices declined by 37% from 2010 to 2017 (source: OECD Analytical house prices indicators dataset), which probably pushed several mortgage borrowers to negative equity position. When considering the wealth shares, the bottom 50% went from holding 14% to 10% of wealth in Greece, from 9 to 6% in Cyprus, and from 14% to 12% in Malta.

Figure 6: Lorenz Curves: Noticeable increases in Gini index (2010 vs. 2017)

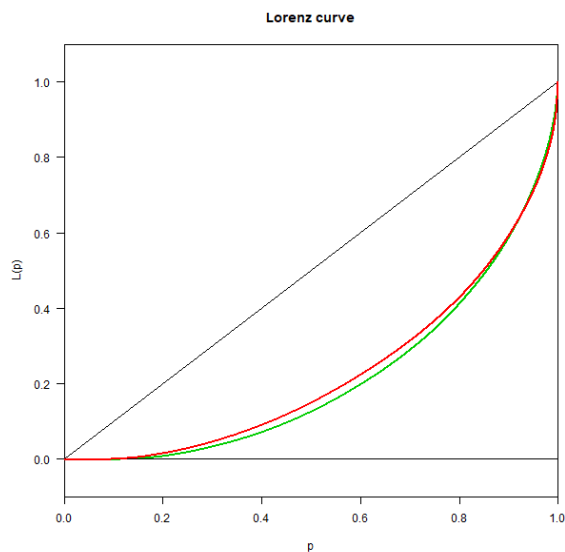
Ireland



Latvia



Poland



Source: Calculations based on the HFCS - waves 2010 and 2017.

Note: the 2014 wave is in green, the 2017 wave is in red.

Figure 6 reveals that the decline in wealth inequality in Ireland and Latvia is to a large extent the elimination of net negative wealth in 2010. Both countries experienced credit-fuelled massive housing booms in the pre-2008 period, which was followed by deep house price reductions, economic contraction, wage decline and increase in unemployment. The fall in housing prices pushed many borrowers to negative net wealth positions, while wage declines and unemployment increases reduced disposable income, which perhaps was compensated by drawing on liquid savings and credit lines. Yet both countries were able to get over these major economic problems, house prices started to recover significantly and were 13% in Ireland and 47% in Latvia higher in 2017 than in 2010 (though have not yet reached the pre-crisis peaks). The house price recovery, along with increased employment and wage increases, likely explain the elimination of negative net wealth positions.

5 - Average wealth portfolio by net wealth quintile in selected Member States

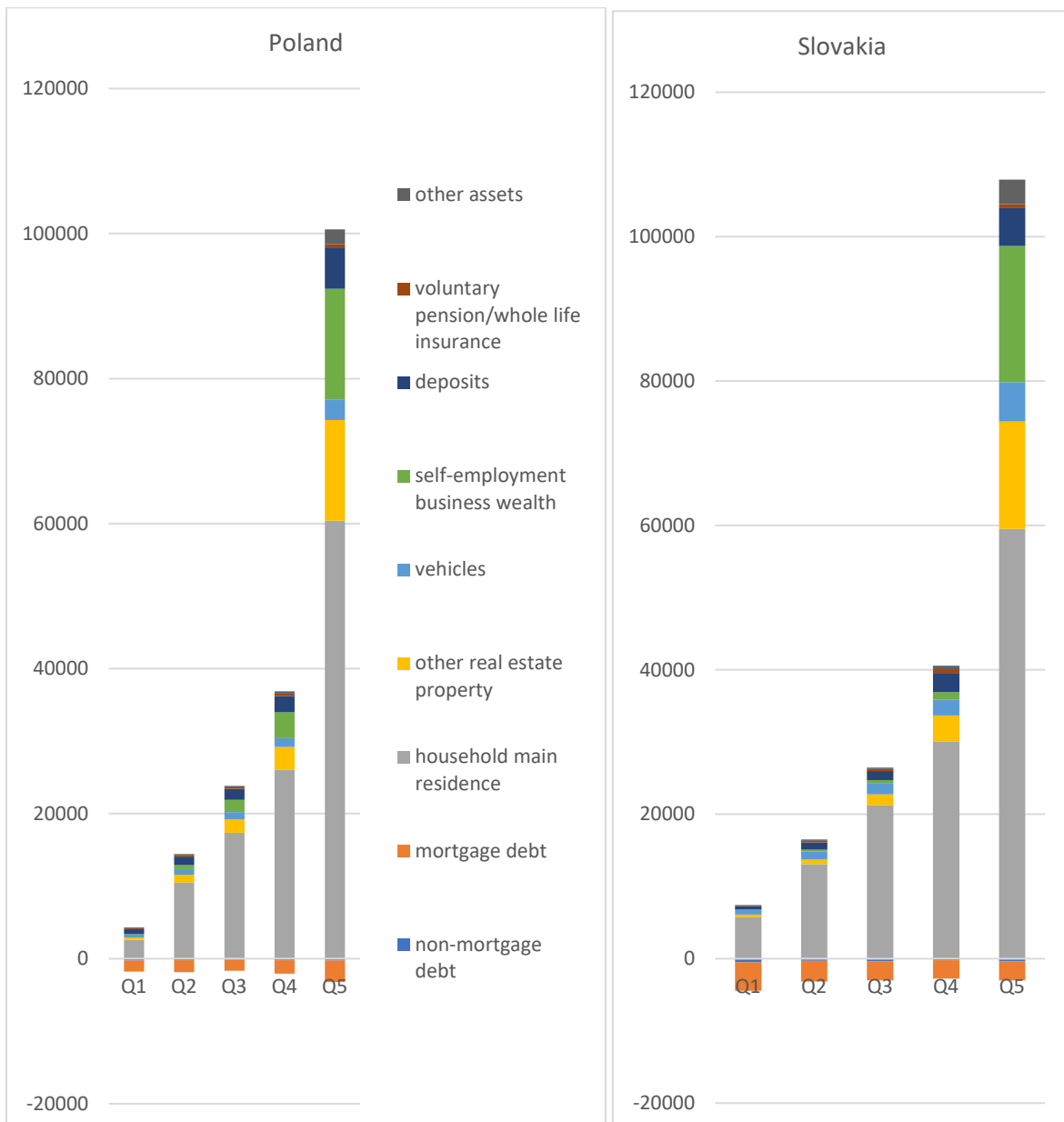
Countries are presented in the order of their Gini index of wealth inequality, from low to high.

Table 2: Average portfolio by net wealth quintile, selected HFCS countries, 2017, in EUR

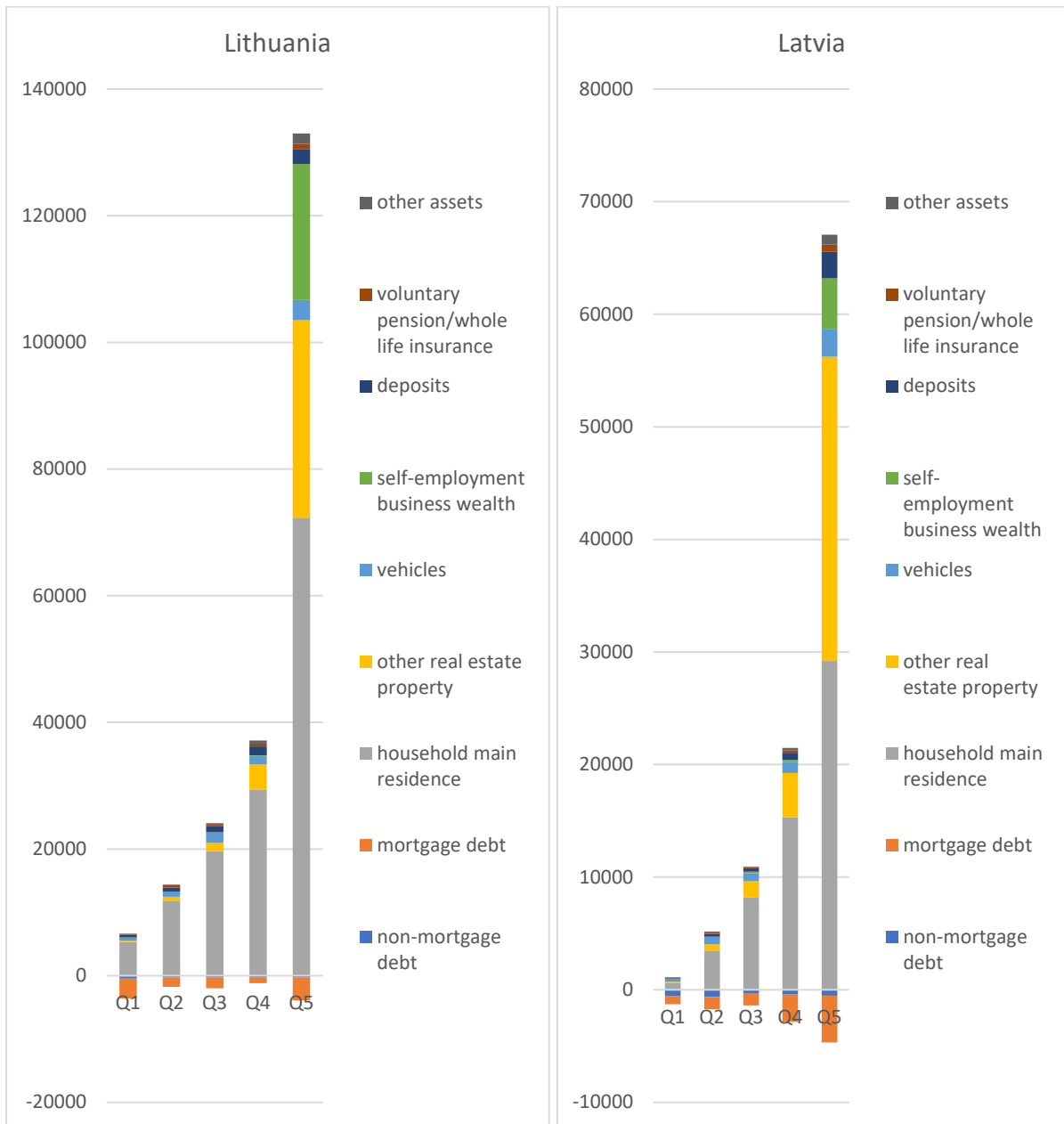
	non-mortgage debt	mortgage debt	household main residence	other real estate property	vehicles	self-employment business wealth	deposits	voluntary pension/whole life insurance	other assets
Poland									
Q1	-265	-1506	2605	291	404	93	679	145	85
Q2	-204	-1643	10483	1095	789	557	1165	208	123
Q3	-194	-1460	17378	1821	999	1710	1507	207	223
Q4	-236	-1816	26086	3109	1206	3579	2255	330	295
Q5	-265	-2946	60400	13891	2843	15269	5703	420	2035
Slovakia									
Q1	-496	-3965	5754	375	688	17	427	117	67
Q2	-305	-2853	13076	666	1111	254	985	219	194
Q3	-393	-2604	21239	1522	1563	404	1260	296	166
Q4	-231	-2526	30114	3578	2161	1053	2656	541	490
Q5	-375	-2621	59513	14900	5437	18865	5225	577	3356
Lithuania									
Q1	-439	-3146	5292	227	539	18	402	141	56
Q2	-267	-1497	11848	613	822	10	621	383	86
Q3	-260	-1706	19671	1321	1614	35	957	266	203
Q4	-238	-936	29402	3953	1348	89	1376	467	505
Q5	-262	-3655	72213	31275	3193	21456	2327	880	1627
Latvia									
Q1	-565	-726	576	129	251	26	75	16	42
Q2	-621	-1090	3482	550	650	32	230	84	144
Q3	-345	-1051	8184	1475	687	137	316	96	52
Q4	-431	-2424	15337	3907	965	204	646	182	228
Q5	-522	-4151	29199	27017	2482	4497	2357	618	883
Austria									
Q1	-2139	-4715	2511	585	1145	92	1606	86	227
Q2	-883	-3291	5227	925	3423	220	7256	474	794
Q3	-372	-10454	38187	3479	4437	920	10929	970	2280
Q4	-600	-9086	82499	8100	5376	3062	14167	1618	2989
Q5	-1221	-11176	182701	77247	9720	104163	32435	3447	16938

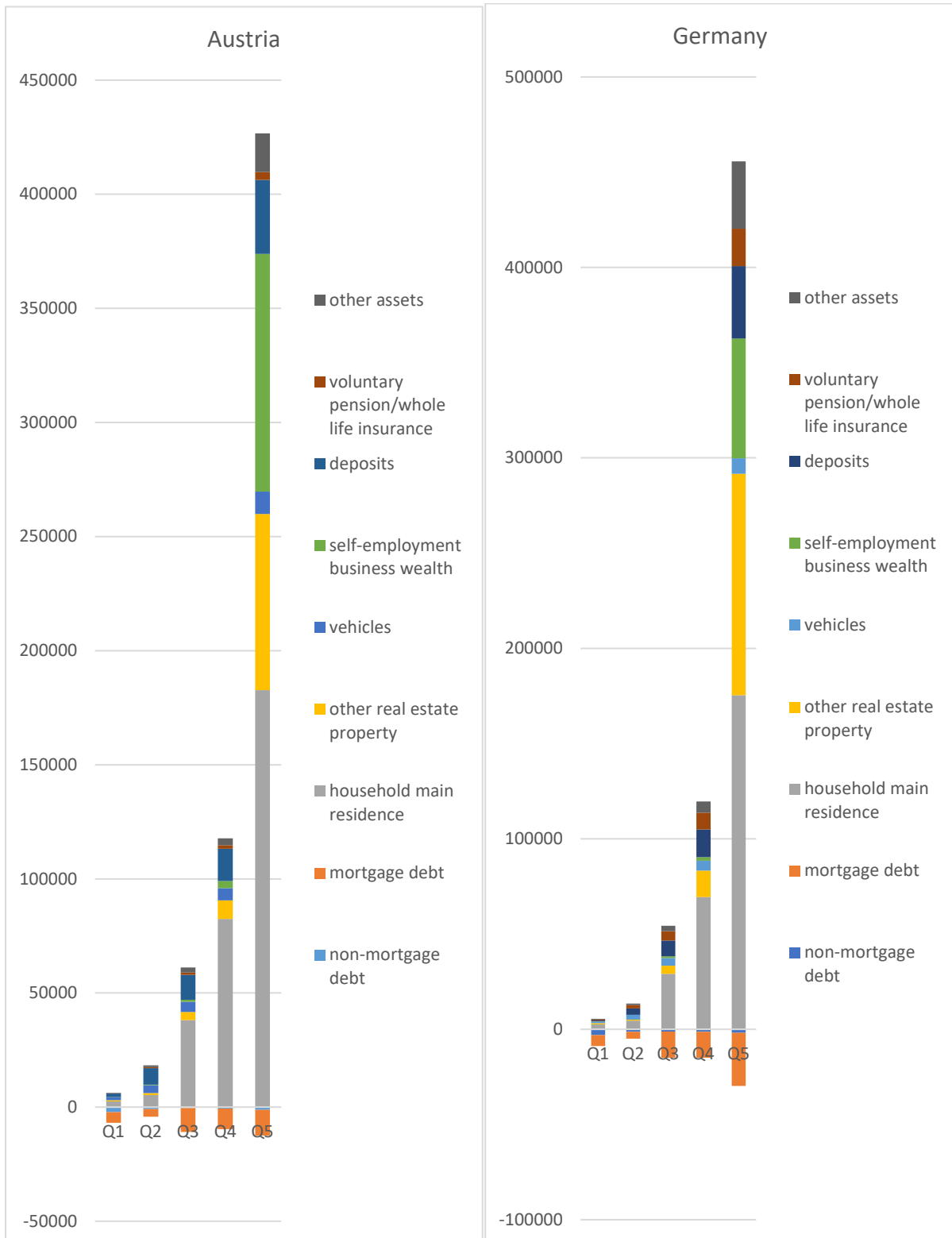
Germany									
Q1	-3009	-5742	2591	626	790	116	622	383	363
Q2	-1376	-3524	4535	574	2454	125	3310	1674	846
Q3	-1194	-13735	29087	4345	3908	969	8353	4867	2772
Q4	-1311	-13572	69460	13821	5179	1958	14449	8855	5825
Q5	-1791	-27956	175381	11628 5	8065	62884	38039	19651	35427
Netherlands									
Q1	-2598	-46757	26150	512	1304	127	2839	1331	473
Q2	-705	-25517	25618	544	2216	76	5879	1903	618
Q3	-335	-41956	53674	949	3171	119	10899	6323	1847
Q4	-775	-45756	87654	2025	4171	1468	15192	11516	2961
Q5	-1417	-47755	169745	26077	7738	24537	45492	28036	71389

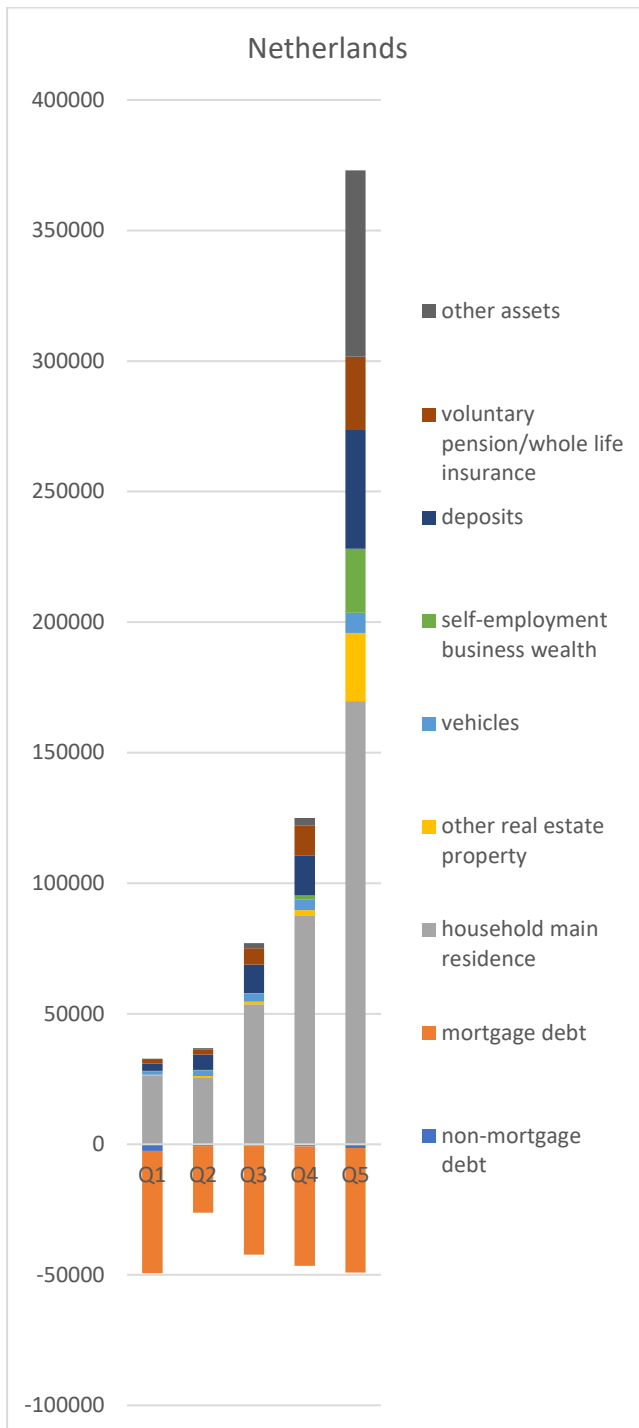
Figure 7: Average portfolio by net wealth quintile, selected HFCS countries, 2017, in EUR



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In Austria and Germany, the two bottom wealth quintiles, have, on average, quite low housing wealth, similar to their average wealth in deposits, and lower than the housing wealth of the bottom quintiles in Slovakia or Poland.

In the Netherlands, households in the bottom wealth quintile have, on average, negative wealth, driven particularly by mortgage debt. A similar situation is in Germany and in Austria.

6 – Educational mobility calculations

This chapter discusses the econometric model used for educational mobility calculation in Chapter 4 of the main report.

A model for assessing educational mobility

Intergenerational educational mobility, that is, whether children will have higher (or lower) educational achievement than their parents by the time they grow up, is an important aspect of social mobility. Important questions include whether parental education level influences offspring educational level, and whether wealth has an additional role in fostering higher education beyond parental education level.

The tool used for further analyses is a *cross-sectional ordered probit model*, where the probability of achieving different levels of education is assessed in relation to the parents' level of education but also to the respondent's age and gender (initially without any information on wealth). In the next stage, wealth proxies are included in the model – to see if they affect educational mobility beyond the impact of parents' education.

This model allows to estimate how much the education of the mother or father affects the probability of an individual achieving alternative educational levels. In particular, the focus is placed on the achievement of the highest level (tertiary) education, depending on the educational level of the parent. This estimate is not a single number, but depends on age and gender, variables which are included in the model.

This model provides accurate results even with sample selection and with the general educational level issues described (under certain assumptions), though the issue of rare combinations not captured by the surveys cannot be addressed.

Before describing the model, let us highlight some data issues.

HFCS

Numerous issues must be considered in estimating educational mobility. There the following limitations to acknowledge in the case of HFCS data:

- Among the 22 countries included in HFCS, educational information is available only for Italy (all three waves), Portugal (second and third waves), and Luxembourg (third wave). Information on parental wealth is unfortunately not available in HFCS and hence we have to use certain proxies for it.
- Information on educational attainment of the respondents and their parents is missing for some respondents. The distribution of those providing the full information differs from those who do not. Inverse probability weighting and multiple imputations are ways to correct for this sampling bias (see supplementary analyses available on request).
- Also, certain parent/offspring combinations are not available in the actual samples. For example, respondents, who are children of parents with upper secondary or tertiary education but have only the primary education themselves, are few or none in some samples (see Table 3 below).

Although similar cases might be rare in real life, their absence in the statistical analysis can limit the accuracy of findings.

- The average education level of both the parents and children cohorts examined increased over the last decades - partly due to mandatory school attendance and expansion of the tertiary education. For example, in Italy in 1992, 8.6% of the 30-34-year olds had tertiary education, which increased to 27.6% for the same age cohort in 2019. In the 55-64 years age cohort, 4.0% had tertiary education in 1992 but 12.8% in 2019. However, the econometric model adopted disentangles the impacts of parental education and wealth from the general increase in educational levels on offspring education.

In generating HFCS results, the three survey waves were assessed separately, as they are meant to be a snapshot of households, though at different points in time. This analysis requires data on educational levels of parents and descendants and information about parental wealth. In the ECB's HFCS, educational information is available for Italy (all three waves) Portugal (second and third waves) and Luxembourg (third wave). Information of parental wealth is unfortunately not available in HFCS, so we must use proxies for that. In this report we consider whether the offspring has received a gift or inheritance as a proxy (which is a binary variable – yes or no). This parental wealth proxy is bound to be imperfect, yet it allows us to make some first estimates that we will double check with using other proxies based on HFCS and by considering other datasets that have information about parental wealth.

We firstly report results on wave 2, for which there is information on the education of parents of respondents for Italy and Portugal. We start by reporting summary statistics on the relation between the level of education achieved by the respondents and by their parents. This is followed by the analysis of what impact of parental education has on offspring education. Finally, we study if parental wealth has an additional role beyond parental education in fostering offspring education.

The analysis is based on ISCED97 levels of education, with 4 categories, which we will refer to as 1 through 4, despite in the dataset, their definition being 1,2,3 and 5:

1. Primary or below (No formal education or below ISCED 0 + ISCED 1: Primary education), 1 in dataset
2. Lower secondary (ISCED 2: Lower secondary or second stage of basic education), 2 in dataset
3. Upper secondary (ISCED 3: Upper secondary + ISCED 4: Post-secondary), 3 in dataset
4. Tertiary (ISCED 5: First stage tertiary + ISCED 6: Second stage tertiary), 5 in dataset

Offspring education as a function of parents' education, or educational transitions, are reported in Table 3.

² Data source: Eurostat's 'Population by educational attainment level, sex and age (%) - main indicators (edat_lfse_03)' dataset.

Table 3: Education outcomes by parents' level of education for individuals above 30**Italy, wave 1**

		Respondent's education			
		1	2	3	4
Father's education	1	30.2%	33.3%	30.5%	5.9%
	2	3.1%	21.6%	59.1%	16.2%
	3	1.6%	5.5%	49.9%	43.1%
	4	0.0%	2.7%	31.4%	66.0%

Note: in wave 1, only information about the father's education is available. In waves 2 and 3, education information about highest educated parent is available.

Italy, wave 2

		Respondent's education			
		1	2	3	4
Education of highest educated parent	1	30%	40%	26%	4%
	2	2%	18%	67%	13%
	3	0%	5%	53%	42%
	4	0%	1%	30%	70%

Italy, wave 3

		Respondent's education			
		1	2	3	4
Education of highest educated parent	1	33.6%	37.4%	25.6%	3.4%
	2	1.6%	21.0%	61.1%	16.3%
	3	0.5%	6.9%	46.6%	46.0%
	4	0.3%	4.9%	24.5%	70.2%

Portugal, wave 2

		Respondent's education			
		1	2	3	4
Education of highest educated parent	1	67%	15%	11%	7%
	2	19%	20%	31%	31%
	3	9%	13%	27%	51%
	4	11%	6%	13%	70%

Disclaimer: This working paper has not been subject to the full Eurofound evaluation, editorial and publication process.

Portugal, wave 3

		Respondent's education			
		1	2	3	4
Education of highest educated parent	1	61%	18%	12%	9%
	2	3%	18%	31%	47%
	3	7%	9%	36%	48%
	4	2%	3%	20%	74%

Luxembourg, wave 3

		Respondent's education			
		1	2	3	4
Education of highest educated parent	1	50%	13%	29%	7%
	2	2%	37%	22%	39%
	3	6%	7%	54%	34%
	4	0%	2%	15%	83%

Note: Results consider multiple imputation and weights; sample restricted to individuals 30 and above. The education variables, both for respondents and for their parents, have not been imputed.

Based on wave 3, a quick comparison seems to show a lower education persistence in Italy, since only 34% of the children of primary-educated parents do not go beyond primary education themselves, against 50% and 61% in Luxembourg and Portugal respectively. In the same way, 70% of children of university-educated parents achieve higher education, while in Portugal it is 74% and in Luxembourg 83%.

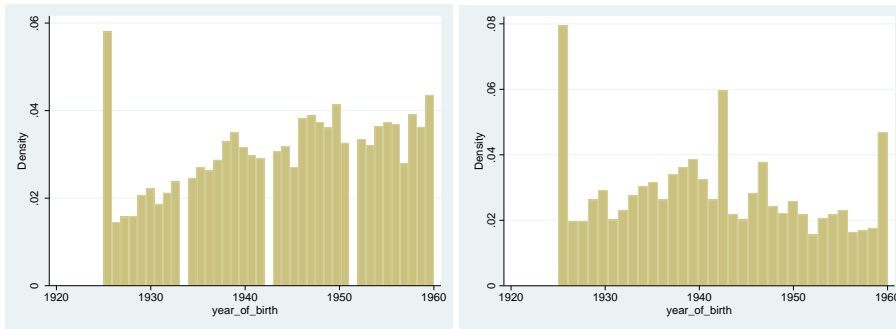
In Luxembourg, parental education seems to confer substantial advantages, with very few individuals not achieving at least their parents' educational level (2% of children of lower-secondary educated parents, 13% of upper-secondary and 17% of university educated)³.

For Italy, there are considerable differences in the age composition of all 50+ individuals and those 50+ individuals who answered the question on their and their parents' educational achievement (Figure 8). There are some differences for Portugal too, though slimmer (Figure 9). The issue might be problematic, given age is related to educational outcomes and parental education outcomes.

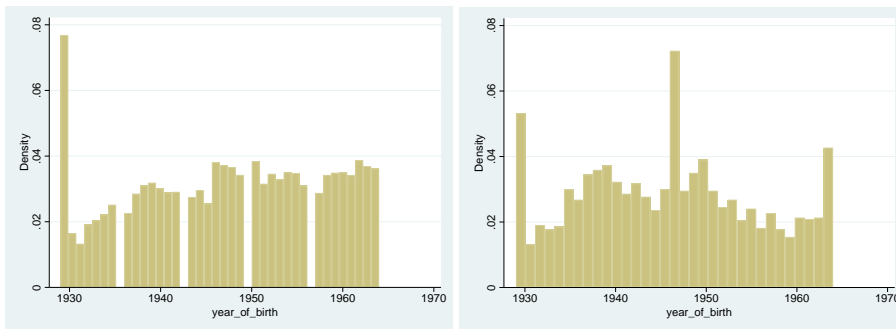
³ In Portugal, values are 3%, 16% and 25%.

Figure 8: Unweighted histogram of 50+ population, HFCS Italy, total (left panel) and with education information (right panel)

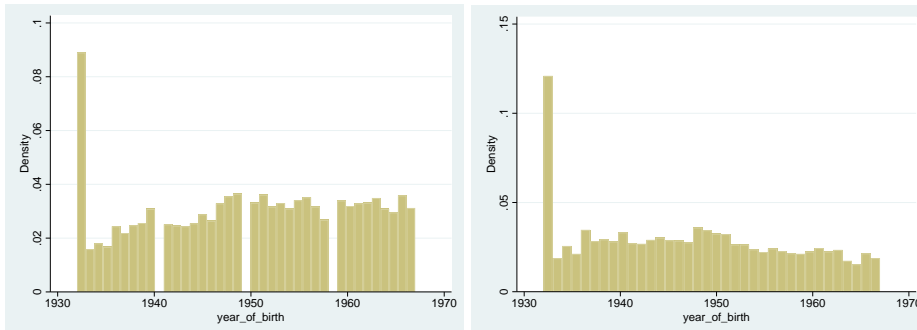
Wave 1



Wave 2



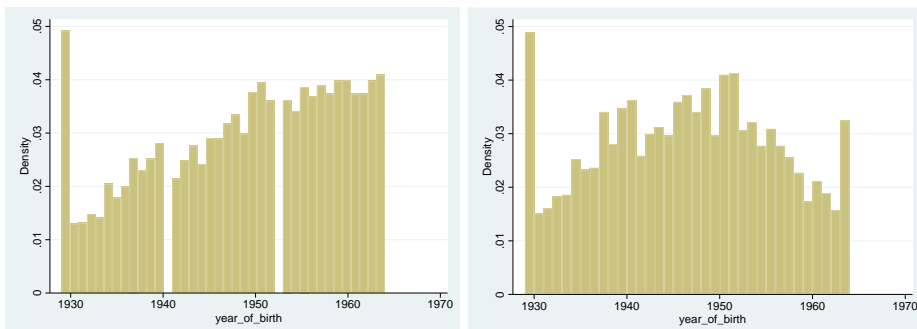
Wave 3

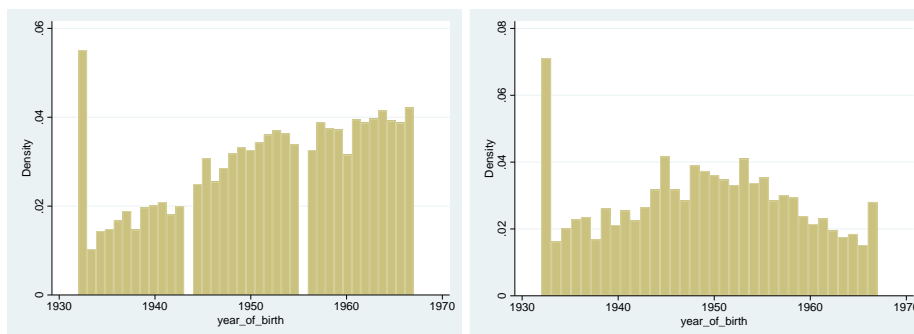


Source: HFCS -wave 2017.

Figure 9: Unweighted histogram of 50+ population, HFCS Portugal, total (left panel) and with education information (right panel)

Wave 2



Wave 3

Source: HFCS.

Therefore, our summary statistics reported in **Error! Reference source not found.** are not representative of the population. To correct the values in **Error! Reference source not found.**3 in a way which is representative of the population's age distribution, we can use inverse probability weighting – where we let the probability of being in the sample depend on the age of respondents and possibly other factors, and individuals with a highest probability of selection are given less weight – or do multiple imputations on the educational outcomes on the same basis, i.e., on the joint distribution of the explanatory variables (also called covariates). In the ensuing weeks, we will undertake this exercise. The goal is to ensure Table 3 is reproduced on a sample which is representative of the actual population age distribution.

Econometric specification

In order to analyse the association between parental educational background and educational outcomes, we resort to a *cross-sectional ordered probit model*, where the probability of achieving different levels of education is allowed to depend on the parents' level of education but also on the respondent's age. This model allows controlling for the sample selection issues described (and therefore inverse probability weighting is not needed for the econometric calculations, it is needed to correct Table 3). Furthermore, in this model we are able to control for the development of both parents and offspring become more educated in more recent decades, partly due to mandatory school laws and the general increase in tertiary education.

We also include available indicators of parental wealth, and, in extensions, other variables.

Ordered probit equations

$$educ_i^* = \sum_{j=1}^4 \rho_{mj} dmothereduc_{ji} + \sum_{j=1}^4 \rho_{fj} dfathereduc_{ji} + \delta_f female_i + \gamma_{age} age_i + \varepsilon_i$$

$$educ_i = 1 \quad \text{if } educ_i^* \leq \mu_1$$

$$educ_i = j \quad \text{if } \mu_j < educ_i^* \leq \mu_{j+1} \quad \text{for } j = 2,3$$

$$educ_i = 4 \quad \text{if } educ_i^* > \mu_4$$

$$(\varepsilon_i) \sim N(0,1)$$

Where:

$educ_i^*$ is a latent variable, not observed, interpretable as the schooling process of individual i

$educ_i$ is the categorical variable we observe, which defines the ISCED1997 level of education the individual has been awarded, coded to 4 outcomes as explained above and which takes such values when the schooling process has overcome certain thresholds μ_j

$dmothereduc_{ji}$ is a dummy variable, which equals 1 if the education of the mother of respondent i is level j , which is also based on ISCED1997

$\sum_{j=1}^4 \rho_{mj} dmothereduc_{ji}$ thus designates four dummy variables

$dfathereduc_{ji}$ is a dummy variable, which equals 1 if the education of the father of respondent i is level j , which is also based on ISCED1997

$\sum_{j=1}^4 \rho_{fj} dfathereduc_{ji}$ thus designates four dummy variables

$female_i$ is a dummy variable which equals 1 if respondent i is female

age_i is a continuous variable representing the age of individual i

The first equation variables can be modified as in a normal regression context, such as to include interactions. The interpretation of interaction effects is however different (see below box on interaction effects).

To allow the coefficient associated with a mother having university education to change for male and female respondents, the following term is added, which is associated with estimating one additional coefficient:

$$\rho_{m4}^f (dmother_{educ_{4i}} \times female_i)$$

We add one such coefficient for each level of the education of the mother and the father, resulting in a total of 8 coefficients more.

We define education of mother and father as four dummy variables instead of as a continuous variable taking values 1 through 4. As a result, there is one coefficient per educational level of each parent.

In this model, with an error term which follows a normal distribution, we can describe the probability of belonging to each education class, which depends on both the parameters estimated and the covariates. The formula for these probabilities is described below.

We designate the variables and their coefficients described above as $x_i' \beta$, for a matter of simplicity of notation. x_i' is a row vector of all covariates (variables included in the model) for individual i and β is column vector of coefficients.

Probability equations

$$\Pr(educ_i = 1|x_i) = \Phi(\mu_1 - x_i' \beta)$$

$$\Pr(educ_i = j|x_i) = \Phi(\mu_j - x_i' \beta) - \Phi(\mu_{j-1} - x_i' \beta) \quad j = 2, 3$$

$$\Pr(educ_i = 4|x_i) = 1 - \Phi(\mu_4 - x_i'\beta)$$

The model is estimated through maximum likelihood, and crucially depends not only on β but also on the thresholds μ_j .

Questions of interest and their estimation

The questions of interest to us are ‘how does variable x affect the probability of an individual achieving level 1,2,3 or 4?’. The central question is ‘how does the education of the mother / father affect the probability of an individual achieving educational level 1,2,3 or 4?’.

In order to make such analyses, we must focus on the *derivatives* of the probability equations, when we speak of the effect of continuous variables, or on the *differences* of the probability equations, when we speak of binary or categorical variables.

The derivative of a probability equation with respect to x_1 is called the *marginal effect* of x_1 , and should always be associated with a particular outcome. We can thus speak of four marginal effects of x_1 , one for each educational outcome observed, $ME_{x_1}^1$, $ME_{x_1}^2$, $ME_{x_1}^3$ and $ME_{x_1}^4$. For example, $ME_{x_1}^1$ is the marginal effect of x_1 on the probability of the offspring educational level being only primary school, where x_1 is one particular continuous variable included in the model, such as age. Their formulas are described below:

Marginal effects of continuous variables

$$ME_{x_1}^1(x_i) = \frac{\partial \Pr(educ_i = 1|x_i)}{\partial x_1} = -\beta_1 \Phi(\mu_1 - x_i'\beta)$$

$$ME_{x_1}^j(x_i) = \frac{\partial \Pr(educ_i = j|x_i)}{\partial x_1} = \beta_1 [\Phi(\mu_{j-1} - x_i'\beta) - \Phi(\mu_j - x_i'\beta)], j = 2,3$$

$$ME_{x_1}^4 = \frac{\partial \Pr(educ_i = 4|x_i)}{\partial x_1} = \beta_1 \Phi(\mu_4 - x_i'\beta)$$

If x_1 is instead a categorical variable, we still refer to *marginal effects*, one per outcome, but we calculate them by taking differences in the probability equations. For instance, in a model without interactions, and where x_i' does not include variables on gender, the *marginal effect* of being a woman on the probability of only achieving primary education is calculated as follows:

Marginal effects of discrete variable, example

$$\begin{aligned} ME_{female}^1(x_i) &= \Pr(educ_i = 1|x_i, female_i = 1) - \Pr(educ_i = 1|x_i, female_i = 0) \\ &= \Phi(\mu_1 - x_i'\beta - \delta_f female_i) - \Phi(\mu_1 - x_i'\beta) \end{aligned}$$

Unlike in an ordinary regression setting, β_1 does not answer these questions about effects directly. It does not inform us directly about the magnitude of the effect of x_1 on the different probabilities. It informs us about the direction of the effects of x_1 , but by construction only for outcomes 1 and 4,

that is, in our case primary education and university education⁴. A positive coefficient means the probability of only having primary education goes down, and the probability of having university education goes up.

We thus do not report results on coefficients, but only on marginal effects, which varies as we will describe later. In our analysis, we report marginal effects at representative values, that is, by setting the remaining covariates at values of interest. For instance, we analyse the effect of the father's education for respondents at different ages and with different levels of mother's education. We will call these *conditional marginal effects* though they can also be called *marginal effects at representative values*.

Sample selection and interaction effects

Several statistics that can be, and commonly are, derived from the ordered probit models are not consistent if the sample is not representative of the population, such as average marginal effects. These statistics depend on the joint distribution of the covariates in the sample, which we have shown is not representative of the population.

We will operate under an assumption of exogenous sampling, under which coefficients will still be consistent, and therefore also conditional estimates, such as marginal effects at specific values of covariates⁵. This assumption, also called selection on observables, implies that the probability of being in the sample is related to age but not to educational outcomes themselves. The distribution of educational outcomes conditional on age is the same in the sample and in the population.

There is another issue, related to sampling design, for which no solution is immediately available. It is not true that at the time of the wave 2 survey there are zero individuals in Italy who did not go beyond primary education born to parents who achieved lower or upper-secondary education (Table 3). They simply have not been sampled. Looking at wave 3, these values are not zero, though small, 0.3% each. Importantly, the survey has not been designed to be representative of the overall country's structure of education, thus, it is expected that relatively rare combinations are not captured. This can harm identification of the coefficients and the accuracy of the summary statistics.

Interaction effects

Even without any interaction, the marginal effect a variable has on outcomes is not constant, since the marginal effects are functions of x_i . That means the effect a variable x_1 or *female* has on the probability of each outcome depends on the value of the remaining covariates.

Without an interaction, a dummy variable already affects marginal effects by changing the thresholds μ_j . Thus, even without an interaction, one can test whether the effect of parental education is different for men and women. Including an interaction, as we do, has a direct effect on the coefficients, as opposed to simply on the marginal effects function and adds flexibility to the

⁴ The equations on the marginal effects of continuous variables show that the sign of ME1 and ME4 is fully defined by beta, since $\Phi(\mu_4 - x_i'\beta)$, being a probability, is necessarily positive. ME2 and ME3 are differences of probabilities, which can be positive or negative.

⁵ Fixing covariates at their average value, however, will not give marginal effects for the average individual either, since the population average and the sample average are different in terms of age.

specification. For an intuitive and graphical explanation of the difference, see Karaca-Mandic *et al* (2012).

Multiple imputation and standard errors

In our econometric models in the HFCS data, standard errors are obtained through the bootstrap replicate weights based on Rao and Wu (1988) and Rao *et al* (1992). Asymptotic standard errors provide similar results.

Regarding multiple imputation, in the HFCS, we have selected only one replicate on which the analysis is performed, replicate one. An alternative is to estimate the same model in each of the five implicates and aggregate marginal effects into a single estimate, where both within-replicate and between-replicate variability is considered. Doing so relies on Rubin's rules which apply to asymptotically normal estimators, such as marginal effects.

When using SHARE data, we resort to few multiple imputed variables. Specifically, only wealth and income of respondents is multiple imputed in our models. Firstly, we use as a single variable the average wealth and average income across replicates. This procedure however ignores the variance between replicates. An alternative would be to estimate all models once per replicate, yet, given this applies only to two variables of our models, we have not done so.

Results

An example of the interpretation of the results

We focus on $ME_{dfathereduc_j}^4$ and $ME_{dmothereduc_j}^4$, for $j = 1, \dots, 4$, that is, the effect of having a father/mother with an education level of 1,2,3 or 4 on the probability of having education of level 4, that is, completing some tertiary education.

The parental education is defined in dummies, where primary education is set as the base level. Our re-adapted marginal effects are thus the difference between i) the probability of achieving higher education if your mother/father has education level 4,3,2 and ii) the probability of achieving higher education if your mother/father only has level 1 (i.e. primary education).

These differences are measured on the y axis of **Error! Reference source not found.10** (and in similar subsequent figures too). These differences are functions of all covariates, in our case, functions of the education of parents, of gender, and of age. As explained above in section 'Questions of interest and their estimation', we will be reporting and interpreting *conditional marginal effects*, where we evaluate those functions at specific values of gender and age.

In Figure 19a, we report on the conditional marginal effects (CME) of father's schooling, keeping mother's education at primary school and changing the age and gender of respondents. As an example, we are calculating three points for a female 30-year old, using the following formulas (for simplicity, we report formulas as if interaction effects were not included):

2.fathereduc

$$\begin{aligned} & \Pr(educ_i = 4 | fathereduc = 2, age = 30, female = 1, mothereduc = 1) \\ & - \Pr((educ_i = 4 | fathereduc = 1, age = 30, female = 1, mothereduc = 1)) \\ & = [1 - \Phi(\mu_4 - \rho_{f2} - \rho_{m1} - \delta_f - \beta_{age} \times 30)] \\ & - [1 - \Phi(\mu_4 - \rho_{f1} - \rho_{m1} - \delta_f - \beta_{age} \times 30)] \end{aligned}$$

3.fathereduc

$$\begin{aligned} & \Pr(\text{educ}_i = 4 | \text{fathereduc} = 3, \text{age} = 30, \text{female} = 1, \text{mothereduc} = 1) \\ & \quad - \Pr(\text{educ}_i = 4 | \text{fathereduc} = 1, \text{age} = 30, \text{female} = 1, \text{mothereduc} = 1) \\ & = [1 - \Phi(\mu_4 - \rho_{f3} - \rho_{m1} - \delta_f - \beta_{\text{age}} \times 30)] \\ & \quad - [1 - \Phi(\mu_4 - \rho_{f1} - \rho_{m1} - \delta_f - \beta_{\text{age}} \times 30)] \end{aligned}$$

4.fathereduc

$$\begin{aligned} & \Pr(\text{educ}_i = 4 | \text{fathereduc} = 4, \text{age} = 30, \text{female} = 1, \text{dmothereduc}_j = 1) \\ & \quad - \Pr(\text{educ}_i = 4 | \text{fathereduc} = 1, \text{age} = 30, \text{female} = 1, \text{mothereduc} = 1) \\ & = [1 - \Phi(\mu_4 - \rho_{f2} - \rho_{m1} - \delta_f - \beta_{\text{age}} \times 30)] \\ & \quad - [1 - \Phi(\mu_4 - \rho_{f1} - \rho_{m1} - \delta_f - \beta_{\text{age}} \times 30)] \end{aligned}$$

The same calculation is done for a male 30-year old, giving 3 more points, for a total of 6 points for 30-year olds.

The calculation is extended to ages 40, 50,60 and 70, generating a total of 6 lines.

The first point on the upper left corner of Panel 1 of in green has a legend 'female=0, 4.fathereduc' and a value of approximately 0.6. It means a 30-year old man, whose mother has only primary school education, is 60% more likely to achieve university education if his father has university education than if the father only has primary education.

When we speak of the effect of a father having university education as opposed to primary education *fixing mother's education at primary school*, results have not been estimated based only on individuals with the (relatively rare) combination of parents where the father complete tertiary education and the mother did not go beyond primary school. The full sample contributes to the estimation of the ordered probit coefficients and thresholds, which in turn allow us to calculate marginal effects⁶.

Comparing marginal effects of parental schooling at different levels of age will allows us to analyse how the relationship between parental education and educational outcomes has changed through time.

Comparing marginal effects of parental schooling for men and women will answer whether mother/father's education effects depend on gender.

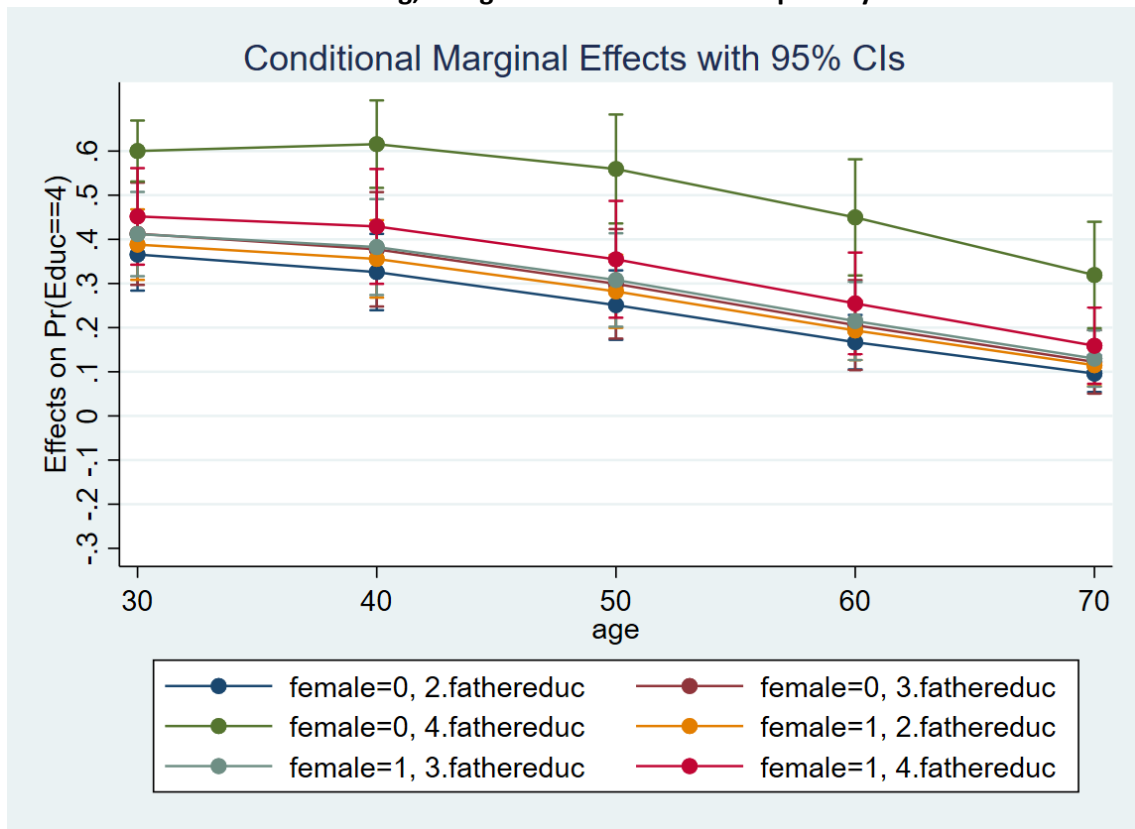
Results

In Portugal, the education of the father is more strongly associated with educational outcomes than the education of the mother, for both men and women, yet the difference is much more striking for men (Figure 10). Indeed, for women, any gain in the mother's education above primary school makes women more likely to achieve tertiary education. For men, only if the mother achieved tertiary education has such an impact.

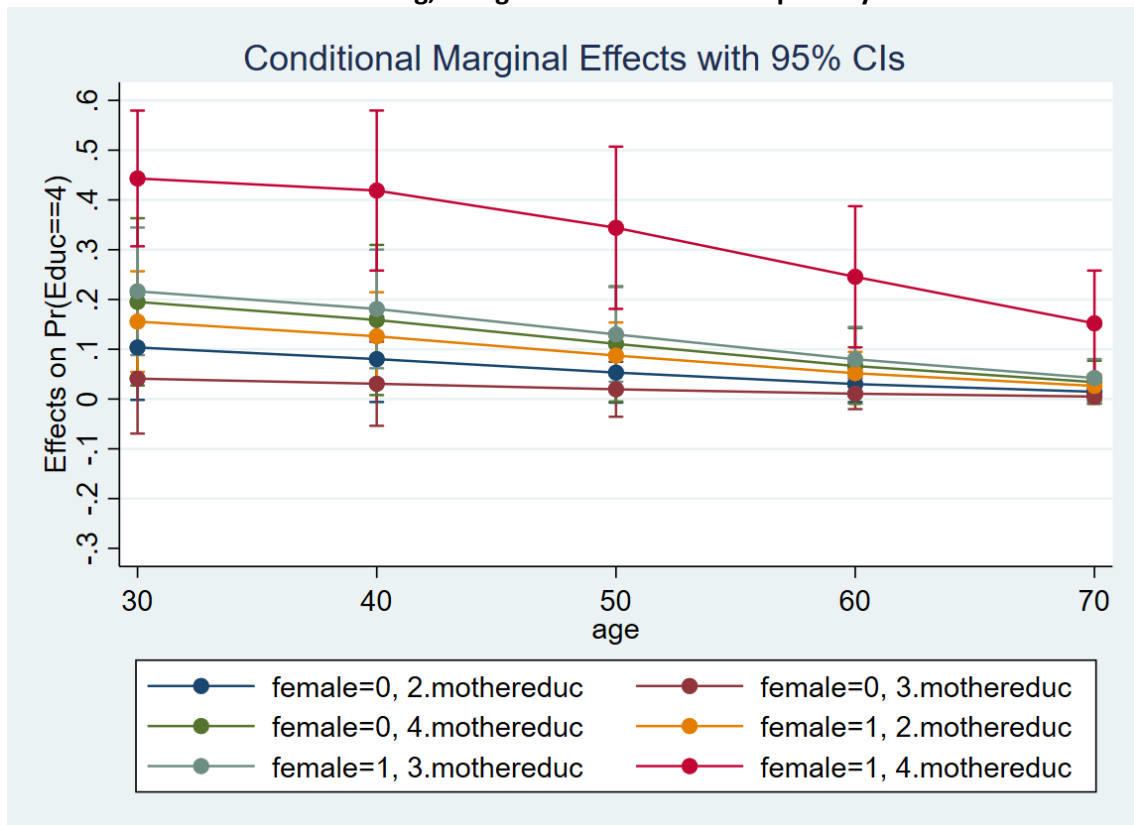
⁶ If certain combinations of dummy variables are rare, there might be an issue of parameter identification. Similar problem emerges in a usual linear regression context.

Figure 10: Portugal CME of mother's and father's schooling on probability of tertiary education (HFCS wave 2)

a. CME of father's schooling, fixing mother's education at primary school



b. CME of mother's schooling, fixing father's education at primary school



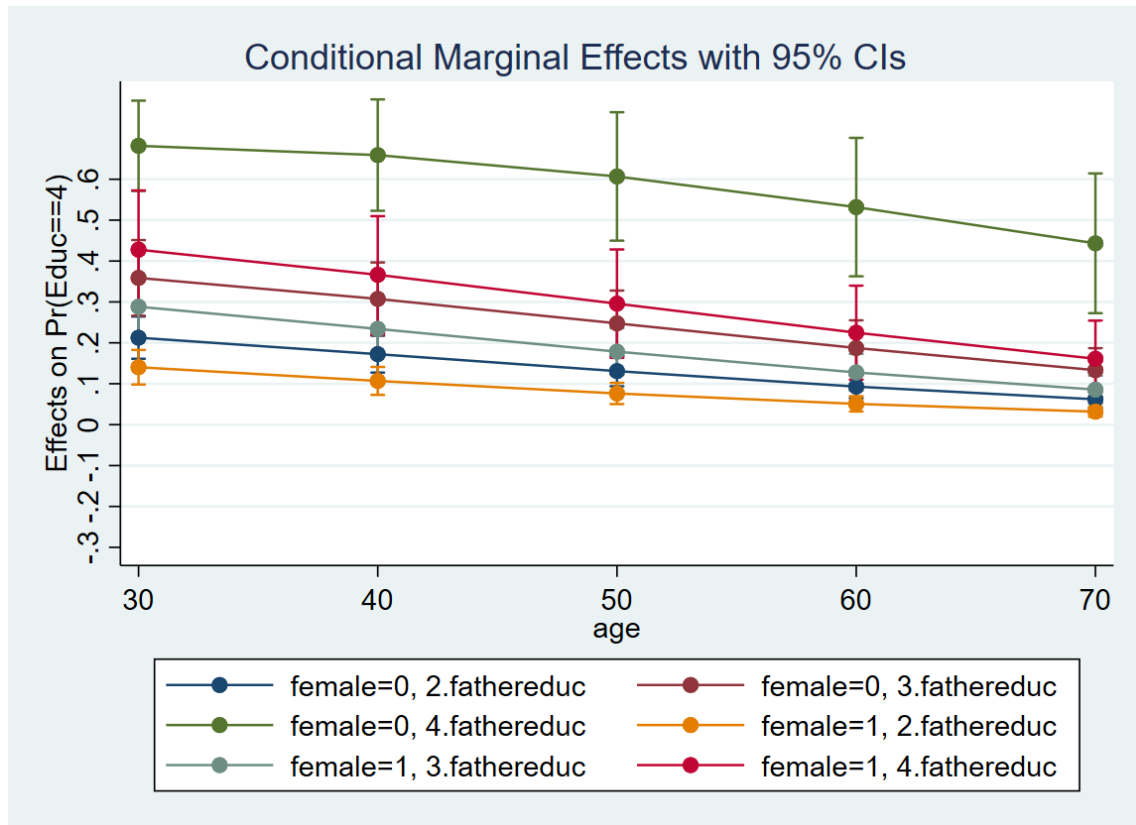
Having a father with higher levels of education makes individuals substantially more likely to achieve tertiary education, yet, the effect is substantially different depending on the age of individuals (marginal effects change considerably with age). Thus, it appears the advantages conferred by parental educational background change through time.

Interestingly, the advantages conferred by higher education in terms of increased probability of achieving tertiary education are stronger for individuals aged 30 than for individuals aged 70. The same is true for the education of mothers, which confers a greater advantage to individuals aged 30 than it does to individuals aged 70.

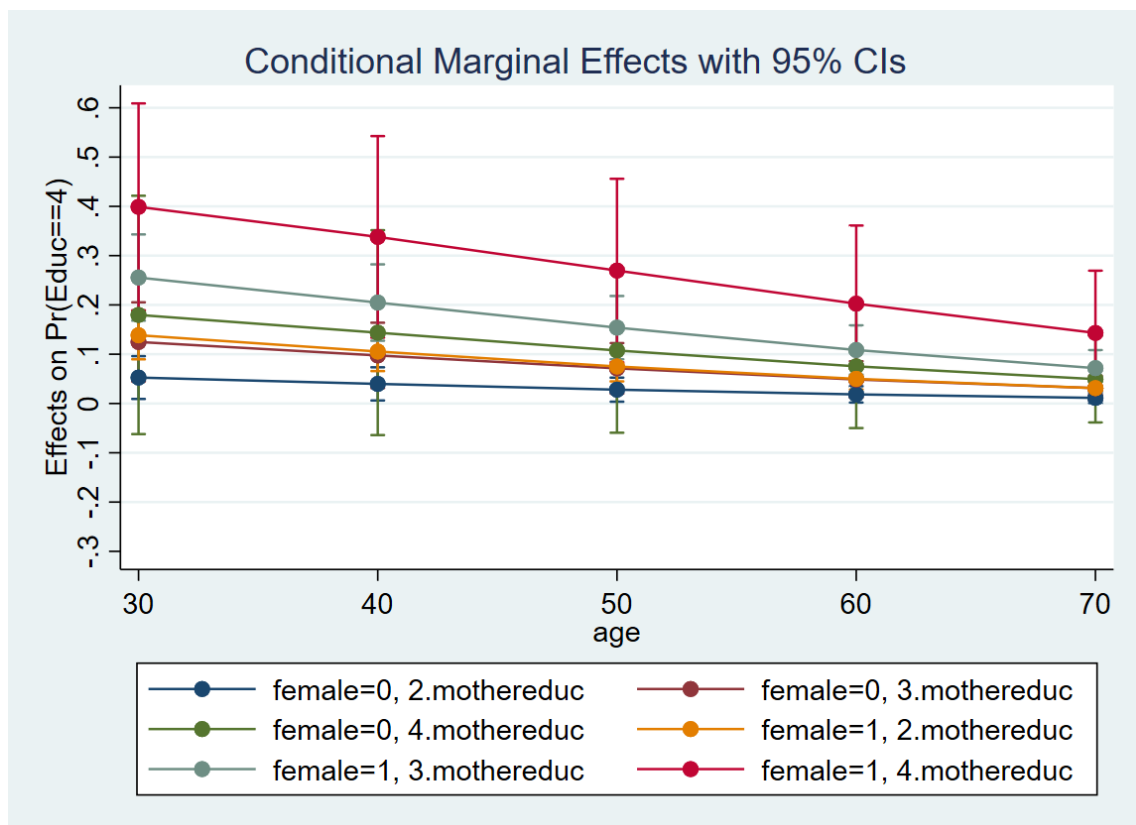
Given that the bulk of 70-year olds attended university about half a century ago, our finding suggests that the advantage conferred by parental educational background was lower half a century ago than now, that is, parental background became more important in recent decades.

Figure 10: Italy CME of mother's and father's schooling on prob. of tertiary education (Wave 2)

a. CME of father's schooling, fixing mother's education at primary school



b. CME of mother's schooling, fixing father's education at primary school



For Italy, some similar patterns arise: the advantages conferred by father's schooling are superior to those conferred by mother's schooling, for both men and women (Figure 10). Yet, while for Portugal, the gains (in probability of tertiary education) for a 30-year old woman of having a father with upper secondary school were of 41.2 p.p. and of having a mother with upper secondary school were of only 21.6 p.p., in Italy, the values are, respectively, 28.8 and 25.6 pp. The same applies to other levels of mother and father education, with in Italy, the advantages conferred to women by the mother's schooling being closer to those conferred by the father's schooling (see the last section of this chapter).

Another difference is that in Italy, for men, their mother having lower secondary or upper secondary education as opposed to primary education confers them an advantage in achieving tertiary education, unlike in Portugal, where gains from the mother's education for men were only discernible when mothers had tertiary education themselves.

In Italy we also see a similar pattern of educational persistence increasing through time, as the advantage conferred by higher education is more substantial for 30-year olds than for 70-year olds. For full information on the conditional marginal effects plotted, see the last section of this chapter.

Wealth effects

In the previous analysis, we have not attempted to discern why is it that parental affects educational outcomes. One possible confounding effect is wealth: parental education might be positively associated with wealth accumulation which, in turn, leads to better educational outcomes.

In trying to assess the effects of parental wealth on educational outcomes through the HFCS, we must resort to wealth transfer variables, as the closest proxy for parental wealth. We investigate i) whether parental wealth transfer is significant for educational outcomes and ii) whether it affects how parental educational background affects children's education.

We add to our specification variable $dparwealth_i$ which equals 1 if respondents have received substantial gifts or inheritance, and zero otherwise.

We assume that a positive response is a proxy for wealthier parents. Some caveats are in order. First, we do not know the amount of gift or inheritance. Second, having received a substantial gift from your family might signal increased parental involvement in the respondent's life, benefitting educational outcomes, regardless of parental wealth. Third, it can also serve to compensate children whose financial achievements are below expectations, perhaps due to suboptimal educational achievement. The latter can be considered in the model through respondent's income, yet, for the second issue, no clear solution is in sight. In the analysis in the SHARE dataset, we resort to more direct measures of parental wealth which might help interpret the results obtained.

We focus on marginal effects but considering all outcomes instead of just tertiary education. We look mostly at $ME_{dparwealth}^1(x_i)$ and $ME_{dparwealth}^4(x_i)$, the effects on the probability of not going beyond primary education and of achieving tertiary education. Again, we analyse *conditional marginal effects*, where we set x_i at different values, mostly, different ages.

For the case of Portugal, having received substantial gifts or inheritance is related with better educational outcomes, reducing the probability of not going beyond primary school

($ME_{dparwealth}^1(x_i)$ is negative) and increasing the probability of achieving some tertiary education ($ME_{dparwealth}^4(x_i)$ is positive).

Importantly, the effect of wealth transfer on educational outcomes have fallen through time according to our estimates, with having received substantial gifts or inheritance conferring less substantial advantages for younger individuals. Individuals who received substantial gifts or inheritance are less likely to not go beyond primary school and more likely to achieve tertiary education, yet, these gains are decreasing with time (smaller for younger individuals, $ME_{dparwealth}^1(x_i, age = 30)$ is less negative than $ME_{dparwealth}^1(x_i, age = 40,50,60,70)$).

For university incomes, it is also the case that the advantage of wealth has fallen through time for individuals of tertiary-educated parents. However, for individuals whose parents are lower-educated, receiving substantial gifts or inheritance still confers a substantial advantage to 30 year olds, similar to that conferred to 60 year olds ($ME_{dparwealth}^4(x_i, age = 30, paredu = 1,2,3) \approx ME_{dparwealth}^4(x_i, age = 60, paredu = 1,2,3)$).

It is also interesting to note that for intermediary outcomes, i.e., for lower secondary and upper secondary education, whether having received substantial gifts or inheritance increases or decreases the likelihood of those outcomes depends on age of respondents.

For older respondents, upper secondary is made more likely by having received substantial gifts or inheritance while for younger respondents, it is less likely. This seems to point in the direction of wealth increasing the probability of being above average education in your cohort. In future work, we will attempt to model outcomes in this way specifically, i.e., in comparison with the average outcome of the birth cohort in question.

When controlling for this indicator of wealth transfer, the relationship between parental education and offspring education remains strong. Moreover, this relationship does not differ substantially between individuals who received substantial gifts or inheritance and those who did not (Table 6).

For Italy, the story around receiving substantial gifts or inheritance is similar – it provides an advantage in terms of educational outcomes, namely reducing the probability of not going beyond primary school, and the advantage is more pronounced for older individuals. For university outcomes, however, the advantage conferred by wealth appears to be substantial - considerably higher than that of Portugal – and increasing, instead of non-changing for low-educated parents and decreasing for higher-educated parents, through time. Having received a substantial inheritance / gift is associated with a 7 p.p. to 8 p.p. higher probability of achieving higher education for 30-year olds in Italy, against only 1.5 to 3 p.p. in Portugal.

In Italy, receiving substantial inheritance or gift also appears to increase the advantages conferred by higher parental education (Table 7).

Impact of parental wealth transfers on the association between parental and offspring education

When controlling for the wealth transfer indicator, the association between parental education and offspring education remains strong,⁷ suggesting that omitting wealth from the earlier calculations did not distort the results much.⁸ This finding, of course, does not mean that parental wealth does not matter for educational outcomes: the calculations reported in the previous section indeed show that parental wealth has an additional impact on offspring education beyond parental education.

SHARE

Wealth effects

We explore the SHARE to investigate how parental wealth affects impacts educational outcomes.

The tables below show, country by country, which variables are statistically significant for educational outcomes. The tables are based on average marginal effects.

Table 4: Respondents: which parental wealth variables are significant for educational outcomes

Country	Variable					N
	Substantial Inheritance	Financial Gift	Any house bequest / gift	Rooms / people	Any feature	
ES	N	N	N	N	Y	588
CH	N	N	Y	Y	Y	1521
SE	N	Y	N	Y	Y	1393
SI	Y				Y	1361
NL	Y					855
LU	Y					1530
IT	Y			Y	Y	1530
DE	Y	Y				2332

⁷ For example, in the case of Luxembourg, the average marginal effect of the father's education on the probability of going beyond a primary education is approximately 1 percentage point lower than when wealth transfers are not included in the model. As an example, for those born in 1985, having a father with a university instead of a primary education is associated with a reduction of 14.3 percentage points in the probability of only achieving a primary education, while, when disregarding wealth, the reduction was 15.5 percentage points. The estimates for Portugal are, respectively, 22.1 and 21.4 percentage points. In Italy, the estimates are, respectively, 7 and 6.8 percentage points.

Estimates of the increase in probability of achieving a tertiary education associated with having a university-educated father instead of a father with only a primary education amounted to 44.3 percentage points for those born in Luxembourg in 1985 – when wealth was disregarded, the average marginal effect was almost the same at 45.3 percentage points. In Portugal, the estimates are 54.0 and 54.7 percentage points, respectively. For Italy, the estimates are 55 percentage points in both models.

⁸ All average marginal effects of parental education attainment were significantly different from 0 at the 1% level.

FR	Y			Y	Y	1256
EE		Y			Y	2505
DK	Y			Y	Y	2240
CZ					Y	2405
HR	Y			Y		697
BE	Y			Y	Y	2425
AT	Y	Y			Y	1983

Note: Only countries with more than 500 observations were considered.

All variables contribute to improve educational outcomes. The exception is Financial gifts in Sweden, which shows a significant, negative coefficient. It is important to bear in mind this effect is conditional on other wealth variables. It might be negative due to financial transfers used as compensation for low economic outcomes.

Table 5: Children of respondents: which parental wealth variables are statistically significant (5% level) for educational outcomes

Country	Variable				N
	Received financial gift from parents	Maximum wealth reported by parents	Minimum wealth reported by parents	Parental income when child is above 30	
AT	Y	Y	Y	Y	5969
BE	10% level	Y	Y		7823
HR	No info				
CZ		Y			8279
DK	10%	10%	Y	Y	5402
EE		Y: mostly increases top outcomes			7279
FR		Y	Y	Y: Protective effects primary school decreasing through time; univ. effect constant	5813
DE	Y	Y		Y	6591
EL				Y	3359
HU	No info				
IE			No info		
IT	Y	Y	Y	Y	5711
LU		Y: less protection through time for primary schools; increasing protection for university			1529
NL			Y	Y	4933
PL		Y	Y	Y	2851
PT	No info				
SI		Y	Y	Y	4894
ES		Y	Y	Y	5814
SE		Y		Y	6757
CH		Y		Y	3965

Persistence of advantage

Table 6: Children of respondents: in which countries is grandparental education statistically significant (5% level) for educational outcomes?

Country	Significant?	Effect and magnitude	N
AT	N		982
BE	N		2139
HR	Y	Upper secondary grandfather: +5 p.p. to 12 p.p. of probability of univ (more important for highly educ fathers). -1 p.p. of primary educ	1237
CZ	Y	All grandfather educ: from 4.6 p.p. up to 28 p.p. gain in probability of univ, increasing with father educ	2628
DK	N		2,659
EE	Y	Upper secondary grandfather and univ grandfather. 1) from 3 p.p. to 6 p.p.; from 7 p.p. to 10 p.p.	1,444
FR	Y	Univ grandfather, 14 to 19 p.p. on univ education	854
DE	N		4134
EL	Not enough data		
HU	Not enough data		
IE	Not enough data		
IT	Y	Upper secondary grandfather, protective effect on going beyond primary school, particularly for low schooled fathers	1384
LU	Y	Lower secondary grandfather, 14 p.p. to 21 p.p. on probability of univ., particularly for those without univ. fathers	1269
NL	Y	Upper secondary grandfather, 8 p.p. on univ., particularly for more educated fathers	1539
PL	Not enough data		
PT	Not enough data		
SI	N		1914
ES	Y	Protective effect on not going beyond primary school, especially	1033

		for lower educated fathers (1 to 2 p.p.)	
SE	N		2461

Overall analysis: how all SHARE waves are incorporated to allow for maximum coverage of age cohorts

When considering educational mobility, the longitudinal character of the SHARE data will not be considered directly, i.e., we will not be exploring the time variability within a single individual. This is because, for the most part, the highest educational level achieved is constant, especially that of preceding generations. The fathers of respondents are at least 58 years old⁹ - if alive. Respondents themselves are above 50+ and, outside a few exceptions, also not undergoing additional education.

For the children of respondents, we use the most recently available information on their educational level (for individuals sampled more than once), and we disregard children below 30 years old. Some sample selection might exist, since individuals who die earlier never give interviews about children above 30.

Given SHARE has a total of 7 waves spaced in time, we can analyse all those born before 1967 who were still alive in 2004, when the first wave of SHARE has been conducted¹⁰. The several waves will this way be used to identify time variability but on the basis of age cohorts, to answer questions on how educational mobility has changed through time.

Some caution is required: as we move to older cohorts, we will come across increasingly important sample selection issues, since all the interviewed individuals were alive in 2004. Individuals born in the 20s and 30s who were still alive in 2004 are not representative of the individuals born in those decades, being substantially healthier (and most likely wealthier). Given one of our central questions of interest is how wealth affects educational mobility, this is an important concern. We firstly address the issue by restricting ourselves to individuals born in 1940 or after (64 or younger in 2004), for whom sample selection is less of an issue.

We want to capture as many individuals as possible and generate a sample which is representative of individuals born after 1940 and before 1967 who were alive in 2004; by checking for the impact of their educational level on their children's educational level, given we eliminate children below 30, we cover individuals born between 1940 and 1987.

We use ISCED1997 educational levels to ensure wider coverage, and again look at educational classes and the probability of transition between them.

⁹ Two respondents in wave 5 report having 58-year old parents, the youngest in the sample.

¹⁰ All respondents from Wave 1 of SHARE (2004) are included, while from subsequent waves only the new respondents are added. This sampling ensures that one particular person appears only once in our dataset.

Detailed tables: Conditional marginal effects (CME) of parental education level on the probability of achieving university education

HFCS

Table 7: HFCS, CME of mother / father educational level on the probability of achieving university education, keeping the father / mother education fixed at primary school, for different ages, Portugal and Italy

a. For men

	ISCED 2	ISCED 3	ISCED 5	ISCED 2	ISCED 3	ISCED 5
	MOTHER PT			FATHER PT		
30	0.104* (0.0538)	0.0410 (0.0563)	0.195** (0.0858)	0.366*** (0.0417)	0.413*** (0.0591)	0.600*** (0.0353)
40	0.0803* (0.0440)	0.0307 (0.0431)	0.159** (0.0770)	0.326*** (0.0441)	0.377*** (0.0661)	0.616*** (0.0506)
50	0.0532* (0.0308)	0.0196 (0.0282)	0.111* (0.0591)	0.251*** (0.0401)	0.299*** (0.0633)	0.559*** (0.0630)
60	0.0301 (0.0185)	0.0107 (0.0158)	0.0663* (0.0388)	0.167*** (0.0314)	0.206*** (0.0520)	0.450*** (0.0672)
70	0.0146 (0.00949)	0.00499 (0.00756)	0.0340 (0.0219)	0.0960*** (0.0213)	0.122*** (0.0367)	0.319*** (0.0615)
	MOTHER IT			FATHER IT		
30	0.0526** (0.0222)	0.125*** (0.0410)	0.180 (0.123)	0.213*** (0.0263)	0.359*** (0.0472)	0.682*** (0.0563)
40	0.0398** (0.0172)	0.0976*** (0.0339)	0.144 (0.106)	0.172*** (0.0230)	0.308*** (0.0454)	0.659*** (0.0695)
50	0.0281** (0.0124)	0.0713*** (0.0261)	0.108 (0.0852)	0.131*** (0.0189)	0.248*** (0.0409)	0.607*** (0.0801)
60	0.0185** (0.00843)	0.0487*** (0.0189)	0.0754 (0.0639)	0.0931*** (0.0146)	0.187*** (0.0345)	0.532*** (0.0863)
70	0.0114** (0.00536)	0.0311** (0.0128)	0.0495 (0.0449)	0.0620*** (0.0108)	0.133*** (0.0273)	0.443*** (0.0871)

b. For women

	ISCED 2	ISCED 3	ISCED 5	ISCED 2	ISCED 3	ISCED 5
	MOTHER PT			FATHER PT		
30	0.156*** (0.0516)	0.216*** (0.0653)	0.443*** (0.0696)	0.388*** (0.0407)	0.412*** (0.0487)	0.452*** (0.0558)
40	0.126*** (0.0452)	0.181*** (0.0608)	0.419*** (0.0820)	0.356*** (0.0448)	0.383*** (0.0554)	0.429*** (0.0664)
50	0.0874*** (0.0339)	0.130*** (0.0485)	0.344*** (0.0832)	0.282*** (0.0422)	0.308*** (0.0540)	0.355*** (0.0675)
60	0.0519** (0.0218)	0.0799** (0.0332)	0.246*** (0.0724)	0.194*** (0.0343)	0.215*** (0.0452)	0.255*** (0.0588)
70	0.0264**	0.0422**	0.152***	0.115***	0.130***	0.159***

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	(0.0121)	(0.0195)	(0.0541)	(0.0241)	(0.0325)	(0.0440)
	MOTHER IT			FATHER IT		
30	0.139*** (0.0250)	0.256*** (0.0446)	0.399*** (0.107)	0.140*** (0.0216)	0.288*** (0.0386)	0.428*** (0.0739)
40	0.106*** (0.0203)	0.205*** (0.0395)	0.338*** (0.104)	0.107*** (0.0174)	0.234*** (0.0347)	0.366*** (0.0731)
50	0.0751*** (0.0155)	0.154*** (0.0328)	0.270*** (0.0950)	0.0763*** (0.0133)	0.178*** (0.0292)	0.296*** (0.0676)
60	0.0501*** (0.0111)	0.109*** (0.0255)	0.203** (0.0809)	0.0509*** (0.00954)	0.128*** (0.0232)	0.225*** (0.0586)
70	0.0312*** (0.00753)	0.0718*** (0.0187)	0.143** (0.0644)	0.0317*** (0.00654)	0.0857*** (0.0174)	0.161*** (0.0476)

Table 8: HFCS, CME of father's education in the probability of achieving university educations according to wealth proxy (having received substantial gift/inheritance), fixing mother's education at primary school

a. PORTUGAL

	Age	ISCED 2	ISCED 3	ISCED 5
No substantial gift/ inh	30	0.372*** (0.0300)	0.414*** (0.0384)	0.518*** (0.0364)
Substantial gift/inh		0.375*** (0.0290)	0.416*** (0.0367)	0.513*** (0.0343)
No substantial gift/ inh	40	0.331*** (0.0318)	0.377*** (0.0425)	0.502*** (0.0440)
Substantial gift/inh		0.344*** (0.0316)	0.390*** (0.0421)	0.511*** (0.0426)
No substantial gift/ inh	50	0.258*** (0.0292)	0.300*** (0.0407)	0.432*** (0.0466)
Substantial gift/inh		0.276*** (0.0301)	0.320*** (0.0418)	0.452*** (0.0467)
No substantial gift/ inh	60	0.175*** (0.0236)	0.209*** (0.0339)	0.331*** (0.0436)
Substantial gift/inh		0.194*** (0.0251)	0.230*** (0.0361)	0.356*** (0.0452)
No substantial gift/ inh	70	0.104*** (0.0168)	0.128*** (0.0248)	0.225*** (0.0362)
Substantial gift/inh		0.119*** (0.0185)	0.145*** (0.0272)	0.248*** (0.0387)

b. ITALY

	Age	ISCED 2	ISCED 3	ISCED 4
No substantial gift/ inh	30	0.167*** (0.0166)	0.306*** (0.0304)	0.536*** (0.0475)
Substantial gift/inh		0.195***	0.343***	0.558***

		(0.0186)	(0.0308)	(0.0430)
No substantial gift/ inh	40	0.131***	0.254***	0.490***
		(0.0139)	(0.0279)	(0.0510)
Substantial gift/inh		0.161***	0.298***	0.530***
		(0.0166)	(0.0301)	(0.0479)
No substantial gift/ inh	50	0.0966***	0.198***	0.426***
		(0.0111)	(0.0241)	(0.0523)
Substantial gift/inh		0.125***	0.245***	0.480***
		(0.0140)	(0.0276)	(0.0511)
No substantial gift/ inh	60	0.0669***	0.146***	0.354***
		(0.00848)	(0.0198)	(0.0515)
Substantial gift/inh		0.0915***	0.189***	0.415***
		(0.0113)	(0.0239)	(0.0523)
No substantial gift/ inh	70	0.0436***	0.101***	0.280***
		(0.00629)	(0.0155)	(0.0485)
Substantial gift/inh		0.0628***	0.138***	0.342***
		(0.00878)	(0.0196)	(0.0513)

SHARE

Table 9: SHARE, CME of mother / father educational level on the probability of achieving university education, keeping the father / mother education fixed at primary school, for different ages, Italy

a. For men

	ISCED 2	ISCED 3	ISCED 5	ISCED 2	ISCED 3	ISCED 5
	MOTHER IT			FATHER IT		
50	0.108**	0.280***	0.617***	0.254***	0.241***	0.412***
	(0.0540)	(0.0997)	(0.166)	(0.0515)	(0.0794)	(0.134)
60	0.0760*	0.217**	0.567***	0.194***	0.183***	0.341**
	(0.0407)	(0.0883)	(0.203)	(0.0442)	(0.0677)	(0.134)
70	0.0474*	0.150**	0.474**	0.132***	0.123**	0.253**
	(0.0273)	(0.0691)	(0.220)	(0.0339)	(0.0511)	(0.118)

b. For women

	ISCED 2	ISCED 3	ISCED 5	ISCED 2	ISCED 3	ISCED 5
	MOTHER IT			FATHER IT		
50	0.207***	0.246***	0.380***	0.146***	0.219***	0.542***
	(0.0455)	(0.0635)	(0.139)	(0.0328)	(0.0531)	(0.0795)
60	0.148***	0.180***	0.298**	0.100***	0.158***	0.462***
	(0.0359)	(0.0523)	(0.130)	(0.0241)	(0.0426)	(0.0862)
70	0.0939***	0.117***	0.210*	0.0613***	0.101***	0.356***
	(0.0254)	(0.0383)	(0.108)	(0.0159)	(0.0306)	(0.0831)

Table 10: Coefficient estimates from the ordered probit model for the probability of achieving tertiary education using SHARE data

	lower secondary father education	higher secondary father education	university father education	substantial wealth transfer	rooms per people when 10 years old	basic amenities	books in the house when 10 years old	performance at school in maths when 10 years old	performance at school in language when 10 years old
Austria	0.0160 (0.0215)	0.120*** (0.0215)	0.168*** (0.0286)	0.0510*** (0.0156)	0.0223 (0.0164)	0.0922*** (0.0151)	0.0542*** (0.00620)	-0.0259*** (0.00830)	-0.0288*** (0.00847)
Belgium	0.124*** (0.0231)	0.156*** (0.0254)	0.197*** (0.0300)	0.0697*** (0.0151)	0.0702*** (0.0176)	0.109*** (0.0220)	0.0381*** (0.00684)	-0.0578*** (0.00850)	-0.0467*** (0.00890)
Croatia	0.0833*** (0.0204)	0.159*** (0.0466)	0.256*** (0.0703)	0.0810*** (0.0271)	0.108*** (0.0372)	0.0270 (0.0212)	0.0427*** (0.0123)	-0.0309*** (0.0120)	-0.0537*** (0.0135)
Czechia	-0.0668 (0.0657)	-0.0359 (0.0657)	0.0768 (0.0703)	0.0152 (0.0102)	0.00526 (0.0145)	0.0351*** (0.0109)	0.0301*** (0.00419)	-0.0639*** (0.00579)	-0.0456*** (0.00598)
Denmark	0.0196 (0.0318)	0.0946*** (0.0194)	0.151*** (0.0331)	0.0657*** (0.0166)	0.0546*** (0.0193)	0.154*** (0.0268)	0.0444*** (0.00725)	-0.0678*** (0.00894)	-0.0508*** (0.00904)
Estonia	0.0701*** (0.0210)	0.0737*** (0.0181)	0.132*** (0.0346)	0.0220 (0.0169)	0.00208 (0.0155)	0.0446*** (0.0142)	0.0455*** (0.00561)	-0.0764*** (0.00775)	-0.0368*** (0.00857)
France	0.127*** (0.0415)	0.0494* (0.0286)	0.200*** (0.0427)	0.0812*** (0.0214)	0.0755*** (0.0210)	0.160*** (0.0297)	0.0649*** (0.00901)	-0.0643*** (0.0109)	-0.0165 (0.0107)
Germany	-0.101 (0.0703)	-0.0193 (0.0688)	0.105 (0.0720)	0.0741*** (0.0161)	0.0114 (0.0182)	0.0403* (0.0229)	0.0634*** (0.00646)	-0.0843*** (0.00867)	-0.0435*** (0.00919)
Italy	0.0520*** (0.0153)	0.0925*** (0.0308)	0.167*** (0.0550)	0.0682*** (0.0120)	0.0429*** (0.0110)	0.0446*** (0.00888)	0.0290*** (0.00471)	-0.0190*** (0.00454)	-0.0471*** (0.00561)
Luxembourg	0.202** (0.0914)	0.126*** (0.0313)	0.485*** (0.0729)	0.0478** (0.0239)	0.0246 (0.0255)	0.0271 (0.0505)	0.0351*** (0.00973)	-0.0440*** (0.0122)	-0.0535*** (0.0146)
Netherlands	0.0796*** (0.0279)	0.0970** (0.0394)	0.110** (0.0513)	0.0749*** (0.0214)	0.0523* (0.0297)	0.0721 (0.0483)	0.0294*** (0.00983)	-0.0435*** (0.0135)	-0.0904*** (0.0135)
Slovenia	0.0229 (0.0250)	0.101*** (0.0257)	0.182*** (0.0524)	0.0919*** (0.0200)	0.0196 (0.0272)	0.0600*** (0.0155)	0.0639*** (0.00731)	-0.0855*** (0.00961)	-0.0411*** (0.0102)

Disclaimer: This working paper has not been subject to the full Eurofound evaluation, editorial and publication process.

Spain	-0.0365 (0.0359)	0.125* (0.0681)	0.166*** (0.0525)	0.00996 (0.0246)	-0.0287 (0.0277)	0.158*** (0.0234)	0.0473*** (0.0107)	-0.0279** (0.0141)	-0.0768*** (0.0175)
Sweden	0.0269 (0.0354)	0.0925*** (0.0289)	0.227*** (0.0367)	0.0210 (0.0181)	0.0601*** (0.0214)	0.122*** (0.0308)	0.0561*** (0.00857)	-0.0607*** (0.0104)	-0.0528*** (0.0111)
Switzerland	0.00754 (0.0157)	0.0466*** (0.0157)	0.131*** (0.0260)	-0.0108 (0.0110)	0.0407*** (0.0122)	0.0814*** (0.0143)	0.0372*** (0.00507)	-0.0262*** (0.00644)	-0.0290*** (0.00657)

Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Separate model was estimated for each countries, which estimate the determinants for achieving only primary education, lower secondary education, upper secondary education, and tertiary education. This table shows the results for tertiary education only.

The first three data columns show estimates for dummy variables of higher father's education. Substantial wealth transfer is a dummy variable. Basic amenities is a dummy variable indicating whether the house had any of the following features: fixed bath, running water, running hot water and central heating (dummy). Books in the house when the respondent was 10 years old is coded as: 1. None or very few (0-10 books); 2. Enough to fill one shelf (11-25 books); 3. Enough to fill one bookcase (26-100 books); 4. Enough to fill two bookcases (101-200 books); 5. Enough to fill two or more bookcases (more than 200 books). performance at school compared to peers in maths at 10 years old (treated as continuous). Performance at school in maths/language when 10 years old includes the answer to the following question: "Now I would like you to think back to your time in school when you were 10 years old. How did you perform in Maths/Language compared to other children in your class? Did you perform much better, better, about the same, worse or much worse than the average? 1. Much better, 2. Better, 3. About the same, 4. Worse, 5. Much worse".

The effect of wealth transfer on education outcomes for different cohorts

The first two data columns of Table 11 show the distribution of the 30-40 and the 60+ cohorts according to education level in Portugal. While three-quarters of the 60+ cohort has only primary education, this share is just 14.9 percent for the 30-40-year cohort. And while only 8.8 percent of 60+ cohort have tertiary education, this share has increased to 31.3 percent for the 30-40-year cohort. These developments highlight the overall increase in education attainment through the past decades.

Notwithstanding the general increase in educational levels, the last two data columns of Table 10 show that the impact of wealth transfer became more important for the younger cohorts. These two data columns report our estimates for the impact of wealth transfer on educational outcomes, and show, for example, that a wealth transfer increased the probability of achieving university education by 0.016 percentage points for the 70-year old cohort, the same effect is 0.0516 percentage points for a 30-year old.

Table 11: Educational attainment for the 30-40 cohort and the 60+ cohort and the effects of wealth transfers on the probability of attaining different educational levels, Portugal

	30-40	60 +	Effect of wealth transfer (30-year old)	Effect of wealth transfer (70-year old)
Primary	14.9%	75.0%	-0.0372	-0.0474
Lower secondary	23.2%	10.1%	-0.0146	0.0158
Upper secondary	30.6%	6.1%	0.0002	0.0156
Tertiary	31.3%	8.8%	0.0516	0.0160

Source: Calculations based on 2017 HFCS.

Note: Effect of wealth transfer corresponds to the average marginal effect (AME) of having received substantial inheritance/ financial gift, with the covariate age set at 30 and 70. Marked in bold whenever AME is statistically different from 0, at the 5% level.

7 - Persistence of educational advantage: impact of grandparents

In the models above of intergenerational transmission of advantage, the underlying assumption is that advantages are fully explainable by the generation immediately before – parents –, that is, that grandparents for instance do not play a role.

Solon (2017) provides a literature review which indicates such assumption might not be too harmful – grandparents do seem to play a role over and above that mediated by parents, but comparatively quite small.

Before using our econometric models to test this, we estimate a simple linear regression between education status of grandchild on the education of her/his parents and grandparents, in order to form a preliminary view on the explanatory power of generations older than parents.

Table 12: Regression of the education status of grandchild on parental and grandparental education

Education	Coef.	St.Err.	t-value	p-value	[95% Conf Interval]	Sig
Parental educ	0.287	0.006	51.77	0.000	0.276 0.298	***
Grandfather educ	0.039	0.006	6.17	0.000	0.027 0.052	***
Grandmother educ	-0.010	0.008	-1.32	0.186	-0.025 0.005	
Female (dummy)	0.018	0.013	1.36	0.174	-0.008 0.044	
Year of birth	0.007	0.001	8.50	0.000	0.005 0.008	***
Constant	-10.271	1.530	-6.71	0.000	-13.269 -7.273	***
R-squared		0.129	Number of obs		26649.000	
F-test		791.384	Prob > F		0.000	

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Source: Calculations based on the SHARE dataset.

Note: Data is unweighted, given that the unit of observation is children, not respondents. Parental education refers to the education of the respondent to the SHARE questionnaire, regardless of whether a man or a woman.

Both the parental education and the grandfather's education is statistically highly significant for the education of the grandchild, while the parameter estimates indicate the grandfather's education matters only about 1/7 of the magnitude of parental education (Table 12). Hence, our results are in line with Colagrossi *et al* (2019), who concluded that beyond a direct parent-to-child association, a direct grandparent effect can also be present. The educational background of the grandmother is not significant for the educational outcome of the grandchild.

A three-generational education persistence has implications for wealth persistence and mobility, given that our earlier calculations confirmed that a higher level of education has a positive impact on wealth. That is, if the grandfather's educational level has an additional impact on the grandchild educational level beyond the parents' educational level, then the educational level of the grandfather has an impact on the wealth accumulation of the grandchild.

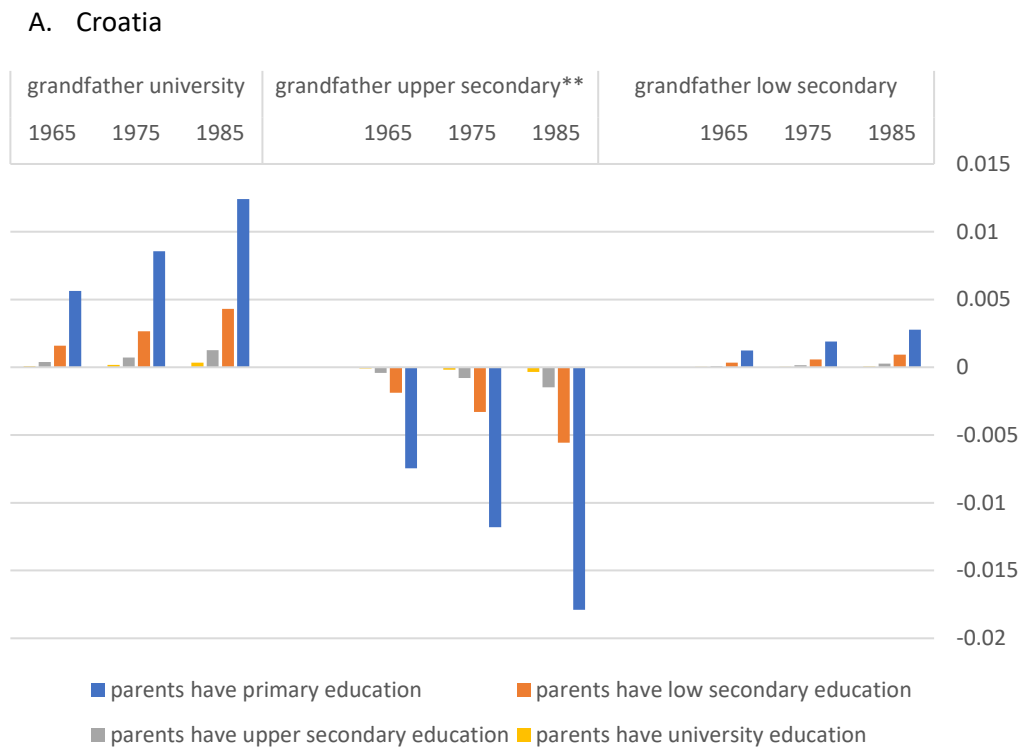
Looking into our educational mobility econometric models, once we have accounted for parental wealth, income, parental school performance relative to peers, and books at home of parents when children, we observe that grandparental education is still statistically significant for grandchildren educational outcomes for several countries, though its effect is a fraction of the effect of parental education.

We consider a total of 15 countries – Austria, Belgium, Czechia, Germany, Denmark, Estonia, Greece, Spain, France, Croatia, Italy, Luxembourg, Netherlands, Slovenia and Sweden – for which we have at least 500 observations for our model of children of respondents.

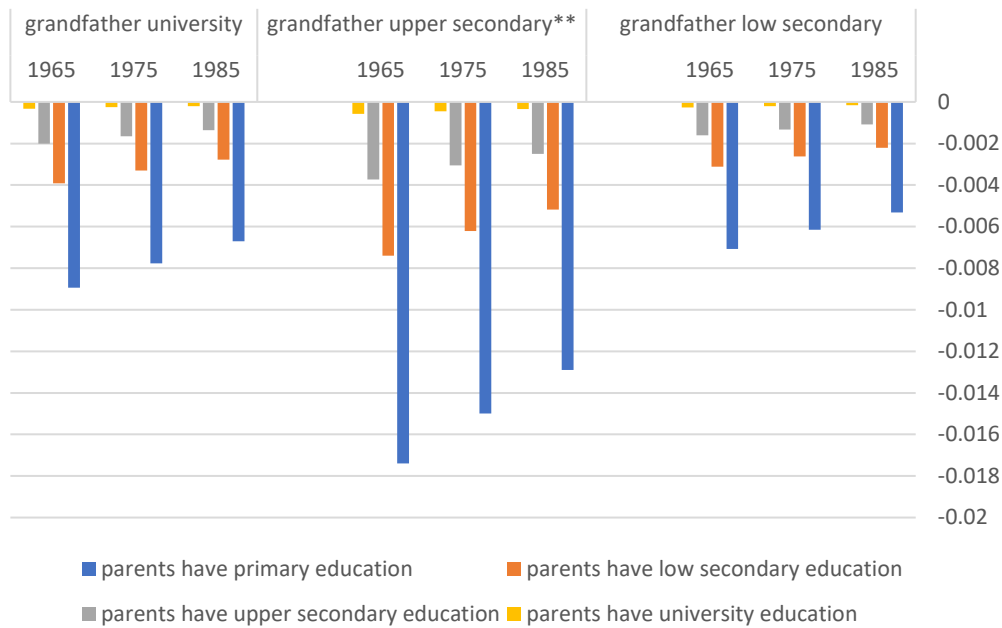
For 9 of the 15 countries, we obtain statistically significant estimates for the impact of grandparents' education. Countries for which we do not find an effect of grandparents' education are Austria, Belgium, Denmark, Germany, Slovenia and Sweden.

For the countries where it is significant, we find a two-fold effect. Firstly, it decreases the probability of grandchildren not going beyond primary school, especially when fathers are low-educated. That is the case in Croatia, Italy and Spain (Figure 11).

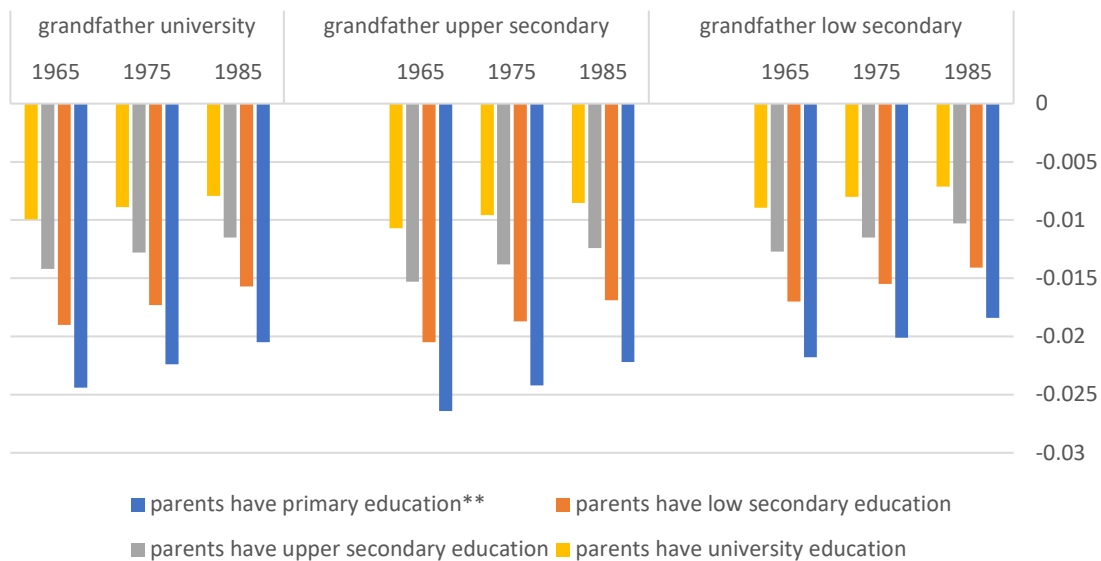
Figure 11: Average marginal effect of grandfather's education on the probability of only achieving primary education, conditional on parental education and year of birth



B. Italy



C. Spain



Source: Calculations based on the SHARE dataset.

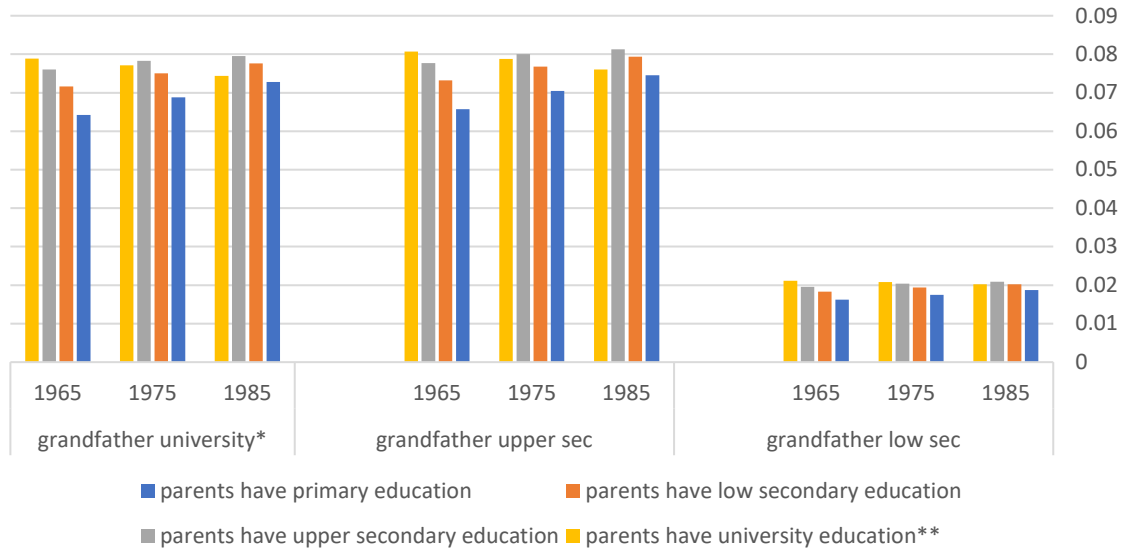
Note: Note: a negative value indicates that a higher grandparental educational level decreases the probability of not going beyond primary education, that is, it increases the probability that the grandchild will go beyond primary education. For Croatia and Italy, only grandfathers having upper secondary education instead of primary education is associated with an increase in the probability of going beyond primary school at a 5% level, conditional on parental education. For Spain, whenever parents have only primary education, any educational attainment of grandparents above primary school is associated (at the 5% level) with an increase in the probability of going beyond primary school education.

Secondly, it also promotes university achievement. Having a grandfather who achieved more than primary school leads to considerable increases in the probability of attaining university education, even if fathers are highly educated already. The effects are present in the Netherlands, Luxembourg,

France, Estonia, Croatia and Czechia and range from 5 p.p. increases in the probability of achieving university education to 28 p.p. in Czechia, where the educational background of grandparents seems to play a substantial role (Figure 12, see also Table 5).

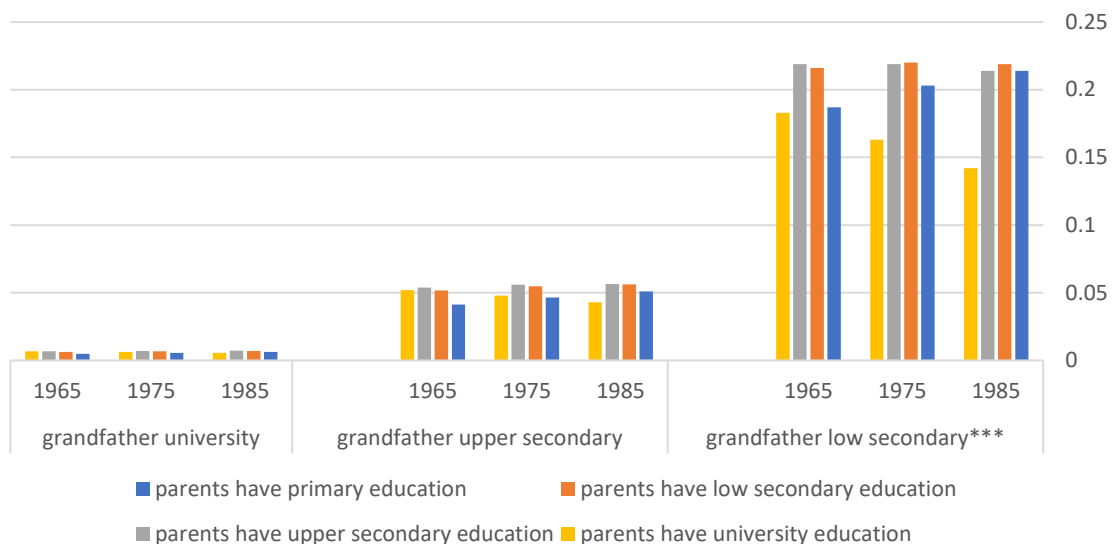
Figure 12: Average marginal effect of grandfather's education on the probability of achieving university education, conditional on parental education and year of birth

A. Netherlands



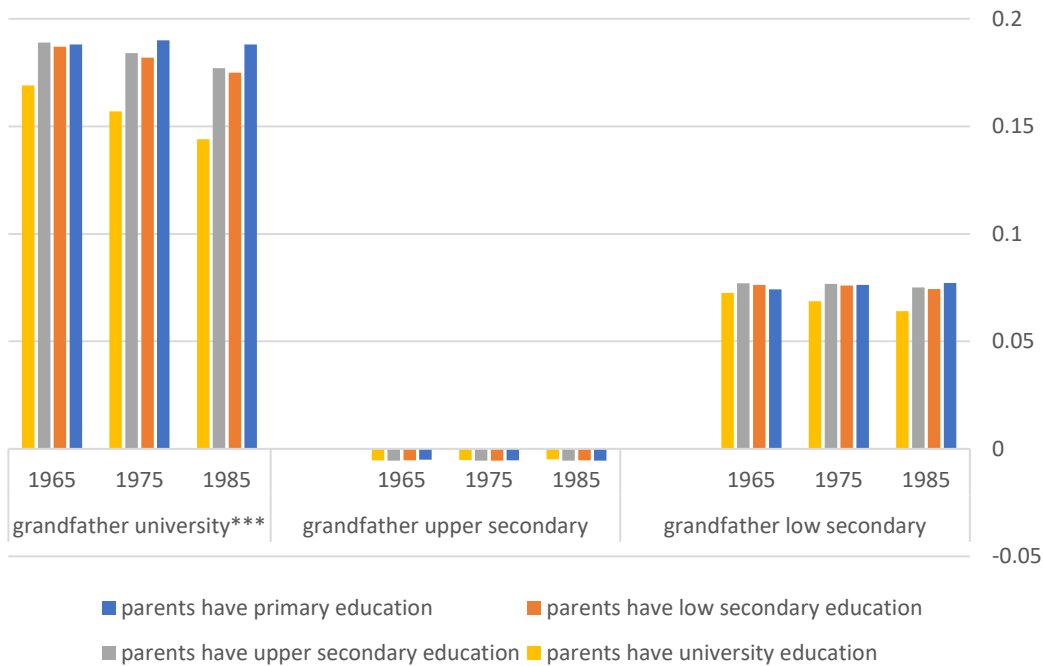
Note: In the Netherlands, having a grandfather who completed university education instead of only primary education is always associated (at the 10% level) with higher probabilities of achieving university education. Whenever parents have university education, having a grandfather with upper secondary or university education is associated with higher probabilities of achieving tertiary education at the 5% and 10% level respectively.

B. Luxembourg



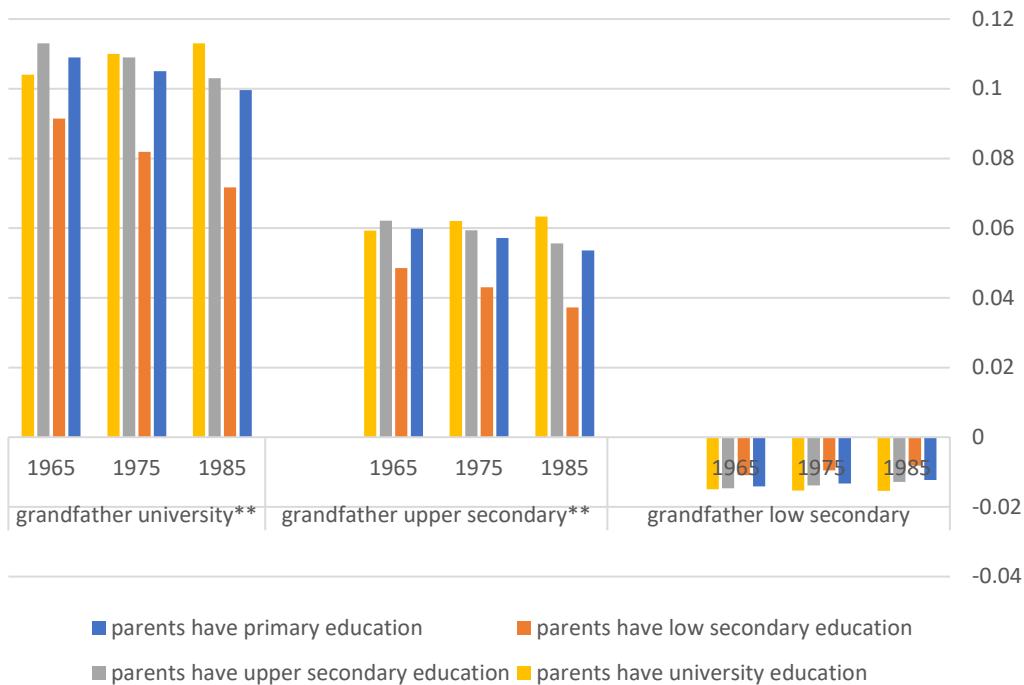
Note: In Luxembourg, having a grandfather with lower secondary education instead of primary education is always associated at the 1% or 5% level with higher probabilities of achieving university education, regardless of the level of education of parents.

C. France



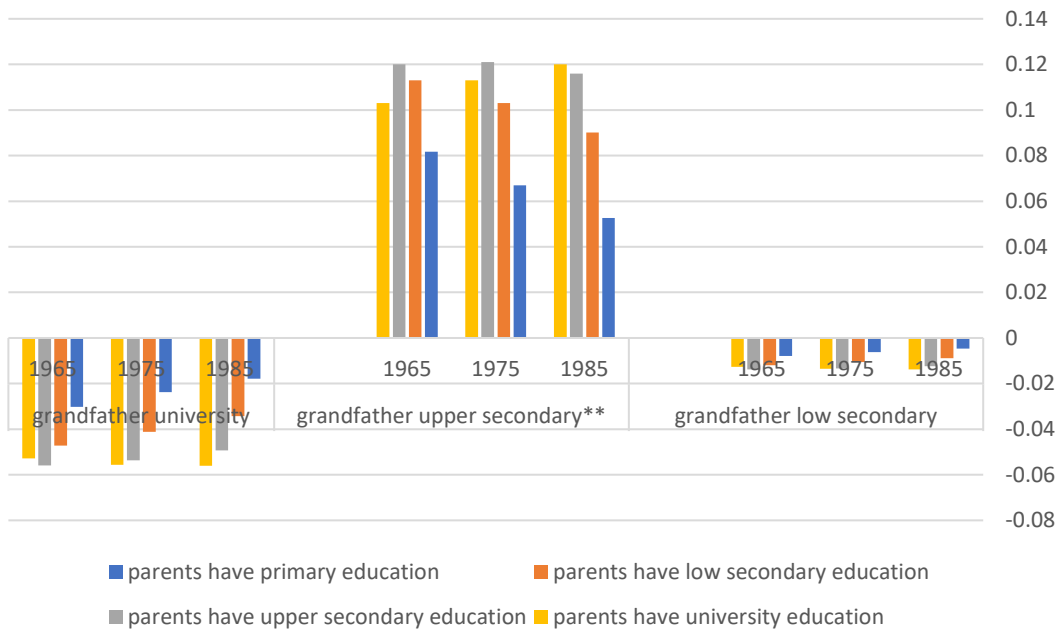
Note: In France, having a grandfather with university education instead of primary education is always associated (at the 1% level) with a higher probability of achieving university education, regardless of parental educational levels.

D. Estonia



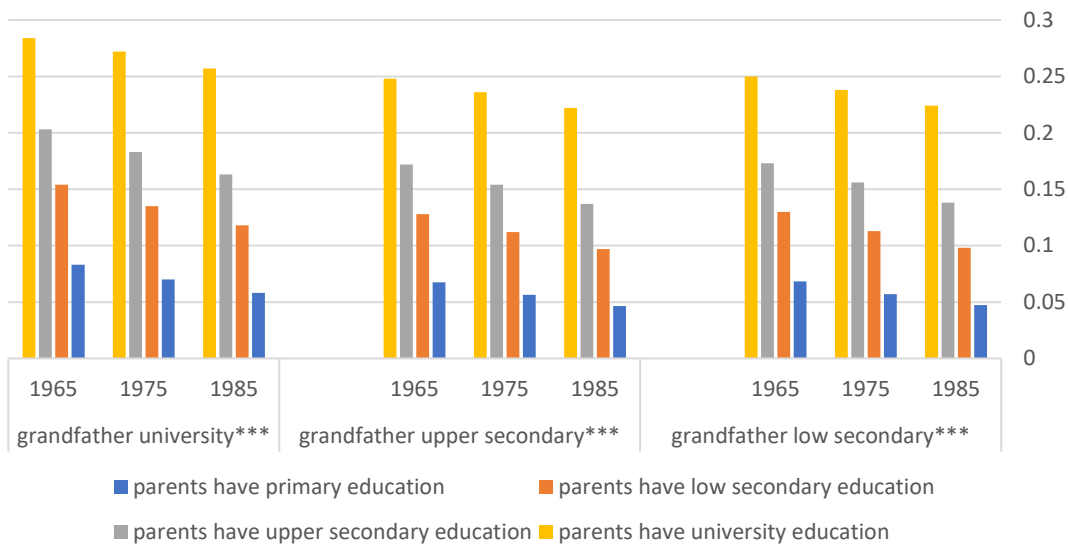
Note: In Estonia, having a grandfather with university education or upper secondary education instead of primary education is always associated (at the 5% level) with higher probabilities of achieving university education, regardless of parental educational levels.

E. Croatia



Note: In Croatia, having a grandfather with upper secondary education instead of primary education is always associated (at the 5% or 10% level) with higher probabilities of attaining university education, regardless of parental education.

F. Czechia



Note: In Czechia, having a grandfather with any educational level above primary education was always associated at the 1% level with higher probabilities of attaining university education, regardless of parental education.

Source: Calculations based on the SHARE dataset.

The data at hands does not allow us to disentangle further the mechanisms possibly at play. For instance, Zeng and Xie (2014) find, for rural China, that the education of deceased and non-co-resident grandparents has no significant effect on grandchildren educational outcomes but that of

co-resident grandparents does. They suggest ‘socioemotional pathways’ are an important part of the story.

While these advantages are considerably smaller than those conferred by parents, they are, in some countries – such as France and Luxembourg but particularly Czechia -, substantial.

The main conclusions from this section are:

- For 9 out the 15 countries considered, the education of the grandfather is statistically associated with the education of grandchildren, even when controlling for parental wealth, income, educational achievement and performance in school vis-à-vis their peers
- Grandfather’s education seems to associate with grandchildren educational outcomes in two ways:
 - It decreases the probability of grandchildren low educational achievements when fathers are low-educated;
 - It increases the probability of university education, regardless of parental education.
- Grandfather’s education is particularly relevant in France and Luxembourg.

8 - Wealth mobility

The following tables pertain to section 'Wealth mobility' of Eurofound (2021, p.79) that is based on SHARE data. Table 12 is a simple cross-section OLS regression with robust standard errors, where the dependent variable is the logarithm of the maximum wealth per household member reported by the SHARE respondent. Tables 13 and 14 show similar results, except the dependent variable is a binary variable which equals 1 whenever the individual belongs to the top wealth quintile.

Covariates considered are:

- Educ: respondent education, categorical, base level primary education;
- Father Educ: father of respondent's education, categorical, base level primary education;
- Mother Educ: mother of respondent's education, categorical, base level primary education;
- Age: age, continuous.
- Log inc: logarithm of income, continuous;
- Fem: dummy variable for female;
- Inh: dummy variable for any substantial inheritance received;
- Fin gift: dummy variable for any financial gift received;
- House bequest: dummy variable for having lived in a house which was a bequest;
- Rooms/ppl: number of rooms / number of people in the household where the respondent lived when 10 years old, continuous;
- Any feature: dummy variable for whether the household where the respondent lived when 10 years old had any of the following basic amenities: fixed bath, running water, running hot water and central heating;
- Books age 10: number of books in the household where respondent lived when 10 years old;
- Maths age 10: whether the individual was much worse, worse, equal, better or much better than his peer at maths in school at age 10, treated as continuous;
- Language age 10: whether the individual was much worse, worse, equal, better or much better than his peer at language in school at age 10, treated as continuous;

Note: N signals non-significant, Y signals significant at least at the 10% level. Whenever it is only at the 10% level (but not at 5%), it is noted in the table. When coefficients are significant, they are reported. The exception is books age 10 and maths age 10, where we only report whether they are associated with higher (written positive) or lower (written negative) wealth.

The three education variables are categorical, thus, it is written which of the categories of education is significantly different from primary education (base level) in its impact of (the logarithm of) maximum wealth per capita. Up refers to upper secondary, low to lower secondary, and univ. to tertiary education.

The construction of the sample follows the methodology explained in Annex section SHARE, 'Overall analysis: how all SHARE waves are incorporated to allow for maximum coverage of age cohorts'.

Table 12 Significant background variables for maximum wealth per capita

Country	Educ	Father Educ	Mother Educ	Age	LOG Inc	Fem	Inh	Fin gift	House bequest	Rooms/ppl	Any feature	Books age 10	Maths age 10	Lang age 10
AT	Y, univ. 47.8%	N	N	N (10 %, 1.4 %)	Y, 61.3 %	Y, - 30.6 %	Y, 71.5 %	N	Y, 41.4 %	N	N	N	N	N
AT, alive	N	N	N	N	Y, 117.1 %	N	Y, 82.2 %	N	Y, 70%	Y, 54%	N	N	Y, positive	N
BE	Y, 58.7%, 70.6%, 92.2%	N	N	Y, +1.4 %	Y, 25.5 %	N	Y, 63.9 %	N	Y, 32.7 %	N	Y, - 40.8 %	N	N	N
BE, alive	Y, 47.5%, 59%, 85%	N	Y, up sec 40%	Y, + 1.5 %	Y, 47.3 %	N	Y, 43.6 %	Y, - 40.7 %	N	N	Y, 39%	N	N	N
CZ	Y, univ 41.1%	N	N	N	Y, 86%	N	Y, 36%	N	N	N	N	N	N	N
CZ alive	Y, 40.8%, 78.4%, 90%	N	N	N	Y, 57.8 %	N	Y, 30.3 %	N	N	N	N	N	N	N
DK	Y, univ 37.2%	N	N	Y, +1.4 %	Y, 98%	Y, - 20.7 %	Y, 63.9 %	N	Y, +39%	N	N	Y, 7.7%	Y, positive	N
DK alive	N	N	N	Y, +2.6 %	Y, 107%	Y, - 30%	Y, 38%	N	Y, 37%	N	N	N	N	N
FR	Y, up sec 35.7%, univ 35.4%	N	Y, - 55.9%	Y, +3.1 %	Y, 63%	N	Y, 40%	N	N	N	N	N	N	N
FR alive	Y, up sec 69%, univ 80%	N	N	Y, +5.1 %	Y, 79.4 %	N	Y, 37.5 %	N	Y, 37%	N	N	N	N	N

DE	N, univ 10% +246.5%	N	N	Y, +2.5%	Y, 127%	N	Y, 70.9%	N	Y, 73.4%	Y, 43%	N	N	N	N
DE aliv e	-	-	-	-	-	-	-	-	-	-	-	-	-	-
IT	Y, up sec 44%, univ 48%	N	N	Y, +3.4%	Y, 38%	N	Y, 55.1%	N	N	N	N	N	N	N
IT aliv e	Y, up sec 78%, univ 108.4%	Y, low sec - 58%	N	Y, +2.9%	Y, 6.5%	N	Y, 50.6%	Y, -46.2%	N	Y, +40.3%	Y, -41%	N	N	N
NL	Y, univ 74%	N	N	N	Y, 23%	N	Y, 87.4%	N	N	N	Y, -86.7%	Y, +16.7%	N	N
NL, aliv e	-	-	-	-	-	-	-	-	-	-	-	-	-	-
SI	Y, up and univ 253%, 286%	Y, low sec	Y, low sec - 80%	N	53.3%	Y, -53.6%	Y, 52.5%	N	N	N	Y, 33%	N	N	N
SI, aliv e	N	N	Y, univ +145.4%	Y, +2.5%	Y, +35%	N	Y, 71%	N	Y, +35.1%	N	N	N	Y, positive	N
SE	Y, up and univ 30%, 32%	Y, low sec 31%	N	N	Y 83.1%	Y, -17%	Y, 35.5%	N	N	Y, 21.3%	N	N	Y, positive	N
SE, aliv e	-	-	-	-	-	-	-	-	-	-	-	-	-	-

Table 13 Significant background variables for probability of belonging to the top wealth quintile (Linear Probability Model)

Country	Educ	Father Educ	Mother Educ	Fem	Inh	House bequest	Rooms /ppl	Any feature	Books age 10	Maths age 10	Lang age 10
AT	Y (univ)	N	N	N	Y, 11.9 p.p.	N	N	N	N	10%	N
BE	Y (secondary and univ)	N	Y, univ	N	Y, 6.5 p.p.		N	Y (negative)	Y (10%)	N	N
CZ	Y (univ)	Y (all)	N	Y (10%)	N		N	N	N	N	N
DK	N	10% (sec)	N	N	Y, 6.6 p.p.		N	N	N	N	N
FR	Y (sec 10%, univ.)	Y (sec. negative)	N	N	N		N	N	Y	N	N
DE	N	N	N	N	Y, 6 p.p.	Y		Y	Y	Y	Y, neg (10%)
IT	Y, low sec (10%), others Y	N	N	N	N	N	N	N	N	N	N
NL	Y, up and univ	N	N	N	Y, 14 p.p.	N	N	N	N	N	N
SI	Y, low 10%, others	N	N	N	Y, 9.3 p.p.	N	N	N	N	N	N
SE	Y, 10% up and univ	N	N	N	Y, 4.3 p.p.	Y	N	N	Y (10%)	Y	N

Table 14: Linear Probability Model: max wealth controlling for income

Country	Educ	Father Educ	Mother Educ	Fem	Inh	House bequest	Rooms /ppl	Any feature	Books age 10	Maths age 10	Lang age 10
AT	Y, univ.	N	N	N	Y, 11.3 pp	N	N	N	N	Y	N
BE	Y, up and univ	N	Y, univ	N	Y, 6.2 pp	N	N	Y, negative	Y, 10%	N	N
CZ	Univ 10%	Y, all, v much	N	N	N	N	N	N	N	N	N
DK	N	N	N	N	Y, 5.1 P.P.	N	N	N	N	N	N
FR	N	N	Y, 10% low sec	N	N	N	N	N	Y (10%)	N	N
DE	N	N	N	N	Y, 6 p.p.	Y	Y (10%)	Y	Y	Y	Y, neg (10%)
IT	Y, sec and univ.	N	N	N	N	N	N	N	N	N	N
NL	Y, sec	N	N	N	Y, 12.6 pp	N	N	N	N	N	N
SI	Y, all	N	N	N	Y, 9.6 pp	N (& fin gift, neg)	N	N	N	N	N
SE	N	Y (10% sec)	N	N	N	Y, 11.5 pp	N	N	N	Y	N

References

- Colagrossi M., d’Hombres B., Schnepf S.V. (2019) [‘Like \(Grand\)Parent, like Child? Multigenerational Mobility across the EU’](#). IZA DP. IZA DP No. 12302.
- Davidson, Russel and Emmanuel Flachaire (2007) ‘Asymptotic and bootstrap inference for inequality and poverty measures’, *Journal of Econometrics*, 141(1), 141-166
<https://doi.org/10.1016/j.jeconom.2007.01.009>
- European Central Bank (2020a) ‘The Household Finance and Consumption Survey: Methodological Report for the 2017 wave’, *Statistics Paper Series N.o. 35*
<https://www.ecb.europa.eu/pub/pdf/scpsps/ecb.sps35~b9b07dc66d.en.pdf?8fcb3cd59213bac0784168618a9b5fb3>
- European Central Bank (2020b) ‘The Household Finance and Consumption Survey: Results from the 2017 wave’, *Statistics Paper Series N.o. 36* https://www.ecb.europa.eu/pub/economic-research/research-networks/html/researcher_hfcn.en.html
- Karaca-Madic, Pinar, Edward C. Norton and Bryan Dowd (2012) ‘Interaction terms in nonlinear models’, *Health Services Research*, 47(1 Pt 1): 255–274 <https://doi.org/10.1111/j.1475-6773.2011.01314.x>
- Midoes Correia, Catarina (2016) ‘Statistical inference for inequality measures: testing the t-approach, a robust alternative to bootstrap-based method’, Thesis for the degree of MSc in Econometrics and Operations Research with a Specialisation in Econometrics, University of Maastricht, the Netherlands
- Neves Costa, Rita and Sébastien Pérez-Duarte (2019) ‘Not all inequality measures were created equal’, *ECB Statistics Paper Series No.31* December 2019
<https://www.ecb.europa.eu/pub/pdf/scpsps/ecb.sps31~269c917f9f.en.pdf>
- OECD (forthcoming), *Inequalities in household wealth – drivers and policy implications*, OECD Publishing, Paris
- Rao, J.N.K, C.F.J Wu and K. Yue (1992) ‘Some recent work on resampling methods for complex surveys’, *Survey Methodology* 2(18), 209-217 <https://www150.statcan.gc.ca/n1/en/pub/12-001-x/1992002/article/14486-eng.pdf?st=xjnNjbqr>
- Rao, J.N.K. and C.F.J. Wu (1988) ‘Resampling inference with complex survey data’, *Journal of the American Statistical Association*, 83(401), 231-241
<https://www.jstor.org/stable/2288945?origin=JSTOR-pdf>
- Solon, Gary (2017) ‘What do we know so far about multigenerational mobility?’, *IZA Discussion Paper Series No. 10623s*
- Zeng, Zhen and Yu Xie (2014) ‘The Effects of Grandparents on Children's Schooling: Evidence from Rural China’, *Demography* 51(2), 599–617, <https://doi.org/10.1007/s13524-013-0275-4>

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