A Hybrid Approach toward Distributional National Accounts for Wealth in Europe with a Special Focus on Housing Wealth

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Abstract

Distributional National Accounts (DINA) link macroeconomic aggregates with distributional information enabling a better understanding of distributional implications of macroeconomic developments, and facilitating more comprehensive policy design and monitoring. This article proposes a practically feasible framework to allocate components of wealth to different sections of society and serves two functions: a comprehensive measure of net worth and a link to macroeconomic statistics. While the article provides results for all components of wealth, it particularly discusses the most important asset class for private households: housing wealth. A pseudo-link is established between the National Accounts' definitions of dwellings and land, and housing wealth as recorded in wealth surveys. Additionally, the article tests the trustworthiness of self-reported property prices and finds that owner-occupiers are collectivity well able to track *changes in prices*, but tend to overstate *amounts* likely resulting from an endowment effect. The degree of over-reporting declines when moving up the income distribution. The article finally provides DINA for wealth and income groups for Austria, Finland, France, Germany and Spain. Results are top-tail adjusted using Pareto and Generalized Pareto models. Large wealth inequality is documented, whereas the degree in inequality differs strongly across components of wealth.

Keywords: Distributional National Accounts (DINA), Endowment Effect, HFCS, Housing Wealth, Micro-macro linkage, Wealth Distribution

JEL codes: D31, D91, E01, R31

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1 Introduction

In the middle of the twentieth century it came to be believed that *a rising tide lifts all boats*, meaning that economic growth would eventually benefit all sections of society by increased wealth and higher living standards (Stiglitz, 2016; Hines Jr et al., 2001). The saying was made famous by a speech held by US president John F. Kennedy in 1963 legitimating public investments into a dam project:[1] "These projects produce wealth, they bring industry, they bring jobs, and the wealth they bring brings wealth to other sections of the United States. [...] As the income of Michigan rises, so does the income of the United States. A rising tide lifts all the boats [...]." This belief, as Stiglitz (2016) further argues, evolved into the specific idea of 'trickle-down economics' that advocates policies favouring the rich as resources given to the top are believed to trickle down to the rest of society eventually and thus everyone benefits from economic growth.[2]

While the post-war period was characterized by rising equality of incomes and wealth, we do observe the opposite trend today (see Piketty, 2013). Stiglitz (2016) concludes that "the rising tide has only lifted the large yachts, and many of the smaller boats have been left dashed on the rocks." Hines Jr et al. (2001) come to the conclusion that the gains from economic growth benefit the disadvantaged at least as much as the advantaged, but that the costs associated with a downturn are disproportionally born by the disadvantaged.

The other way round, inequality also affects the potential of economic growth: the macroeconomic wealth effect links permanent changes in households' wealth (directly or indirectly via a credit channel) to consumption (Lettau and Ludvigson, 2004). An unequal distribution of wealth (and thus also unequal access to credit) potentially leads to differential magnitudes of the wealth effect across sections of society (Arrondel et al., 2015, find a decreasing wealth effect when moving up the distribution in France). Differences in the marginal propensity to consume out of wealth is also a key indicator for understanding the transmission of monetary policy into the real economy. The OECD reports the harmfulness of income inequality on long-term growth as in high-income countries people in disadvantaged households struggle to access quality education implying large amounts of wasted potential and lower social mobility. It is also pointed out that high wealth inequality limits members of the lower middle class to invest (among others) in human capital, which can weaken potential growth (OECD, 2015).

Thus, macroeconomic developments and inequality need to be studied and monitored simultaneously. For that endeavour, suitable distributional data is needed. Distributional data should not stand alone but should rather be linked to the single most important framework to monitor macroeconomic developments: the System of National Accounts. Linkage ensures that economic growth and inequality are seen as two sides of the same coin, and supports a better understanding of the existence and mechanisms of 'trickling effects' as well as the design and monitoring of macroeconomic policies.

Thus, what is needed are *Distributional National Accounts* (DINA), that break down (components) of income, consumption and wealth as recorded in the National Accounts (NA) for different sections of society. DINA thus establish a link between GDP growth, which emerges from NA, and different sections of society. Wealth may be broken down by income and wealth

[1] Speech by John F. Kennedy on October 3, 1963: "Remarks in Heber Springs, Arkansas, at the Dedication of Grers Ferry Dam." The American Presidency Project: `http://www.presidency.ucsb.edu/ws/index.php?pid=9455` retrieved June 25, 2018.

[2] The 'rising tide hypothesis', however, would be equally in-line with a 'trickle-up' theory (giving more resources to the poorest members of society and eventually everyone will benefit) and a 'build-out form the middle' approach, where primarily the middle class is supported and 'trickling effects' in both directions will ensure that all benefit.

groups, but ideally also groups formed by demographic characteristics such as age, residency (urban versus rural) and gender. Following Fessler and Schürz (2017), a break-down by different functions of wealth (renters, owners and capitalists) would ease the interpretation of inequality.

The idea of distirbutional accounts is an old one. Piketty (2003) revived the work pioneered by Kuznets (1955), who combined tabulated income data with national income series. Piketty's work for France was extended to the US (Piketty and Saez, 2003) and the UK (Atkinson, 2005). The focus was to measure to income shares over time. This interest has led to the creation of *The World Top Incomes Database* (WTID), which was later transformed into the *WID.world* (Alvaredo et al., 2017) database with an extended focus on income and wealth.

This stream of literature further developed into measuring the entire distirbution in a consistent way with the national accounts. Garbinti et al. (2018) compile DINA for national income in France spanning the period 1900 to 2014. Fixler and Johnson (2014) and Fixler et al. (2017) compile such break-downs for the US.

Institutional effort in the form of international working groups has been initiated by the *Organisation for Economic Co-operation and Development* (OECD), *Eurostat* (the statistical institute of the EU) and the *European Central Bank* (ECB). The joint OECD-Eurostat *Expert Group on Measuring Disparities in a National Accounts Framework* focuses on distributional indicators for income and consumption (see Zwijnenburg et al., 2017), while the ECB *Expert Group on Linking Macro and Micro Data for the Household Sector* (EG-LMM) works on linking micro data obtained from the *Household Finance and Consumption Survey* (HFCS) with macro data from the financial/national accounts to derive DINA for wealth (see EG-LMM, 2017).

While research for income is well developed, less work has been done for wealth. This article aims to fill this gap: it provides an overview regarding concepts and definitions, and discusses micro data sources suitable for distributional break-downs. A particular focus is the measurement of housing wealth in surveys and the NA, and the top tail of the wealth distribution, which contributes heavily to total wealth.

The focus is Europe and forward-looking: how can DINA be gradually incorporated into the framework of regularly compiled official statistics and how can this be done in a as harmonized way as possible across countries?

I propose a hybrid approach that takes into account that a complete integration of distributional data into the framework of NA is currently infeasible as finer break-ups and more harmonization between macro and micro data would be needed. Hybrid DINA consist of two parts: the *integrated account* contains variables on the balance sheet that can directly be linked with micro data providing the distributional structure. The *supplement account* adds further variables necessary to obtain a comprehensive measure of total wealth but that are currently not linkable. Changes in the way micro data is collected and finer break-downs of national accounts will gradually enable a re-allocation of variables from the supplement account to the integrated account. Consumer durables such as vehicles fall outside the scope of NA but are important for a comprehensive measurement of wealth. Such variables will thus always remain in the supplement account.

The hybrid approach enables the compilation of DINA at an early point in time as full integration (which is currently not feasible in many countries) is not a prerequisite but can be achieved over time. At the same time, the approach guarantees that distributional data still provides a comprehensive picture of all components of net worth. Thus, from the very beginning onward DINA serve two functions: first, DINA establish a link between aggregate macroeconomic indicators and the system of measuring macroeconomic activity, the NA. The linkage enables an understanding of the allocation of gains and costs associated with macroeconomic trends and, vice versa, monitoring the influence of inequality on the wider economy. Second, DINA constitute by themselves a comprehensive measure of wealth inequality (and similarly for income and consumption inequality), which thus needs to cover all relevant components of wealth.

I use the HFCS as the main source of micro data. I make use of residential property price indices (RPPIs) to check the reliability of self-reported housing wealth in HFCS. The analysis requires long-term RPPIs, which are available for Belgium, Germany, France and Ireland.

It turns out that collectively survey respondents are well aware of price developments in the housing market. Qualitative cross-sectional variation in implicit depreciation rates inherent in the self-reported data match findings in market data as well as theoretical expectations. However, a general upward bias is observed that could be interpreted as an owner-pride or endowment effect. Thus, housing wealth may be slightly overstated when measured from a survey. Additionally, I find that the degree of over-reporting decreases when moving up the income distribution. These findings are also relevant for compiling distributional break-downs for income, which regularly rely on surveys to impute unobserved income flows from owner-occupied housing (see Garbinti et al., 2018).

I make use of rich lists reporting the names and net worth of the wealthiest individuals and families in a country and data on top wealth shares obtained from the WID.world database (Alvaredo et al., 2017) to adjust for the insufficient representation of the top tail in surveys. I apply a standard Pareto top tail adjustment and provide novel robustness checks relying on a Generalized Pareto Distribution.

The missing top tail, in contrast to general over-reporting of housing wealth, leads to lower HFCS aggregates in all components including housing wealth. Further research is needed to identify, which effect dominates for housing wealth.

I compile hybrid DINA for five European countries (Austria, Finland, France, Germany and Spain) for one year by merging top-tail-adjusted HFCS with national accounts data. The importance of the top-tail adjustment correlates strongly with the quality of the strategy applied in the respective countries to oversample wealthy households. Most components of financial wealth are fully integrated into the national accounts, a pseudo-link is established for housing wealth, and remaining asset classes are captured in a supplement account.

I find large concentrations of business wealth at the top of the distribution: in Austria and Germany the wealthiest 20% own roughly 97% of total business wealth. This share is lower but still above 90% in the other countries. Housing wealth is less unequally distributed and constitutes the most important asset class. Owner-occupied housing constitutes the largest share of total housing wealth across all countries and across groups formed by wealth or income.

Largest inequality is found in Austria and Germany, and lowest in Spain and Finland. France consistently lies in between.

The remainder of this article is organised as follows: section 2 proposes the hybrid approach, discusses micro and macro data, and how to link them. The following section 3 describes measurement issues related to housing wealth in detail and performs empirical analyses testing the trustworthiness of self-reported property prices. Issues related to the bad representation of the top tail are discussed in section 4 and a top tail adjustment is performed. Thereafter, section 5 presents empirical DINA results for wealth and income groups. Finally, section 6 concludes. A comprehensive appendix complements the article with detailed numerical results, further background information and mathematical derivations.

2 Distributional National Accounts: A Hybrid Approach

2.1 Macroeconomic Statistics: More Than Mere Numbers

The National Accounts constitute the most important and longest established framework measuring macroeconomic developments. They report economic activities within and across economic sectors – households, businesses, the government and the rest-of-the world. They measure the flow of gains from economic activity to the respective sectors taking into account taxes and transfers, and highlight how these gains are distributed to consumption, savings and investment.

The *System of National Accounts* (SNA) constitutes a harmonized standard for national accounting.[3] Although countries generally follow the standard, it is not legally binding and deviations do occur. In contrast, the *European System of National and Regional Accounts* (ESA, 2010), which also follows the SNA but provides more details, is legally binding for EU member states.

However, the NA and its most important output – *Gross Domestic Product* (GDP) – have also been criticised for following too narrow and partly out-dated concepts (see for instance Coyle, 2017). Points of critique include the treatment of natural resources/environmental externalities (e.g., the loss in biodiversity), the omission of home production, the representation of free online services and open-source software as well as other issues related to digitalization, and the general question whether a measure of economic activity is appropriate or whether more direct measures of well-being should be targeted (see Hamilton and Hepburn, 2017).

Regarding the latter issue, GDP growth may be a misleading indicator as it may not benefit all residents equally. In fact, since all these measures are macro-aggregates, it may well be the case that GDP growth is distributed very unequally among different sections of society. It is also not clear whether 'winners' and 'losers' change over time or whether these groups stay rather the same. More transparency regarding the effect of growth on inequality is likely to affect the interpretation and perception of macroeconomic indicators.

Coyle (2017), who elaborates on the *Political Economy of National Statistics*, argues that statistics are not 'neutral', but they feed back into our way of thinking: "[S]tatistics [...] help shape the reality, as much as reality determines which statistics are defined and collected" (page 22). Mügge (2016) conceptualizes macroeconomic indicators as "powerful ideas" and states that "[they] are political in both their origins – the choices for or against particular formulas to calculate them – and in their consequences – their use in public policy and the debates surrounding it." Consequently, "indicators specify what counts, for example, growth" and "[w]hen policy-makers and citizens accept these particular construction of macroeconomic concepts, the ideas that inform them solidify power relations by legitimizing some course of action and delegitimizing others." Finally, citizens will use these indicators as yardsticks to gauge whether policies, and subsequently politicians, are serving them well.

The discussion about the adequacy of currently measured indicators has been boosted by the *Commission on the Measurement of Economic Performance and Social Progress* headed by Joseph Stiglitz, Amartya Sen and Jean-Paul Fitoussi (also known as the *Stiglitz-Sen-Fitoussi commission*; see Stiglitz et al., 2010), which was created in 2008 on the initiative by the French government aiming to assess the limits of GDP as an indicator of economic performance and social progress, and investigate which additional information and indicators would be needed. They point towards the same direction when stating that "what we measure shapes what we collectively strive to pursue – and what we pursue determines what we measure."

[3] The most recent 2008 SNA standard is the outcome of joint initiative between the *United Nations*, the *European Commission*, the *OECD*, the *International Monetary Fund* and the *World Bank Group*.

The commission lists a number of recommendations how to change current measurement practises. Recommendation 4 states that more prominence should be given to the *distribution* of income, consumption and wealth that should be reported next to average (or aggregate) numbers. They also stress that these dimensions should be linked to each other.

2.2 Integration versus Dashboard Approach

Integrating distributional information into the existing system of macroeconomic indicators is crucial if distributional statistics should be considered and discussed as prominently and broadly as other macroeconomic indicators. For this purpose, linking macro data as reported in the NA with distributive information stemming from micro data is essential. The result is called DINA: *Distributional National Accounts.*

The term suggests that NAs should be taken as they currently are and simply enriched by distributional break-downs. Such distributional break-downs can be compiled from survey data, and/or administrative and register data.

This is, however, not the view followed in this article, as I do believe that the NA are partly too narrow in their scope when it comes to measuring net worth of private households. Also, some concepts that are appropriate for the system of NA may not be suitable for measuring wealth distributions comprehensively as the NA have not primarily been designed to measure households' wealth. For instance, NA leave out consumer durables – such as vehicles – although they play a similarly important role in total private wealth as listed shares or holdings in investment funds. The recording of dwellings and land is very specific in the NA and suboptimal when aiming to better understand private wealth and its distribution.

Thus, the view taken here is that DINA should be understood *more broadly* than just a breakdown of existing NA aggregates. The appropriateness of DINA should not be limited by the specificities of the NA, but DINA should rather be constructed to be as meaningful and easy-to-interpret as possible.

Hence, the framework of DINA suggested here relies on NA whenever appropriate but calls for finer break-ups of NA whenever needed and additional "supplement" information when essential to achieve a meaningful overall wealth measure. This approach, which neither aims for a complete separation between NA and distributive indicators (a "dashboard" approach), nor a complete alignment of distributional indicators to the current NA framework (an "integrated" approach) is labelled the "hybrid approach."

The hybrid approach serves two functions of DINA: (i) a link between macro-data and distributional data, and (ii) a comprehensive measure of wealth distributions by itself.

Answers to the question of how to deal with comparability issues between micro and macro data usually go into the direction of either restricting the analysis to well-comparable components or analysing wealth distributions without relating them to NA. Either approach is limited to serve only one function of distributional data. Although the focus of this article is wealth, a similar case can be made for DINA for income and consumption.

Table 1 shows the hybrid DINA approach schematically. Let there be $n + m$ components of wealth (assets and liabilities alike) that are essential to describe households' wealth appropriately, whereas n components are linkable between the micro and macro source and m components do not meet a sufficient level of comparability.

Table 1: Hybrid DINA.

	Integrated Account			**Supplement Account**			**Net worth**
	Component 1	...	*Component n*	*Component* $n+1$	...	*Component* $n+m$	
Group 1	$a^I_{1,1}$	...	$a^I_{1,i}$	$a^S_{1,n+1}$	...	$a^S_{1,n+m}$	$\sum_{j=1}^{n} a^I_{1,j} + \sum_{j=n+1}^{n+m} a^S_{1,j}$
$\vdots$	$\vdots$	...	$\vdots$	$\vdots$	...	$\vdots$	$\vdots$
Group g	$a^I_{g,1}$	...	$a^I_{g,n}$	$a^S_{g,n+1}$	...	$a^S_{g,n+m}$	$\sum_{j=1}^{n} a^I_{g,j} + \sum_{j=n+1}^{n+m} a^S_{g,j}$
Aggregate	$\sum_{i=1}^{g} a^I_{i,1}$	...	$\sum_{i=1}^{g} a^I_{i,n}$	$\sum_{i=1}^{g} a^S_{i,n+1}$	...	$\sum_{i=1}^{g} a^S_{i,n+m}$	$\sum_{i=1}^{g} \left(\sum_{j=1}^{n} a^I_{i,j} + \sum_{j=n}^{n+m} a^S_{i,j} \right)$

Notes: The table provides a schematic picture of hybrid DINA. Out of the $n+m$ components of wealth (assets and liabilities), n are possible to be linked to headings in the NA. The remaining m components are (currently) not linkable. To ensure that a measure of total net worth is comprehensive, all $n+m$ components are summed up. Thus, a *horizontal* interpretation of group-specific net worth is possible. Reading DINA in *vertical* direction leads to totals for each component. Within the integrated account, vertical sums equal totals reported in the NA, whereas in the supplement account no corresponding NA total is required.

Groups are defined via socio-economic or demographic characteristics, or functions of wealth. For instance, wealth or income groups can be established by grouping households into net worth or income quintiles.

Over time, n should increase and m decrease, whereas the total number of components $n+m$ is not meant to change. Re-allocating more components from the supplement account to the integrated account is called the *integration process*. Integration can be achieved by establishing additional split-ups in the NA and creating sub-categories not currently existent in the NA framework.

The more components are integrated, the better the link to GDP will eventually be. (Temporarily) including non-integrated components into DINA will serve the second function of DINA: Meaningful overall distributional statistics that are not limited in comprehensiveness due to linking difficulties.

For all $n + m$ components, group-specific aggregates are computed from the micro source. Groups can be formed by net worth or income quintiles, functions of wealth, or by relying on qualitative characteristics.

The n well-comparable components are linked to the respective NA instruments, i.e., group-specific sub-aggregates are scaled to exactly match the NA aggregate. The scaling ensures that totals are consistent and at the same time that the relative distribution reported by the micro data source is conserved. The set of linked components form the *Integrated Account*.

The remaining m components are not sufficiently comparable but still essential to describe households' wealth in its entirety. These components are not scaled but directly compiled from micro data. These m components form the *Supplement Account*.

Group-specific net worth is obtained by horizontally summing over all group-specific components of wealth.[4] Totals for each component of wealth are obtained by vertically summing over the group-specific sub-aggregates. Total net worth is thus either the sum over group-specific net worth or the sum over component-wise aggregates.

It is likely that further work on integrating and harmonizing micro and macro data will lead to an increase in well comparable components n and a decrease in insufficiently well comparable components m. Since the set of components needed to comprehensively describe households' net worth is defined *a priori*, i.e., $n+m$ is fixed, the size of DINA will not change due to advancements in the *integration process*. Nor will group-specific aggregates suffer from comparability issues over time.[5]

2.3 Surveys – A Suitable Data Source to Measure Wealth Distributions?

Regarding micro data sources, there are two main approaches (and hybrids thereof) how to measure the distribution of households' wealth: approaches based on household surveys and approaches based on administrative data.

The major advantage of administrative data is its objectivity and its comprehensiveness. If a certain information is collected, there is usually no opt-out option of citizens. For instance, information on labour income is reported to authorities directly by the employer and is thus available for the entirety of all tax-payers in a country.[6]

Administrative data are usually not collected for the purpose of measuring wealth inequality. Thus, statistical procedures need to be applied to infer wealth from data that measure wealth only implicitly (see also Alvaredo et al., 2016). The *Income Capitalization Method* relies on taxable income flows from assets such as dividends or earned interest. Form observed taxes paid, one can – relying on a number of assumptions regarding rates of return, etc. – infer the total stock of a particular asset class owned by a household.

The *Estate Multiplier Method* relies on data related to inheritance taxes and aims to infer the wealth of the living from the wealth of the deceased. Also this method needs to establish a number of modelling assumptions including extrapolated mortality rates and the treatment of assets exempt from inheritance taxes.

[4]Note that liabilities enter the account with a negative sign.

[5]Due to fixing $n + m$ there are no comparability issues arising from changes in the definition of net worth. However, when integrating further components these components will be affected by scaling, which – in the case of large quantitative mismatches – still lead to breaks in the series. These breaks are, however, of a different quality than breaks induces by changes in the concept of net worth.

[6]Tax avoidance can cause issues regarding comprehensiveness (see Alstadsæter et al., 2017, 2018). In particular, non-labour income is likely to be incompletely covered in official statistics relying on administrative data.

Net wealth taxes, i.e., recurrent taxes on individual net wealth stocks, could be directly used to impute individual net worth. However, such taxes are not very common and, if applied, have usually long lists of exemptions. The OECD reports that the number of OECD countries levying individual net wealth taxes dropped from twelve in 1990 to four in 2017 (OECD, 2018, page 16). These four countries are France, Norway, Spain and Switzerland.

Further complications related to tax data stem from the fact that only parts of wealth (i.e., the particular assets that the tax refers to) are captured, that the unit of measurement is often the individual rather than the household,[7] and that the data usually lacks information on socio-economic and demographic characteristics needed to create multi-dimensional break-downs of total wealth.

When aiming for internationally comparable statistics, the issue of fundamental differences in tax systems and recording practises lead to additional challenges.

Wealth surveys, in contrast, are designed to collect all dimensions of wealth at once and additionally provide a long list of socio-economic and demographic information characterizing each household. Surveys also capture asset classes that do not generate income flows (such as owner-occupied housing). Survey weights facilitate grossing up results to the entire population. In contrast to tax systems that differ strongly between countries, surveys can more easily be harmonized to produce comparable data across countries. The HFCS is the result of a harmonization process of wealth surveys across European countries co-ordinated by the ECB. The *Luxembourg Wealth Study* collects and harmonizes wealth surveys for several countries globally.[8] The OECD (2013) provides international guidelines for micro statistics on household wealth that are broadly followed facilitating international comparability.

Surveys, however, suffer from other types of drawbacks: They rely on sophisticated sampling techniques to guarantee that survey weights lead to accurate results on a country level. To sample households register data is needed and the sampling is only as good as the underlying register. Also, sampling procedures for complex, multi-purpose surveys (such as the HFCS) are complicated and not free from errors. As the registers used for sampling differ substantially across countries, the sampling techniques constitute an obstacle in terms of harmonization. For instance, Luxembourg relies on social security registers to sample households for the HFCS. Since employees of European and international organizations do not have a social security number, these people are excluded.

As wealth is usually very concentrated at the top end of the distribution, it is particularly important that the sampling procedure leads to an adequate representation of the top tail in the final sample. Thus, for most wealth surveys some type of oversampling strategy is applied to have more observations describing the top tail and simultaneously decreasing the impact of every single observation preventing results from being too much driven by outliers. Oversampling can only be applied when the register data used to sample households can be linked to net worth or other information that correlates with net worth. The availability of such data as well as the authorization to use them for this purpose differs across countries. This limits the reliability of data produced without oversampling or relying on a very indirect way of oversampling, and also counteracts comparability across countries.[9]

[7] There is no consensus on whether the unit of recording should be individuals of households. Whereas income is generally attributable to an individual, joint ownership of (housing) assets, and thus also their joint benefit, is common practise.

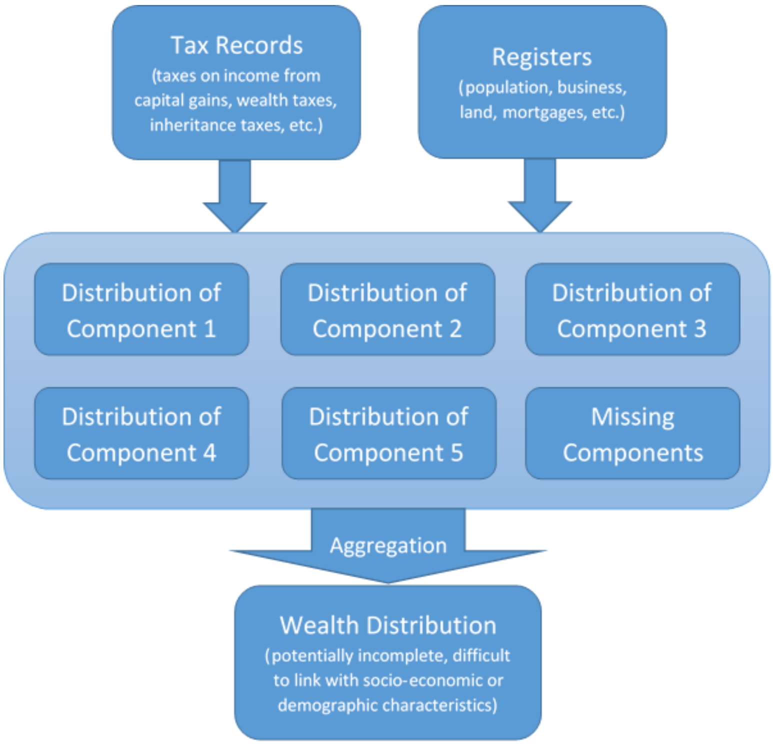
[8] See `http://www.lisdatacenter.org/our-data/lws-database/`.

[9] See section 4 and Table 4.6 in HFCN (2016) for an overview of oversampling strategies applied in the HFCS. See also Chakraborty and Waltl (2018) for a discussion of the consequences of shortcomings regarding oversampling procedures.

Furthermore, surveys are costly and time-consuming. The fieldwork often runs for several months, and data validation and processing needs additional time, which is why survey data is usually only disseminated with a substantial time lag. Also, surveys are not conducted at high frequency. The HFCS takes place every two to three years only.

Lastly, surveys rely on the ability and willingness of survey participants to accurately respond to all questions. Whereas some questions are easy, others are fairly complicated: estimating the current market value of one's property or business is a complicated task. Whereas business owners or shareholders may be better informed about their possessions due to reporting obligations, owner-occupiers may have less incentives to closely follow trends in housing markets. The latter issue will be discussed in more detail in section 3.

Figure 1: Wealth Distributions: Administrative Data.

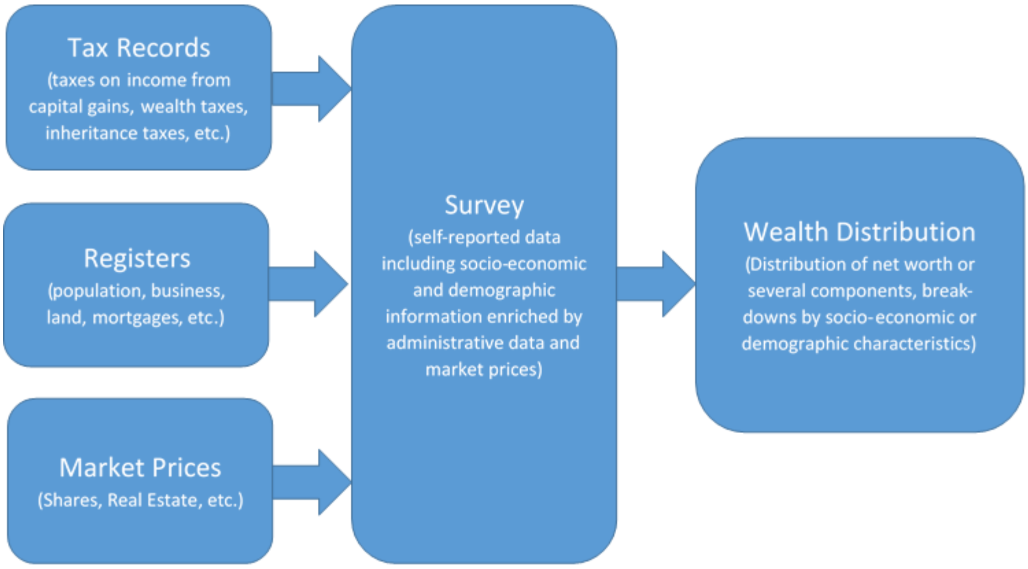


The shortcomings related to surveys can partly be circumvented by enriching them with administrative (tax records and registers) data and information on market prices. For instance, labour income may not be asked for in the survey interview but – with permission of the interviewee – be taken from administrative records. Likewise, mortgage registers or registers documenting the ownership of stocks, investment funds holdings and real estate can help improving the quality of surveys. As discussed above, such additional data can also be used to improve the sample design (in particular for oversampling).

Statistical matching of survey data with other data sources (e.g., market prices) is a possibility to validate survey responses and adjust whenever it seems appropriate. Countries with digitalised land castrates can use this information to link land and properties to survey participants. This data together with automated property valuation models based on market prices can eventually also be used to perform plausibility checks regarding self-reported property prices.

Figure 1 and Figure 2 illustrate how wealth distributions can be compiled relying on administrative data only or by linking administrative, self-reported and market price data via a survey.

Figure 2: Wealth Distributions: Self-Reported, Administrative and Market Price Data.



The degree to which administrative data is currently used when compiling surveys differs strongly across countries. There is a lot of progress regarding the collection and digitalisation of data, which offers large potential towards increased quality of official statistics.[10]

In the HFCS, Finland is the superstar when it comes to combining register and survey data (see HFCN, 2016, pp. 24–25). Register data is directly used for all income variables except private transfers and interest received, the ownership and number of cars and other vehicles, business wealth, ownership and values for mutual funds, bonds and listed shares, and education. Additionally, the value of the household main residence and other properties was estimated based on the *Population Information System* and the data in the tax administration's housing company stock register. The values of vehicles were estimated making use of data in several vehicle registers, price register systems and websites advertising boats for sale. Several components of liabilities were estimated by combining information on tax registers and survey data. Likewise, deposits and contributions to voluntary pension schemes are only partly collected during the interview.

2.4 Established Links between the HFCS and NA

The HFCS has been specially designed to measure households' wealth, its composition and its distribution across households with different characteristics. In contrast, the NA have not been designed for this purpose, but aim to measure the performance on an economy and the contributions of different sectors. Households form just one out of several sectors.

The wealth concept followed in the HFCS is consistent with the *OECD Guidelines for Micro Statistics on Household Wealth* (OECD, 2013), which are the result of a broad discussion on how to define wealth in an internationally comparable, feasible and meaningful way.

Following the OECD guidelines, wealth is understood as "ownership of economic capital. It is viewed as a dimension of people's economic (or material) well-being, alongside income and

[10]Linking survey and administrative data is, however, a delicate issue and needs broad public approval. Usually, interviewees need to give their consent when their survey responses are linked to other data sources on an individual level. The legal requirements regarding the possibility to use register data differs across countries. Jäntti et al. (2013) discuss the use of register data in the context of the EU-SILC survey (European Union Statistics on Income and Living Conditions).

consumption. There are other concepts of capital that are important to people's well-being and complement the concept of economic capital, such as human capital, social capital and collectively-held assets. However, while they may have considerable economic value to the people that possess (or have access to) them, they are not material assets and liabilities over which people can exercise ownership rights. They are, therefore, deemed to fall outside the scope [of the guidelines]"[11] and also this article. I also exclude any intangible assets like state pension and other social security wealth.

In this article, net worth is composed of twelve components. Table 2 provides details and definitions.

Table 2: Assets and Liabilities part of Net Worth.

		HFCS		National Accounts	
		Code	Description	Code	Description
1	Liabilities	DL1000	Total outstanding balance of household's liabilities	F.4	Loans (Liabilities)
2	Deposits	DA21011	Value of sight accounts	F.22	Transferable deposits
		DA21012	Value of saving accounts	F.29	Other deposits
3	Bonds	DA2103	Market value of bonds	F.3	Debt securities
4	Investment Funds	DA2102	Market value of mutual funds	F.52	Investment fund shares or units
5	Listed Shares	DA2105	Value of publicly traded shares	F.511	Listed shares
6	Other Businesses	DA2104	Value of non self-employment private business		
		DA1140	Value of self-employment businesses		
7	Real Estate (business)	DA1121	Value of other real estate property used for business activities		
8	Real Estate (non-business)	DA1122	Value of other real estate property not for business activities		
9	Household's Main Residence	DA1110	Value of household's main residence		
10	Vehicles	DA1130	Value of household's vehicles		
11	Valuables	DA1131	Value of other valuables		
12	Other	DA2106	Value of additional assets in managed accounts		
		DA2107	Money owned to household		
		DA2108	Value of the other assets		
		DA2109	Voluntary pension/whole life insurance		

Notes: The table summarizes the definitions of all components of net worth used in this article. Further details about HFCS variables can be found in the variables catalogue.[12] Details regarding the NA instruments are documented in ESA (2010). HFCS counterparts in the NA are only provided in case of high conceptual comparability as assessed by EG-LMM (2017). The items 5, 6 and 7 jointly form the component *Business Wealth*. The sum over items 7, 8 and 9 constitutes .

The EG-LMM analysed the conceptual definitions of several variables/instruments appearing in the HFCS and the households' sector balance sheet in the NA. The results are documented in EG-LMM (2017). As indicated in Table 2, liabilities, deposits, bonds, investment funds and

[11] See OECD (2013), page 26.

[12] The Houshold Finance and Consumption Survey, Wave 2, Core and derived variables catalogue: `https://www.ecb.europa.eu/home/pdf/research/hfcn/HFCS_Core_and_derived_variables_Wave2.pdf?8d19475a7edb8ff7de6d99a885e527ec`, retrieved June 27, 2018.

listed shares are conceptually well-comparable across the two data sources.

Appendix A briefly summarizes the established links and remaining challenges for each component of net worth, except housing wealth, which is discussed and analysed in detail in section 3.

3 Housing Wealth

3.1 Conceptual linkage between micro and macro data

3.1.1 Separation of Land and Structure in the National Accounts

Housing wealth constitutes the most important asset class for large sections of society. A home is often the single most important asset a household possesses and it is a source of essential services – housing is a basic human need. Mortgages with housing as collateral are, at the same time, the most important types of liabilities in the household sector (see also Figure 14 and Figure 15). The accuracy of housing wealth is thus crucial when aiming for a comprehensive measure of total wealth.

In the NA, housing wealth is spread over several instruments: *Dwellings (AN.111)*, *Buildings other than dwellings and other structures (AN.112)*, and *Land (AN.211)*.

The instrument *dwellings* refers to residential buildings excluding land. In the household sector, *buildings other than dwellings and other structures* mainly include buildings (excluding land) used for production (and thus non-residential/business) purposes by sole proprietors and partnerships.[13] Dwellings and other buildings are to be recorded at market prices. In the household sector, the aggregate *dwellings* is substantially larger than the aggregate for other buildings.[14]

Land comprises all types of land and is valued at its current market price. ESA (2010) foresees to split land into four sub-categories: *Land underlying buildings and structures (AN.2111)*, *Land under cultivation (AN.2112)*, *Recreational land and associated surface water (AN.2113)* and *Other land and associated surface water (AN.2119)*. Numbers for such detailed break-downs are, however, currently not available.

When owning a house, typically also the underlying land is owned.[15] In the case of condominia, ownership usually comprises the individually owned part of the structure as well as a share of the collectively owned parts of the structure and underlying land. Thus, an intuitive and common way of thinking of housing wealth is to treat the structure and the underlying land as a bundle of goods. This approach is also followed in the HFCS.

In practical terms, the total value is often more relevant than the separate values of structure and land, e.g., when using housing wealth as a collateral for a mortgage. Likewise, it is hard to imagine to sell a structure but keep the land, or vice versa. Thus, when liquidating housing wealth – by borrowing against or selling it – it is the value of the bundle that counts rather than the separate values.

Measuring separate values implicitly assumes the absence of emergence or bundling/interaction effects, i.e., it is assumed that the sum of the value of the structure and the value of the land equals the total value although the whole might well be more valuable than the sum of its

[13] See also the discussion about producer households and quasi-corporations in Appendix A.

[14] Table 8 reports NA balance sheet items for the household sector in Austria, Finland, France, Germany, Belgium, Italy and the Netherlands in 2014: the share of non-residential buildings in the total of all structures ranges between 3.4% in Belgium and 15.6% in Austria.

[15] There are diverging ownership arrangements. For instance, it is possible that a private household only owns the structure but leases the underlying land. I do not follow the consequences of such ownership arrangements in this article but focus on the most common case of joint ownership of structure and land.

parts: a specific structure might be designed to fit well the physical characteristics of a land plot (e.g., steep terrain or waterways lancing the plot) and thus be worth more when it comes together with this specific land plot. Contrarily, a land plot might be worth more in the absence of a structure that would need to be demolished before the full potential of the plot could be exploited.

In the NA, however, it is important to distinguish between *produced* and *non-produced* assets. While the structure is produced, the underlying land is not. Thus, the price of the structure can be interpreted as the cost of rebuilding it. The price of land has no such interpretation. Structures, in contrast to land, depreciate due to wear and tear.

Larson (2015) points out the difficulties resulting from this requirement: "[u]rban land is typically transacted as part of a bundle including structures and other improvements, making separated land value data difficult to estimate and tabulate. Because the most valuable land is in cities, the issue of land-structure value separability is fundamental to national land value accounting."

Whereas information on dwellings is generally available in the NA of European countries, information on land is still scarce. A first transmission of the value of land is required in the EU as of end-2017. However, there are still substantial data gaps and methodologies are still not fully established in all countries.[16]

In the NA, the value of structures (net of underlying land) is usually estimated via the *Perpetual Inventory Method* (PIM). The stock of dwellings is thus the result of accumulated flows of past investments in dwellings (*Gross Fixed Capital Formation* (GFCF) of dwellings, and substantial repair and maintenance) adjusted for depreciation.[17] The price index associated with dwellings is consequently a construction cost index.

Estimating the value of land is less straight-forward (see Eurostat-OECD, 2015, regarding details about different methodologies). A comprehensive bottom-up approach would require data on the ownership of each parcel, its type (farmland, residential, etc.) and an estimate of its price. Data on the ownership (private households, government, corporations, etc.) and the type of land is usually available in the cadastre. However, accurate valuation of all land parcels is difficult. Transactions of vacant land, that could feed into (for instance hedonic) valuation models are rare. Particularly in dense urban areas, prices for vacant land are rarely observed, which means that there are hardly any price observations such an imputation can be based on. Thus, high-quality price indices and average prices are hardly available or, if available, not broadly applicable.

Different types of land (land underlying structures, vacant land belonging to different land use zones, etc.) in different locations are expected to follow distinct appreciation trends. Thus, very specific price indices indeed would be needed. Extrapolating from land prices observed in distinct locations and for different types of land is likely to introduce measurement error.

In contrast, measuring the value of real property comprising land *and* structures, i.e., the *combined value of real estate*, appears to be easier as such combined prices are usually observed in the market.

Although the combined value is not directly needed for the compilation of NA, it can serve to compute the value of land indirectly. Standard property price indices are constructed based

[16] Available data is presented in Table 8.

[17] The PIM requires crucial assumptions on the depreciation pattern of structures such as an average service life, survival patterns and write-off profiles.

on transactions and thus reflect the joint price inflation of land and dwellings.[18] Additionally, information on the stock of housing wealth may be available from public real property appraisals (usually needed for real estate taxation) or census information combined with appropriate market price data. Whereas stock information may only be collected infrequently, more frequent price indices can serve to update the value in intermediary periods.

Alternatively, the HFCS could be used as a new data source providing information on the value of housing wealth for the household sector every two to three years for a large number of European countries.[19] For that, it is important to understand, whether self-reported values in the HFCS are accurate and trustworthy.

The combined value of real estate together with the value of dwellings allows one to estimate the value of land as a residual. The residual approach guarantees that total housing wealth is in-line with the independently measured value of the housing stock. Consequently, the accuracy of the split into land and structure depends solely on the quality of the estimated value of dwellings.

In contrast, when land is measured directly, measurement errors in both components, dwellings and land, may imply a very different aggregate than the independently measured stock of housing wealth. In this case, both, the value of dwellings and the value of land, are the result of a demanding modelling exercise, whereas the combined value can be estimated more directly. Thus, the residual approach is likely to generate more meaningful results when evaluated against the reliability of the value for total housing wealth. Admittedly, this is not the prime goal of NA.

As mentioned before, the HFCS constitutes a rather new data source that may help to estimate the combined value for the household sector.[20] If this information is used to impute the value of land residually, a perfect link between micro and macro data is established that also serves the compilation of DINA.

3.1.2 Generic Differences between National Accounts and the HFCS

Beside the separation between land and structures, there are further generic issues that currently limit using NA data directly for the compilation of DINA (see also EG-LMM, 2017, Box 3: Housing and other non-financial assets). These problems appear to be particularly relevant when the combined value can not be interpreted in a similar way as the HFCS housing wealth.

First, it is not possible to distinguish land underlying residential structures from land underlying other (e.g., commercial) buildings owned by sole-proprietors and partnerships. Hence, a separation between business and non-business/residential use of land is not possible when using the final numbers reported in the NA. Separate categories would be very informative for analysing the distribution of several components of wealth.

For structures, the separation into residential and non-residential buildings is possible due to the separate categories *Dwellings* and *Buildings other than dwellings and other structures.*

In the HFCS, a separation between residential housing wealth and real estate used for business purposes is possible. The HFCS also allows one to distinguish residential housing wealth by housing tenure providing a very insightful separate aggregate for owner-occupied housing wealth. This is currently not possible in the NA.

[18]There are attempts to separate indices into a structure and land component to serve national accounting purposes (see Diewert et al., 2015).

[19]Luxembourg currently investigates the potential to use the HFCS for this purpose or whether to rely on cadastre and land transaction data.

[20]It does, however, not solve the problem for other sectors.

Second, in Europe it is currently not possible to distinguish between non-financial assets owned by households and such assets owned by *Non-Profit Institutions Serving Households (NPISHs)*.[21] NPISHs are separate legal entities serving households, which are private non-market producers, and include, for instance, churches and religious societies, political parties, charities, trade unions, and social, cultural, recreational and sports clubs. The separation is currently only possible for financial assets/liabilities.

Third, the separation of the value of land and structure is not consistent: Paragraph 7.52 of the ESA (2010) manual states that: "If the value of the land cannot be separated from that of buildings or other structures situated on it, the combined assets are classified together in the category of the asset that has the greater value." It is thus unclear, how "clean" the data is.

Finally, the NA treat property owned by residents but located abroad very differently than property located in the country of residence. If immovable assets (land, buildings, etc.) are owned by a resident and located in the resident's country, these assets appear as non-financial asset on the balance sheet of the household sector. In contrast, when the immovable asset is located abroad, a so-called *notional resident unit* (NRU) is created for statistical purposes. This NRU is treated as a resident quasi-corporation, that appears as a *financial asset* (more precisely as Other Equity, F.519) in the NA of the country of the owner's residency.

A questionnaire[22] sent to central banks in Europe by the ECB in 2017 revealed that many countries face difficulties in collecting reliable data that can be used to properly measure immovables assets held by residents abroad. Some countries assess the possibility to use HFCS data for this purpose.

Information about the location of the properties (i.e., whether they are located in another country or not) is not available in the harmonized HFCS data set provided by the ECB. Some countries, however, do collect this extra information as part of their national amendment to the HFCS. The possibility to distinguish domestic and foreign assets would be important for the integration of housing wealth.

Savills plc., a provider of global real estate services, provides information on cross-border investments into European real estate markets. They report that in 2017, cross-border investment as compared to domestic investment in Europe are large in all 16 countries analysed and accounted between 24% in Greece and 89% in Poland.[23] Although these numbers do not completely align with what should be measured in the NA (Savills' numbers include institutional investors and all types of real estate), the substantial shares should create concerns regarding adequate reflection of these asset types in the NA.

The HFCS collects information on the current value of the *Household Main Residence* (HMR), as well as the current value of other properties. It also collects information on the use of these properties, thus enabling a distinction between business and private use. In particular, for properties other than the HMR, interviewees are asked to specify the property's *type* (house or flat, apartment building, industrial building/warehouse, building plot/estate, garage, shop, office, hotel, farm, or other) and the *use* (household's holidays or other private own use, business activities by someone in the household, rented or leased to a business or people outside the household, vacant, free use for others, or other).

These classifications are useful to keep as they refer to very different functions of housing wealth: Owner-occupied housing provides shelter to its inhabitants thus fulfilling a basic human need.

[21] The households sector (S.14) and the NPISH sector (S.15) are merged into a single number.

[22] A report summarizing the conclusions from this exercise is available upon request (see Giròn et al., 2017).

[23] See `http://pdf.euro.savills.co.uk/european/briefing-notes/eib-march-2018.pdf`, retrieved on June 14, 2018.

Other properties not used for business purposes are rather a store of value and thus refer to the asset dimension of housing. In contrast, dwellings and land used for business purposes are productive investments.

If land is measured as a residuum based on a well-measured and well-interpretable combined value of real estate, this combined value can be linked to the HFCS total. The desirable split-ups can be achieved by exclusively relying on the HFCS. DINA are then not affected by the split-up of the combined value into components of structure and land, and not affected by assumptions behind the PIM applied to derive the value of dwellings.

If land is independently measured and the sum of the values of land and dwellings cannot be interpreted as a meaningful measure of total housing wealth, a link with the HFCS is problematic due to the before mentioned measurement problems related to both, dwellings and land, and the generic issues in the NA.

In this article, I thus establish a *pseudo-link* of housing wealth to the NA by assuming a residual approach towards the measurement of land using the HFCS as the basis. This means that I deduct the value of dwellings reported in the NA from the combined housing wealth implied by the HFCS and treat the result as the value of land. The resulting estimate for land is not perfect since the value of dwellings suffers from including of NPISH and other generic issues in the NA,[24] and the inclusion of real estate assets located abroad in the HFCS. Still, this attempt guarantees perfect alignment between the NA and HFCS aggregate per construction, hence serve the purpose of DINA, and is in-line with NA requirements. Given the yet scare data on land in the NA, the pseudo-link additionally provides benchmark estimates for this asset class.

3.2 Can Self-Reported Values be Trusted?

Although the concept of housing wealth as defined in the HFCS is well-suited for measuring total wealth, a major concern is the adequacy of self-reported values. In a survey setting, the interviewee is asked to give an estimate of the current value of her owner-occupied dwelling as well as all other properties she may posses.

The owner is asked to anticipate the outcome of a bargaining process: she is not asked to state the price for which she is willing to sell the property nor an estimate of the 'fundamental price' but really what she thinks she could earn when the dwelling was put on sale at the day of the interview. This is anything but easy.[25]

One could argue that the self-estimated, subjective price is the relevant value when it comes to owners' financial decision-making. Goodman Jr and Ittner (1992), who find a bias in owner estimates of house values of plus six per cent, point out that for purposes like household consumption and savings behaviour owners' perceived home value may indeed be the appropriate measures of housing wealth. However, is it also the right price when the aim is an objective measure of wealth?

Agarwal (2007) concludes over the literature assessing the accuracy of self-reported prices that: "[t]here is general agreement [. . .] that homeowners significantly misestimate their house value." He reports substantial average absolute mis-estimation found by previous studies (mainly focusing on the US) ranging between 14% and 25%. Although evidence is not fully consistent

[24]The value of land in this setting equals the combined value for S.15 minus the value of dwellings for S.14 *plus* S.15. However, the share of S.15 in the value of dwellings is expected to be negligibly small for dwellings (see also EG-LMM, 2017, Box 3: Housing and other non-financial assets).

[25]When a person plans to buy or sell property, she is likely to seek advise from real estate experts. It is, however, more than unlikely that such costly actions are taken when preparing for the HFCS interview.

(for instance, Kain and Quigley, 1972, find a negative bias in owners' estimates), there is a tendency that homeowners *over*estimate the price and rental potential of their dwelling.

Likewise, Heston and Nakamura (2009) document that equivalent market rents (i.e., hypothetical rental prices homeowners think they could earn when renting out their owner-occupied dwelling) reported by owner-occupiers are on average higher than market rents in the US. The authors speculate that this over-reporting might be due to an "owner-pride factor." In psychology and behavioural economics, it is well known that people ascribe more value to their possessions merely because they own them (endowment effect), which is closely related to loss aversion (see Kahneman and Tversky, 1979; Thaler, 1980; Knetsch, 1989, for the origins of these lines of research). Particularly long-term owners are likely to be sentimentally attached to their homes and owners may like some particular features of their home (which is also why they designed it in that way) that might not correspond to the taste of an average buyer.

The endowment effect also helps explaining the experimentally observed differences between the maximum willingness to pay (WTP) for a good and the minimum amount demanded for the same, the willingness to accept (WTA). These two numbers should be (almost) identical according to standard economic theory and thus equal to "the" market price, but are regularly found to diverge substantially in experiments (see for instance Kahneman et al., 1990). It is likely that the HFCS elicits a WTA (greater than WTP) and hence overstates aggregate housing wealth.

Whereas the accuracy of self-estimated prices has been studied before, there is hardly any evidence whether assessment errors vary across different sections of society. It is, however, likely that the ability to assess the price of a dwelling correlates with financial literacy (which is known to correlate with gender; see Lusardi and Mitchell, 2008, and education – and thus also with income), time, way of acquisition of the dwelling (someone who has recently bought the property has naturally more knowledge than someone who has inherited the dwelling a long time ago and does not plan to sell it any time soon) and different degrees of loss aversion.

One could also speculate about *intentional* misreporting being linked with other socio-economic characteristics: There is evidence that (at least in Europe) people tend to consider themselves as part of the middle class: According to a survey quoted by the *Frankfurter Allgemeinen Zeitung (FAZ)* in 2016, 71% of Germans think that they belong to the middle class – a share much higher than estimated by official statistics.[26] Poor households thus may have an incentive to over-report, whereas rich housholds may desire to do the opposite. There is indeed evidence that wealthy households tend to generally under-report their wealth (see OECD, 2015, Box 6.2). At the same time, Choi and Painter (2018) find that intentional *over-reporting* of housing wealth is more common among households with negative equity, i.e., the poorest households. Thus, there is reason to believe that, due to systematic under- and over-reporting, a (housing) wealth distribution measured from a voluntary survey is less extreme than in reality.

3.3 Empirical strategy

3.3.1 Residential Property Price Indices

I first analyse whether the temporal evolution of housing prices are well reflected in HFCS data. Thus, I analyse whether implied *changes* in prices are comparable to what standard residential property price indices (RPPIs) based on transaction data report. Transaction data

[26] The survey was conducted by *YouGov*. The subjective share of members of the middle class is compared to estimates by the OECD or the *German Institute for Economic Research (DIW)*, which come to the conclusion that roughly 60% of all households belong to the middle class. See `http://www.faz.net/-hx6-8e72h`, 6. June 2018.

do indeed reflect the outcome of a bargaining process. Cases where WTP and WTA could not be matched, i.e., unsuccessful trades, would not show up in transaction data.

I compute quality-adjusted[27] *subjective* RPPIs (S-RPPI) from HFCS data. The resulting indices are usually much longer than official RPPIs. I thus also make use of historic long-term indices provided by Knoll et al. (2017) and Lyons (2018).

Mathä et al. (2017) perform a similar analysis making use of the first wave of the HFCS. They compute the evolution of average price.[28] They find quite close correspondence with RPPIs for most countries. Henriques (2013) performs a similar comparison for the *US Survey of Consumer Finances (SCF)*. She finds that during the boom, self-estimated prices increased much more rapidly than reported by the RPPI, while after the bust, self-reported prices fell slightly less. The overall pattern of price changes is well tracked by survey participants' self-reported estimates.

The HFCS asks for self-estimated current market values for all real estate propoerties. For the household main residence (HMR), owners are also asked to report the year and mode of acquisition, i.e., whether the dwelling was purchased, self-constructed, inherited or received as a gift.[29]

Additionally, owners are asked to report the purchase price or (in case of other ways of acquisition) give an estimate of the value of the dwelling upon acquisition. In the latter case, the historic dwelling price is completely subjective. In the first case, an objective acquisition price is supposed to be reported.[30] The current estimate of the house price is always subjective.

I make use of these pairs of prices to construct a subjective *Quasi-Repeat-Sales Index.* A standard repeat-sales index (see Bailey et al., 1963; Case and Shiller, 1987, 1989) relies on pairs of prices for dwellings that were sold at least twice. The logged ratio of prices related to subsequent sales is regressed on dummy variables indicating the period of first and repeated sale, i.e.,

$$\log\left(\frac{P_{i,t}}{P_{i,s}}\right) = \sum_{t=0}^{T} \tau^t D_i^t + \varepsilon_i^t, \tag{1}$$

where $P_{i,t}$ and $P_{i,s}$ denote the prices of dwelling i at times t and s respectively, and D_i^t denotes dummy variables with entry 1 for the period of re-sale, -1 for the period of the first sale and 0 otherwise. Finally, ε_i^t denotes an independent and identically distributed error term.

The estimated coefficients $\hat{\tau}^t$ are used to construct the price index: the change in prices between the base period 1 and period t is given as

$$a_1^t = \exp\left(\hat{\tau}^t\right),$$

which forms the index. I call this index the *subjective residential property price index (S-RPPI).*

[27]RPPIs are usually quality-adjusted to account for differences in the mix of characteristics in dwellings and ensure that like is compared with like. See Hill (2013) and de Haan and Diewert (2013) for an overview of property price index construction techniques.

[28]Mathä et al. (2017) compare the average price of dwellings acquired in a specific period with the average self-reported current price for the same dwellings. This implies a certain degree of quality-adjustment, but does not make use of the full information in the data due to averaging. The resulting, rather wiggly indices are smoothed ex-post and compared to RPPIs.

[29]For Finland this data is not available. For France, this information is only available in the second wave.

[30]The question remains whether – particularly when the dwelling was purchased a long time ago – home-owners do remember the acquisition price correctly, or do have the relevant documents available and use them (as encouraged by the interviewer) during the interview. Thus it is fair to assume that also this price is at least partly subjective.

To construct S-RPPIs, I pool data from the first and second wave of the HFCS, which increases the number of price pairs substantially.[31] I treat the year where the HFCS fieldwork took place as the period of the repeated 'sale'. Indices for countries that did not participate in the first wave are based on second wave data only.[32] (See also footnote 29.) I include only reported values and leave out imputed ones.[33]

The ECB also compiles an aggregate RPPI for the euro area (EA). I use the index that reports changes in house prices for EA-17, i.e., the euro area as composed in 2011 including 17 countries.[34] The EA-RPPI is a weighted mean of individual, country-specific RPPIs. Weights correspond to GDP.

To create a subjective counterpart, I calculate a weighted average over all S-RPPIs belonging to the EA-17. The weights are held constant over the period and refer to the 2013 GDP at market prices. As the HFCS lacks data to compile a S-RPPI for Finland, this country is excluded. Finland's share of euro area GDP amounts to roughly 2% only, which is why the impact of this exclusion is expected to be minor.

Figure 3 shows S-RPPIs together with transactions-based, objective RPPIs for the four countries, where long-enough objective indices are available: Belgium, Germany, France and Ireland.[35] The bottom left panel plots the results for the euro area. The bold line indicates the part of the S-RPPI index, where data from all EA-17 (excl. Finland) are available. The index is also calculated when S-RPPIs are not available for all countries. The coverage of the index in terms of per cent of euro area GDP ranges between 10.4% and 97.9% and is indicated by the horizontal lines at the bottom of the plot.

Note that the objective indices are far from harmonized in terms of geographical coverage, types of dwellings and transactions covered, data sources used and index construction methodology applied (see Table 9). The subjective indices presented here are, in contrast, fully harmonized and show price developments for owner-occupied residential dwellings. The indices do not perfectly represent the stock of all owner-occupied dwellings due to item non-response in the HFCS and pooling over two HFCS waves. However, they come close to that and it is fair to say that the indices present the (subjectively measured) price development of the housing stock as of 2009 – 2014.[36]

Subjective and objective indices, in general, follow a very similar trend, which supports the assumption that – at least collectively – people have a quite accurate perception of general price developments in housing markets. Whereas there are some countries where the comparison yields worse results (see Figure 8), the aggregate result for the euro area is striking.

For many countries there is only a very short objective index available, which complicates comparability. However, in particular for these countries, the subjective indices provide new insights into the long-term trends in housing price inflation and help to put current develop-

[31] Subsequent HFCS wave will include panel components, which can then be used to track self-estimated prices over time.

[32] Indices start in the earliest year for which there are at least five acquisition prices. This guarantees that early index numbers are not driven by too few observations.

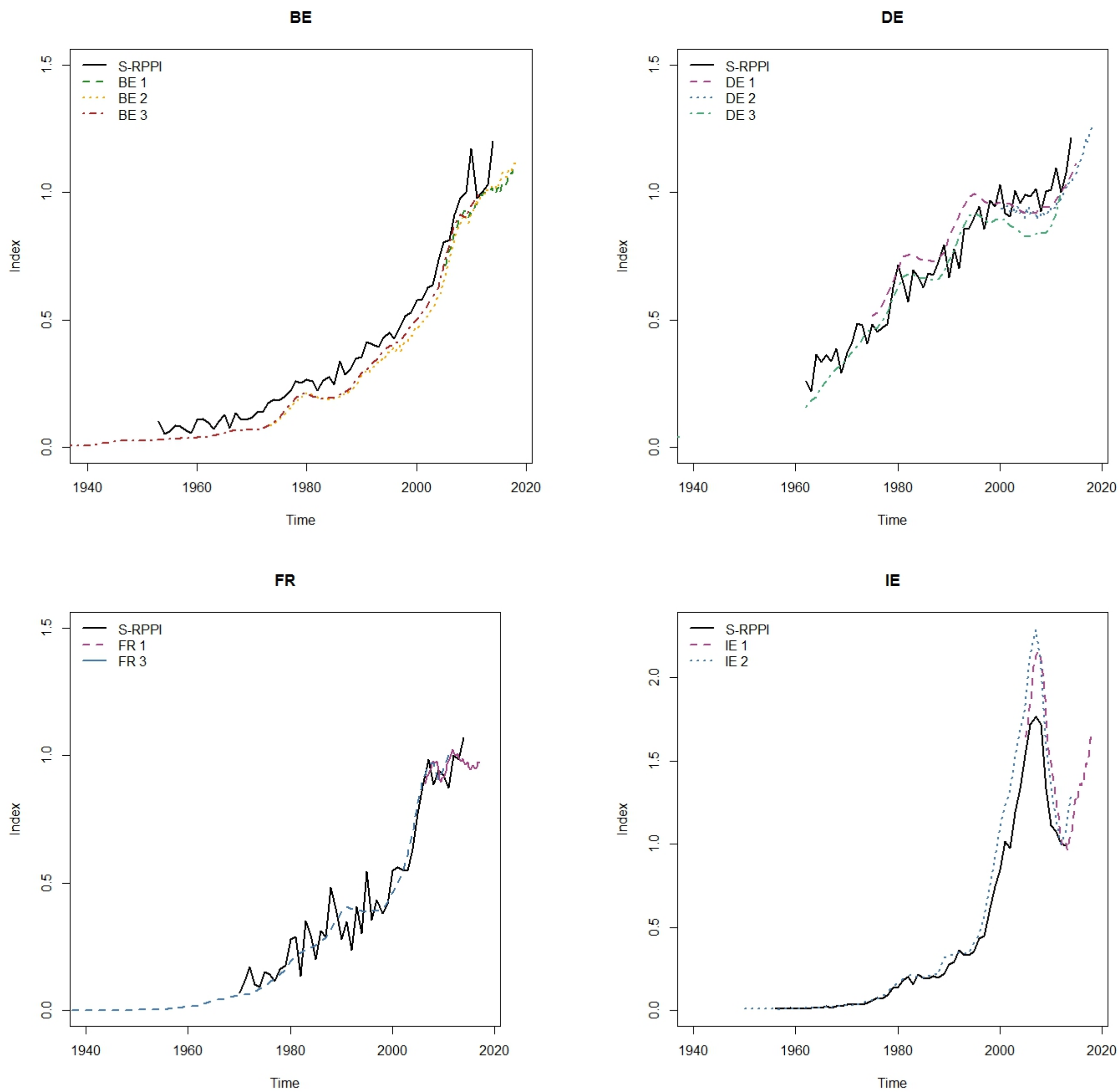
[33] Values are imputed when interviewees refuse to provide an answer to a particular question. The HFCS imputation process aims for consistency of the joint distribution of all HFCS variables, i.e., missing values are imputed to guarantee that the originally observed joint distribution is conserved.

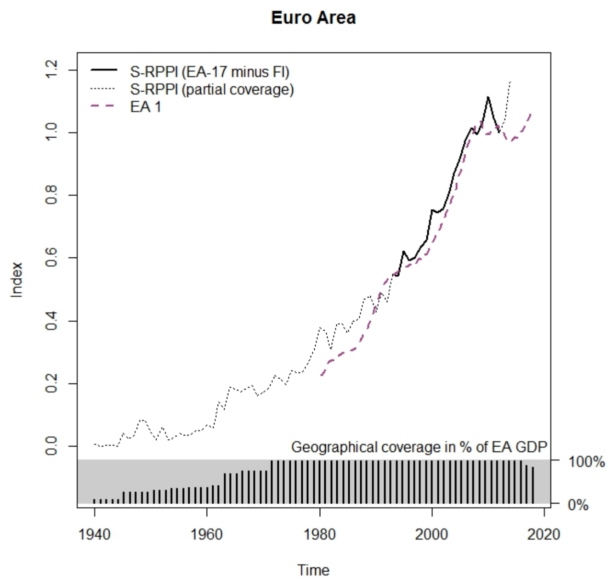
[34] These countries are: Austria (AT), Belgium (BE), Finland (FI), France (FR), Germany (DE), Ireland (IE), Italy (IT), Luxembourg (LU), The Netherlands (NL), Portugal (PT), Spain (ES), Greece (GR), Slovenia (SI), Cyprus (CY), Malta (MT), Slovakia (SK) and Estonia (EE).

[35] Figure 8 in Appendix B shows results for other countries. The appendix also provides methodological details regarding the objective indices.

[36] The HFCS fieldwork took place in the years 2009 – 2011 (wave 1) and 2012-2015 (wave 2).

Figure 3: Subjective versus objective indices.





Notes: The figures compare S-RPPIs estimated from pooled HFCS data to objective, transactions-based RPPIs. All indices are nominal and normalized with respect to the year 2012 or, in case of quarterly data, the average in 2012. The euro area figure also shows the coverage of the index measured as share of EA GDP (ranging between 10.4% and 97.9%). Figures are provided for countries, where objective indices are at least as long as subjective indices. Figure 8 in Appendix B provides results for more countries. Details about the objective indices are provided in Table 9.

ments into perspective. The more HFCS waves become available, the longer and more reliable the subjective indices get as more and more price pairs enter the index, i.e., with new data the index grows into the past.

3.3.2 Linking Acquisition Prices to Current Prices

Collectively people seem to be able to track *general trends* in housing prices well. This section evaluates whether *amounts* appear to be trustworthy too. When aiming for distributional statistics on housing wealth, it is important to understand whether different sections of society provide systematically biased estimates of housing prices as speculated in section 3.

Property prices change due to depreciation (wear and tear), renovation, maintenance and repairs, and due to general price fluctuations in the housing market.[37]

Let the price of property i in period t be $P_{i,t}$ and I_t the index number of a RPPI in period t relative to a base period. Then the general property price inflation between period $t-1$ and t equals

$$a_{t-1}^{t} = \frac{I_t}{I_{t-1}} - 1.$$

The prices of property i in subsequent periods are connected via

$$P_{i,t} = P_{i,t-1} \cdot (1 + a_{t-1}^{t}) \cdot (1 - \delta_i), \tag{2}$$

where δ_i is a property-specific depreciation rate net of maintenance and repairs.

Depreciation rates are likely linked to the age of the structure but also to the owner's ability to pay for maintenance. I neglect the age and thus time-dependency of the depreciation rate and, for now, also assume a constant depreciation rate for all types of owners, i.e., $\delta_i = \delta$. Hence, model (2) assumes a *constant geometric depreciation pattern.*

Under this assumption, the price recursion can be solved backwards to obtain the relationship of the prices of any property at two points in time s and t with $s < t$ (to enhance readability, I suppress dwelling subscripts):

$$P_t = P_s \cdot (1 - \delta)^{t-s} \cdot (1 + a_s^t). \tag{3}$$

Rearranging equation (3) and taking logarithms yields

$$\log \frac{P_t}{P_s} = \log(1 - \delta) \cdot (t - s) + \log(1 + a_s^t).$$

A Taylor series approximation for $\log(1 - \delta) \approx -\delta$ (valid for small values of δ) leads to a linear model that can be estimated via standard OLS:

$$\log \frac{P_t}{P_s} = \delta \cdot (s - t) + \log(1 + a_s^t) + \varepsilon. \tag{4}$$

Table 3 and Figure 4 report estimation results.[38] Implied net depreciation rates are generally very low – much lower than the 2% that Harding et al. (2007) estimate for the US. Net depreciation is even negative on average in Germany and Ireland! These low rates indicate that either owner-occupiers invested heavily in maintenance and renovation, or, on average, German and to a lesser extend also Belgian, French and Irish home-owners believe that their own homes outperformed the market.

[37] Changes in preferences and tastes over time as well as gentrification may also play a role.

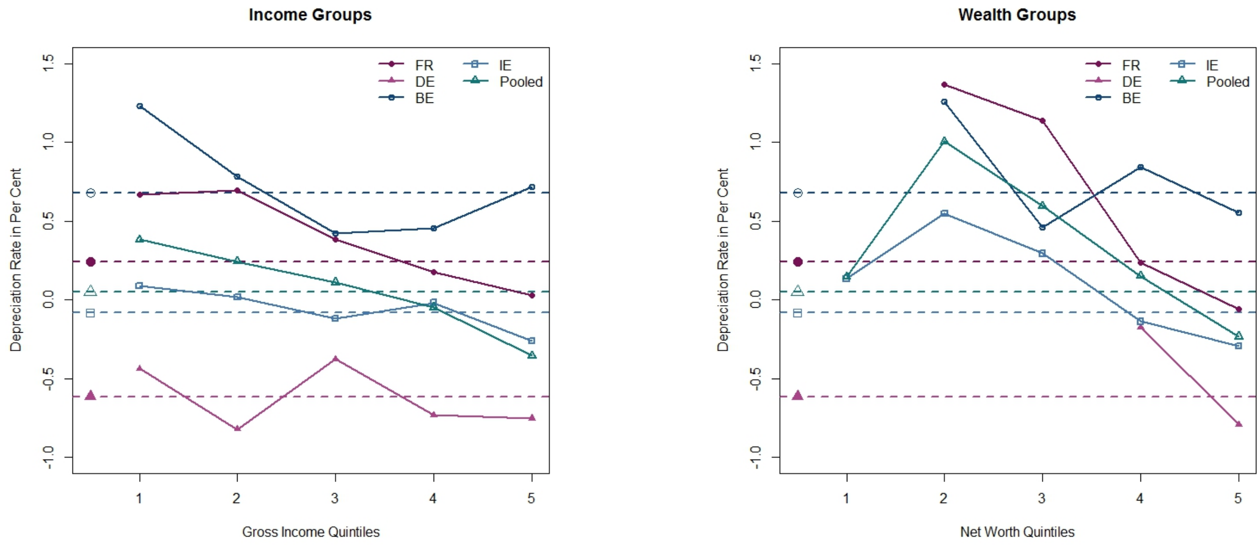
[38] Note that the coefficient associated with changes in general house prices is forced to equal one following model (4).

Table 3: Implied Net Depreciation Rates.

			Wealth groups					Income groups				
		All	1st	2nd	3rd	4th	5th	1st	2nd	3rd	4th	5th
BE	$\hat{\delta}$	0.68***	*-3.72*	1.26***	0.46***	0.84***	0.55***	1.23***	0.78***	0.42***	0.45***	0.72***
	n	1477	14	207	313	386	557	160	247	334	346	390
	R^2	83.64	34.37	73.05	89.3	81.29	85.4	76.79	85.96	86.83	82.79	80.08
DE	$\hat{\delta}$	-0.61***	*0.13*	*-0.94*	*-0.34*	-0.18	-0.79***	-0.44	-0.82***	-0.38*	-0.73***	-0.75***
	n	2558	37	23	248	667	1583	103	241	380	557	1277
	R^2	48.81	11.57	20.87	25.12	39.6	57.69	42.95	51.77	44.27	52.15	41.76
FR	$\hat{\delta}$	0.24***	*0.91*	1.37***	1.14***	0.24**	-0.06	0.67**	0.7***	0.39**	0.18	0.03
	n	6791	50	308	1249	1869	3254	344	582	915	1389	3561
	R^2	62.00	28.83	39.91	53.03	62.67	65.51	60.63	57.39	63.22	59.24	64.32
IE	$\hat{\delta}$	-0.08*	0.14**	0.55**	0.29	-0.14$^{\cdot}$	-0.29***	0.09	0.02	-0.12	-0.02	-0.26***
	n	3448	463	239	818	920	1008	552	484	630	785	997
	R^2	89.23	82.26	78.99	86.67	90.05	91.07	87.38	89.17	91.43	90.3	87.42
Pooled	$\hat{\delta}$	0.05$^{\cdot}$	0.15	1.00***	0.59***	0.15**	-0.23***	0.38***	0.24**	0.11$^{\cdot}$	-0.05	-0.35***
	n	14274	564	777	2628	3842	6402	1159	1554	2259	3077	6225
	R^2	73.6	72.02	63.39	71.36	74.28	74.94	78.74	75.09	76.41	72.17	59.75

Notes: The table reports implied net depreciation rates $\hat{\delta}$ in per cent estimated from model (4). Additionally, the number of observations n and the adjusted R^2 in per cent is reported for each model. Estimated values from models with very low numbers of observations and low R^2 are typed in italics. The bottom panel reports results when pooling all four countries. Statistical significance is coded following the standard notation: '***' if the p-value is lower than 0.001, '**' if the p-value is lower than '0.01', '*' if the p-value is lower than 0.05, '.' if the p-value is lower than 0.1 and ' ' otherwise. Estimations are based on second wave HFCS data.

Figure 4: Implied Net Depreciation Rates.



Notes: The figure show estimated implied net depreciation rates for income and wealth groups. Dashed lines indicate the overall value. Estimates are left out when the number of observations or the R^2 of the model is insufficiently low (see Table 3).

This findings hints toward the afore mentioned owner-pride factor / endowment effect, which has already been documented in other (mainly US) surveys applying distinct methodologies. Additionally, endowment effects are well-studied in psychology and behavioural economics. Thus, I include such an effect *explicitly* into the theoretical model (3) as an additional "owner premium" e on the cumulative average appreciation rate:

$$P_t = P_s \cdot (1 - \delta)^{t-s} \cdot (1 + a_s^t) \cdot (1 + e).$$

Log-linearization yields

$$\log \frac{P_t}{P_s} = e + \delta \cdot (s - t) + \log(1 + a_s^t) + \varepsilon, \tag{5}$$

i.e., the endowment effect enters the econometric model as an intercept. The interpretation of an endowment effect suggests that $e > 0$. This is, however, not imposed in the estimation.

The results are unambiguous: The endowment effect is estimated to be positive and substantial for all countries and all groups. It ranges between 5.8% in Germany and 28.7% in Belgium (FR: 26.7%, IE, 17.4%). Explicitly modelling an endowment effect generates more realistic estimated net depreciation rates: While it is still negative on average in Germany (-0.42%), annual net depreciation amounts to 1.29% in France, 1.55% in Belgium and 0.53% in Ireland.

This finding suggests that overall housing wealth is likely to be overstated in the HFCS. Enriching the HFCS with market prices may thus help to increase confidence in survey results.[39]

I also estimate group-specific depreciation rates by restricting the input data into model (3) to groups that are determined by either income or net worth quintiles (see Table 3). Low income households may not be able to invest as much in maintenance and repairs as higher

[39] A follow-up project will investigate the feasibility of incorporating market prices into the Luxembourgian HFCS (3rd wave). This project will also experimentally test for the existence and magnitude of an endowment effect in this setting.

income households. Also, the share of people per square meter of housing tends to be higher at the lower end of the distribution. Both effects would lead to higher depreciation rates at the lower end of the income distribution. Likewise, the share of land in the value of the property is likely higher at the top end of the wealth distribution. As land in contrast to structure does not depreciation, one would expect lower depreciation rates when moving up the wealth distribution.

I find that net depreciation rates are generally downward-sloping when moving from the low end to the high end of the income or wealth distribution (see Figure 4). This finding is more pronounced for wealth quintiles than for income quintiles:[40] Wealth quintiles are largely determined by housing wealth. Thus, this result can also be interpreted as lower depreciation rates for more expensive homes, which is consistent with findings based on transaction data by Bracke (2015) for London, and Hill and Syed (2016) and Waltl (2018) for Sydney.

Note that differences in depreciation rates could also stem from differential price appreciation rates across different segments or locations. RPPIs only capture an average housing price inflation. But, the results being quite consistent across four countries that experienced very distinct housing price dynamics over the time period covered and that are currently in different phases of the housing cycle, increases confidence in the conclusion.[41]

The interpretation of the endowment effect e in model (5) changes, when estimating it for different groups. In this case, not an *overall* premium but a *group-specific* premium is added. Thus, e_{group} also captures potential differential misreporting.

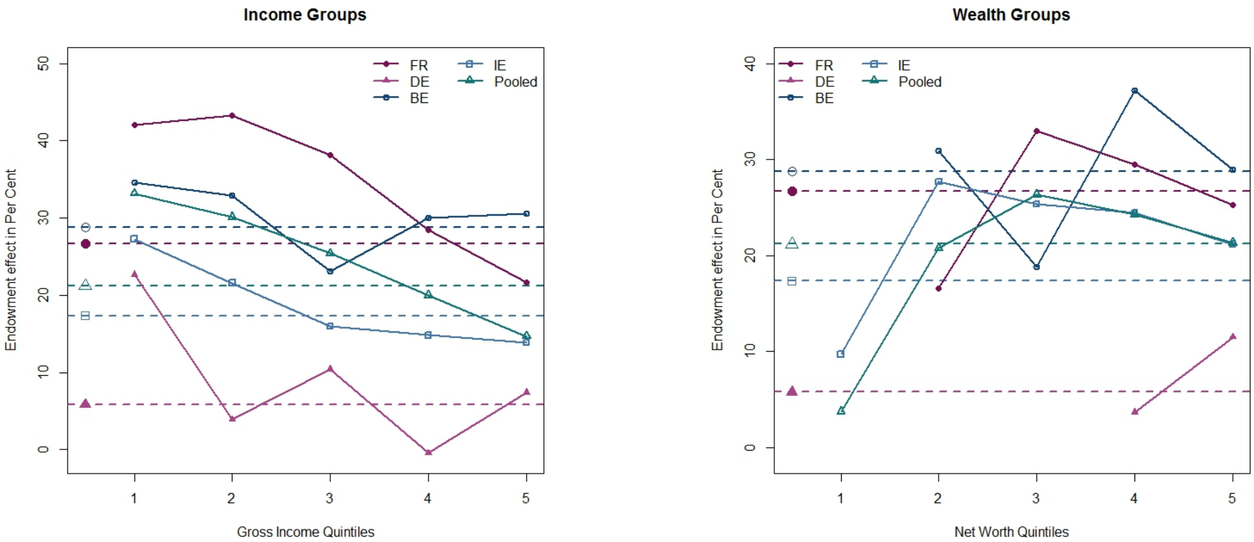
Figure 5 shows estimated values for e_{group} for income groups. I find that the combined endowment / differential misreporting effect is downward-sloping with increasing income. Assuming a constant endowment effect wealth or income groups, this suggests that *ceteris paribus* lower income households tend to rather over-report housing wealth whereas high income households tend to rather under-report. In fact, subtracting the overall endowment effect from the group-specific values ($e_{group} - e$) leads to positive values at the lower end of the distribution and negative values at the top in France, Ireland and the pooled model. These findings support differential misreporting in housing wealth as discussed in subsection 3.2, i.e., larger inequality in housing wealth than concluded from the HFCS.

For wealth groups, the findings are less clear: There are no clear trends for net worth quintiles two to five and $e_{group=1}$ is substantially lower in Ireland. Thus, it is not clear whether there is a systematic differential misreporting effect across wealth groups. Note that net worth is (particularly for net worth groups two to four) largely determined by housing wealth and thus the grouping be net worth may also be affected by differential misreporting. Thus, a different approach (ideally relying on external market data) needs to be applied to fully answer the question of differential misreporting across wealth groups.

[40] Particularly in Germany, housholds belonging to the lower end of the wealth distirbution rarely possess real estate assets – the home-ownership rate in Germany is substantially lower than in the other countries. Thus, results for low-wealth groups in Germany (and in a lesser extend also in France) need to be treaed with caution. Eurostat reports the following home-ownership rates for 2014: EU 69.9%, AT 57.2%, BE 72.0%, DE 52.5%, FI 73.2%, FR 65.0%, IE 68.6% and ES 78.8% (based on EU-SILC data). See Figure 14 for the relative importance of real estate assets for different parts of the distribution. Figure 15 depicts the share of renters and owners by wealth groups.

[41] There is no consistency in appreciation rates of different price segments over the business cycle, which could otherwise raise concerns regarding bias in δ: Guerrieri et al. (2013) document, by studying 29 metropolitan housing markets in the US, that initially low-priced neighborhoods appreciate more than high-priced neighborhoods during city-wide housing booms. Waltl (2016) investigates the Sydney housing market and finds that during a boom initially low-priced homes in sub-urban areas experienced highest appreciation rates whereas after the peak those houses also lost more in value than inner-city, initially high-priced houses.

Figure 5: Endowment effect and Differential Misreporting.



Notes: The figure shows estimated overall endowment effects. Additionally, group-specific results are plotted that may also capture differential misreporting.

3.3.3 Consequences for DINA

The previous sections performed tests on whether self-reported market prices for the HMR are a reliable source of information. These tests are implicit, but the fact that for four different countries, qualitative results are quite consistent, conclusions are credible.

There are four main findings: first, I looked at implied *price changes in the overall owner-occupied housing market*. Collectively, people are able to track changes in market prices (measured by RPPIs) surprisingly well.

Second, depreciation patterns inherent in HFCS data (downward-sloping pattern with increasing income and/or wealth) are in-line with empirical studies based on transaction data and theoretical arguments.

Third, implied net depreciation rates are very low hinting toward an owner-pride factor / endowment effect, which has been documented in other (mainly US) surveys, and is well-grounded in psychology and behavioural economics. I also modelled such a factor explicitly as an additional "owner premium" on housing price appreciation. Feeding this model with data results in a positively estimated premium and also more realistic depreciation rates. Thus, bias in HFCS results due to such a factor is indeed very likely.

Finally, I find indication for differential misreporting across income groups. More specifically, the findings suggest that low income households tend to over-report and high income households to under-report housing wealth. Findings are ambiguous for wealth groups.

The conclusions are mixed: generally, market features are surprisingly well reproduced in the HFCS. Aggregates obtained from the HFCS are, however, likely to be too high.[42] I find systematic differential misreporting across income groups implying that measured housing wealth inequality relative to income is likely to be lower in the HFCS than in reality. In contrast, no

[42]This holds true only in the absence of sampling errors, i.e., when analysing the reported values only ignoring, for now, a unit-non-response bias affecting the representativeness of the top tail.

systematic differential misreporting is found for net worth groups indicating that the wealth distribution relative to net worth groups can be trusted. To fully confirm the latter statement, a closer inspection using market prices would be needed.

4 The Missing Wealthy

Wealth is heavily concentrated at the very top. The *2018 WID.World World Inequality Report* documents that global wealth inequality was rising over the past decades and that the global level (represented by China, Europe and the US), the share of total wealth held by the top 1% increased from 28% in 1980 to 33% today. "Wealth is substantially more concentrated than income. The top 10% owns more than 70% of the total wealth in China, Europe, and the United States, the bottom 50% owns less than 2%, and the middle 40% ('the global wealth middle class') owns less than 30%."[43]

Also private companies put efforts into measuring the concentration of global wealth and come to similar conclusions: The *2017 Credit Suisse Global Wealth Report* finds that "[t]he share of the top 1% has been on an upward path ever since [the crisis], passing the 2000 level in 2013 and achieving new peaks every year thereafter. [...] The top 1% own 50.1% of all household wealth in the world."[44] Similarly, the *2017 Boston Consulting Group Global Wealth Report* finds that in 2016, the share of financial wealth held by millionaires accounted to 45% globally and to 30% in Western and 52% in Eastern Europe, respectively. The share held by the wealthiest of the wealthy (what BCG calls ultra-high net worth individuals, UHNW, which are individuals owning more than 100 million USD) accounted to 8% globally and in Western Europe, and even to 19% in Eastern Europe.[45]

The HFCS is a voluntary survey aiming to collect information on people's assets and liabilities. Wealth is a very sensitive topic to be covered in a survey and it is known that it is particularity difficult to adequately capture the wealthiest household in such a survey.

Oversampling wealthy households helps to increase the precision of survey results at the very top. If, however, wealthy households are more likely to refuse participation than other households, oversampling is unable to correct a resulting *unit non-response bias*. Indeed, Bach et al. (2015); Vermeulen (2016, 2018) and Chakraborty and Waltl (2018) document that wealth distributions implied by surveys alone are not able to capture the very top adequately.

Due to the sheer importance of the wealthiest of the wealthy, there is no excuse not to take an extra effort to properly capture them when aiming for a comprehensive and informative measure of total wealth.

A way around this problem is to replace the top tail of the survey-implied wealth distribution by a parametric model. The model of choice is usually a Pareto distribution. The parameters of the Pareto distribution can be estimated by enriching the top survey observation with additional observations describing the fortunes of the wealthiest of the wealthy. These additional data points can be taken from so-called rich lists such as the *Forbes World's Billionaires list* aiming to list all US-Dollar billionaires in the world or national rich lists aiming to report the names and fortunes of the wealthiest 50 to 500 individuals or families in a country (see Bach et al., 2015; Vermeulen, 2016, 2018; Chakraborty and Waltl, 2018).

[43] 2018 WID.world World Inequality Report, http://wir2018.wid.world/, retrieved on June 26, 2018.

[44] 2017 Credit Suisse Global Wealth Report, https://www.credit-suisse.com/corporate/en/research/research-institute/global-wealth-report.html retrieved on June 26, 2018.

[45] 2017 BCG Global Wealth Report, http://image-src.bcg.com/Images/BCG-Transforming-the-Client-Experience-June-2017_2_tcm58-161685.pdf, retrieved on June 26, 2018.

If available, administrative data obtained form tax records can be used to adjust the top tail in a survey (see, e.g., Garbinti et al., 2018). This approach is to be preferred, but such data is in-existent in many countries.

4.1 Empirical Strategy

I substitute the survey-implied top tail of the wealth distribution by a parametric model, namely the Pareto or Generalized Pareto distribution (GPD). The top tail starts at 1 million euros.[46]

For countries, where there are observations from national rich lists (preferable as more observations are included) or the Forbes World's Billionaires are available, I apply the *regression method* proposed by Vermeulen (2018) to adjust the top tail. This method combines top survey data with rich list observations to estimate the parameters of a Pareto distribution replacing the top tail in the survey. Thereafter, I re-distribute adjusted top wealth to several asset classes following the *analytical approach* proposed by Chakraborty and Waltl (2018).

Relying on rich lists is problematic as they are not compiled following transparent and reproducible methodology. The lists do not follow a consistent measurement unit: sometimes individuals are listed, and sometimes fortunes are reported for the nuclear and or extended family. Some names on these lists may refer to non-residents.[47]

For France, I perform a novel robustness check making use of top wealth shares compiled from income tax files and reported in the WID.world database. I use a GPD adjustment of the top tail closely following Blanchet et al. (2017) together with an extension of Chakraborty and Waltl's approach to break down adjusted wealth at the top to several asset classes. Appendix C describes the methodology in detail.

Table 4: Rich Lists and Oversampling Strategies.

Country	HFCS field work (second wave)	Oversampling (second wave)	Year of rich list	Rich list compiler	No. of obs.
Austria	06/2014 – 02/2015	No	2014	Trend	100
Finland	01/2014 – 05/2014	Personal income data	2014	Arvopaperi	50
France	10/2014 – 02/2015	Personal wealth data	2014	Capital	100
Germany	04/2014 – 11/2014	Regional indicators, income	2014	Manager Magazin	500
Spain	10/2011 – 04/2012	Personal taxable wealth	2013	El Mundo	200

GPDs are a family of heavy-tailed distributions containing the standard Pareto distribution as a special case. The non-standard members are less restrictive modelling choices: average wealth is not forced to increase proportionally when moving up the distribution, i.e., the crucial modelling assumption in the standard Pareto case regarding the choice of starting point is less relevant (see Blanchet et al., 2017).

As expected, all top tail adjustments increase total wealth. The choice of rich list (Forbes or national rich list) seems irrelevant for France. Relying on income tax data leads to a smaller but similar adjustment.[48]

[46] See Chakraborty and Waltl (2018) for robustness checks with this regard.

[47] The lists have therefore been checked by members of the EG-LMM. Non-residents were removed and entries likely referring to family clans are randomly split into two to four separate observations.

[48] Alstadsæter et al. (2017, 2018) document large holdings of wealth in off-shore tax havens. They conclude that the top shares estimated from the income tax files alone constitute a lower bound of the true wealth share. Thus, a larger adjustment seems appropriate.

Table 5: Adjusted and Unadjusted HFCS Aggregates.

		Austria		Finland		France		Germany		Spain	
		Unadj.	Adj.	Unadj.	Adj.	Unadj.	Adj.	Unadj.	Adj.	Unadj.	Adj.
1	Liabilities	66.60	67.18	113.97	116.04	961.57	1,011.85	1,020.92	1,063.36	607.55	628.72
2	Deposits	98.75	107.42	51.21	53.02	556.64	600.11	1,007.80	1,062.18	330.60	349.21
3	Bonds	5.27	5.45	1.24	1.87	17.83	28.27	71.92	79.87	14.01	18.50
4	Investment Funds	17.07	27.32	13.79	17.22	65.31	80.02	206.86	253.08	45.72	53.61
5	Listed Shares	5.13	5.87	26.09	29.98	141.19	207.37	146.80	203.11	74.06	85.06
6	Other Businesses	189.61	439.06	34.01	46.61	1,033.54	1,351.47	1,179.28	1,672.31	553.83	650.06
7	Real Estate (business)	20.58	15.43	13.69	14.11	44.95	49.65	169.28	185.87	93.61	107.08
8	Real Estate (non-business)	99.84	153.71	116.98	125.97	1,220.34	1,397.52	1,503.12	1,799.55	1,097.95	1,303.46
9	Household's Main Residence	531.39	632.77	332.79	337.86	3,661.84	3,794.60	4,071.01	4,687.75	2,674.60	2,772.76
10	Vehicles	32.14	37.61	25.99	26.74	222.16	234.73	283.14	289.59	128.77	131.37
11	Valuables	11.87	12.90	–	–	387.97	409.53	112.46	129.57	44.92	53.47
12	Other	42.05	38.76	6.48	6.64	289.71	399.29	409.97	515.48	210.36	299.59
	Total	1,120.29	1,543.49	736.23	776.08	8,603.04	9,564.40	10,182.54	11,941.73	5,875.97	6,452.89
	Change		+37.78%		+5.41%		+11.18%		+17.28%		+9.82%

Notes: The table reports unadjusted and adjusted HFCS totals for different components of net worth in billion euro. *Sources:* HFCS (2nd wave), own calculations.

Table 4 summarizes the national rich lists used to perform the adjustment at the top as well as details about the oversampling strategies applied in the HFCS (HFCN, 2016, page 36). Adjusting the top tail leads to an increase in total wealth. These increases transmit to increases in (almost all) components of wealth including liabilities (see Table 5). For conceptually well comparable instruments, coverage ratios (HFCS aggregates over NA aggregates) can be calculated before and after the adjustment. Table 6 reports the results.

Table 6: Adjusted and Unadjusted Coverage Ratios.

		Austria		Finland		France		Germany		Spain	
		Una.	Adj.	Una.	Adj.	Una.	Adj.	Una.	Adj.	Una.	Adj.
1	Liabilities	39.6	39.9	90.5	92.1	84.1	88.5	65.3	68.0	74.8	77.4
2	Deposits	45.7	49.8	63.7	66.0	47.1	50.8	54.8	57.8	43.7	46.1
3	Bonds	12.9	13.3	23.2	35.1	21.5	34.0	42.3	47.0	28.2	37.3
4	Investment Funds	35.6	56.9	92.6	115.6	24.4	29.9	48.1	58.8	29.2	34.2
5	Listed Shares	27.1	31.0	101.4	116.4	90.4	132.8	63.8	88.2	56.7	65.1

Notes: The table reports unadjusted and adjusted coverage ratios in per cent. Totals in the national accounts are averages over the quarters overlapping the HFCS fieldwork period. *Sources:* HFCS (2nd wave), ECB, own calculations.

The oversampling strategies differ strongly across countries. In Spain and France, the underlying data to oversample wealthy households is ideal as it is based on personal wealth data. In Finland, no such data is available, but oversampling is applied based on personal income data. In Germany, an indirect oversampling strategy is applied relying on regional indicators: strategically more households are sampled from high-income municipalities and wealthy street sections in municipalities with more than 100,000 inhabitants. Austria, in contrast, does not oversample at all. Remember that in Finland many variables are not collected via a survey but directly taken from registers (see subsection 2.3).

One would thus expect, that a top tail adjustment is least important in Finland, Spain and France, and most important in Austria, which is indeed the case. The overall increase in net worth amounts to 5% in Finland, 10% and 11% in Spain and France respectively, 17% in Germany and 38% in Austria. Relying on WID.world wealth shares, the adjustment for France is slightly less (8%).

These differences in oversampling and the subsequent differences in the reliability of the top tail suggest that survey results (aggregates and means) should not be compared when refraining from a top tail adjustment. Although such a top tail adjustment is not ideal due to model assumptions and the usage of less trustworthy rich list data, when ignoring the differences in the accuracy of the top tail one runs the risk to draw biased conclusions from cross-country comparisons. Thus, the hybrid DINA presented in the next section rely on top-tail adjusted HFCS data.

5 Distributional National Accounts

Net worth is defined as total assets minus liabilities. The assets included follow the definition of net worth in the HFCS. All components are listed in Table 2.

Highly comparable variables (as indicated in Table 2) form the *integrated account* of the hybrid DINA. All other variables currently enter DINA the *supplement account*. This is a very conservative approach. The number of linkable variables is likely to increase in the course of the work of the EG-LMM. Housing wealth is integrated via a *pseudo link*.

Table 7: Structure of Hybrid DINA.

	Liabilities	Deposits	Bonds	Inv. Funds	Listed Shares	Other Businesses	Real estate (business)	Real estate (non-business)	HMR	Vehicles	Valuables	Other	Net Worth
							Housing Wealth						
					Business Wealth								
I II III IV V	Integrated Account					Supplement Account		Pseudo-integrated Account		Supplement Account			
Σ													

Table 7 shows the structure of the hybrid DINA listing all variables that enter either the integrated, pseudo-integrated or supplement account.

5.1 A "Pseudo Link" for Housing Wealth: The Value of Land as a Residual

As discussed in section 3, there are two major generic problems regarding non-financial assets in the NA: first, assets owned by NPISHs are indistinguishable from asserts owned by private households, and, second, land underlying non-residential buildings and structures, and/or used for production by sole-proprietors and partnerships are indistinguishable from total land.

The report of the EG-LMM (2017) states that the share of NPISH in dwellings (AN.111) is expected to be small, whereas in other asset classes it may be considerably larger.

In the HFCS, housing wealth can be strictly separated into business and non-business (residential) use. Treating the NA instrument dwellings as pure residential and free from NPISH, one can compute the implied value of residential land owned by the household sector by deducting the value of dwellings from the HFCS total of residential housing wealth (see lines *(3a)* and *(3b)* in Table 8). This can be done by relying on the unadjusted or adjusted HFCS totals.

Without a top tail adjustment, the implied value of residential land owned by the household sector is lower than the overall value of land (except as in Finland), implying a share of NPISH and non-residential land in the total value of land of roughly 20% in Belgium and the Netherlands, 36-38% in Germany and Austria, 51% in Italy and 58% in France.

When performing a top-tail adjustment, the share shrinks to virtually zero in Austria and Germany, and is reduced in France.

Given the differences in scope of the NA and the HFCS, coverage ratios do not only measure a quantitative mismatch between NA and HFCS totals but also a quantification of the different scopes. Generally, coverage ratios are large but smaller than 100% when refraining from a top tail adjustment. A top tail adjustment increases coverage ratios and leads to a virtually perfect match in Austria and Germany.

A pseudo-link is established by interpreting the sum of the implied value of residential land owned by private households (lines (3a) and (3b) in Table 8) and the NA total for residential dwellings as total housing wealth excl. NPISHs and non-residential land. This is per construction equal to the HFCS housing wealth indicated by coverage ratios reaching 100% (line (5c) in Table 8). This concept is followed in the hybrid DINA presented in the next section.

Table 8: The value of land as a residual.

		Austria	Finland	France	Germany	Spain	Belgium	Italy	The Netherlands
(1)	*National Accounts* (incl. households and NPISHs)								
(1a)	Dwellings (residential)	393,350	249,464	3,460,226	4,047,208	–	516,509	2,510,419	691,289
(1b)	Other buildings (non-residential)	72,714	23,374	169,263	436,184	–	18,280	340,755	67,358
(1c)	Land (res. + non-res.)	380,465	118,636	3,352,400	2,385,159	–	783,401	3,554,082	651,649
(1d)	Total; *(1a)+(1b)+(1c)*	846,529	391,474	6,981,889	6,868,551	–	1,318,190	6,405,257	1,410,296
(1e)	Total excl. other buildings; *(1d)-(1b)*	773,815	368,100	6,812,626	6,432,367	–	1,299,909	6,064,501	1,342,938
(2)	*HFCS Housing Wealth* (residential, only households)								
(2a)	Unadjusted	631,228	449,771	4,882,177	5,574,125	3,772,551	1,143,699	4,258,282	1,205,889
(2b)	Adjusted	786,477	463,827	5,192,118	6,487,307	4,076,224	–	–	–
(3)	*Implied Value of Land Owned by Private Households* (residential); *(2)-(1a)*								
(3a)	Unadjusted	237,878	200,307	1,421,951	1,526,917	–	627,188	1,747,862	514,600
(3a')	Unadjusted; share of *(1c)*	37.48	X	57.58	35.98	–	19.94	50.82	21.03
(3b)	Adjusted	393,127	214,363	1,731,892	2,440,100	–	–	–	–
(3a')	Adjusted; share of *(1c)*	X	X	48.34	X	–	–	–	–
(4)	*Implied Housing Wealth* (non-residential and NPISH); *(1d)-(2)*								
(4a)	Unadjusted	215,301	X	2,099,712	1,294,426	–	174,493	2,146,975	204,407
(4b)	Adjusted	60,052	X	1,789,771	381,244	–	–	–	–
(5)	*Coverage Ratios; (2)/(1e)*								
(5a)	Unadjusted	81.57	122.19	71.66	86.66	–	87.98	70.22	89.79
(5b)	Adjusted	101.64	126.01	76.21	100.85	–	–	–	–
(5c)	Pseudo link *(2)/[(1a)+(3)]*	100.00	100.00	100.00	100.00	–	100.00	100.00	100.00

Notes: Amounts are in million euro. National accounts data are for 2014 and refer to AN.111 Dwellings, AN.112 Other buildings and structures, and AN.211 Land for the combined household and NPISH sector (S.14 + S.15). HFCS values exclude housing wealth for business use (i.e., DA1122 plus DA1110). Coverage ratios are defined as HFCS total over NA total. *Source:* 2nd wave HFCS, Eurostat.

5.2 Integration into National Accounts

Integration requires distributional break-downs to sum up to NA totals. This is achieved by proportionally scaling group-specific HFCS sub-aggregates guaranteeing the preservation of the distributional attributes. Before scaling, I apply an adjustment of the top tail, which is needed to obtain comparable results as argued in section 4.

Let y_j denote the NA aggregate for a component j entering the integrated account and

$$\sum_{i=1}^{g} x_{i,j}^{I}$$

the corresponding top-tail adjusted HFCS aggregate, whereas $x_{i,j}^{I}$ denotes the group-specific sub-aggregates for group i. In the case of groups formed by wealth qunintiles, $x_{5,j}^{I}$ is corrected upwards due to the top tail adjustment.

In the case of groups formed by income quintiles, the allocation of adjusted wealth to income quintiles[49] is slightly more complicated. The top tail is divided into four strata determined by net worth. Within each stratum the share of total wealth held by each income quintile is calculated. The adjusted tail wealth for each instrument and strata is re-distributed to income quintiles following the originally observed shares. This means that all income quintiles may be affected by the top tail adjustment. In practise, the top quintiles are more affected due to correlation between wealth and income.

Distributional indicators for component j and group i are given by

$$a_{i,j}^{I} = x_{ij}^{I} \cdot \frac{y_j}{\sum_{i=1}^{g} x_{i,j}^{I}}.$$

Thus, each group-specific aggregate $a_{i,j}^{I}$ is scaled by its inverse coverage ratio and the aggregate equals the NA total

$$\sum_{i=1}^{g} a_{i,j}^{I} = y_j.$$

For housing wealth, the coverage ratios are per construction equal to 100%, thus

$$a_{i,housing}^{I} = x_{i,housing}^{I}.$$

Components entering the supplement account are not scaled but enter the account directly, i.e., $x_{i,j}^{S} = a_{i,j}^{S}$.

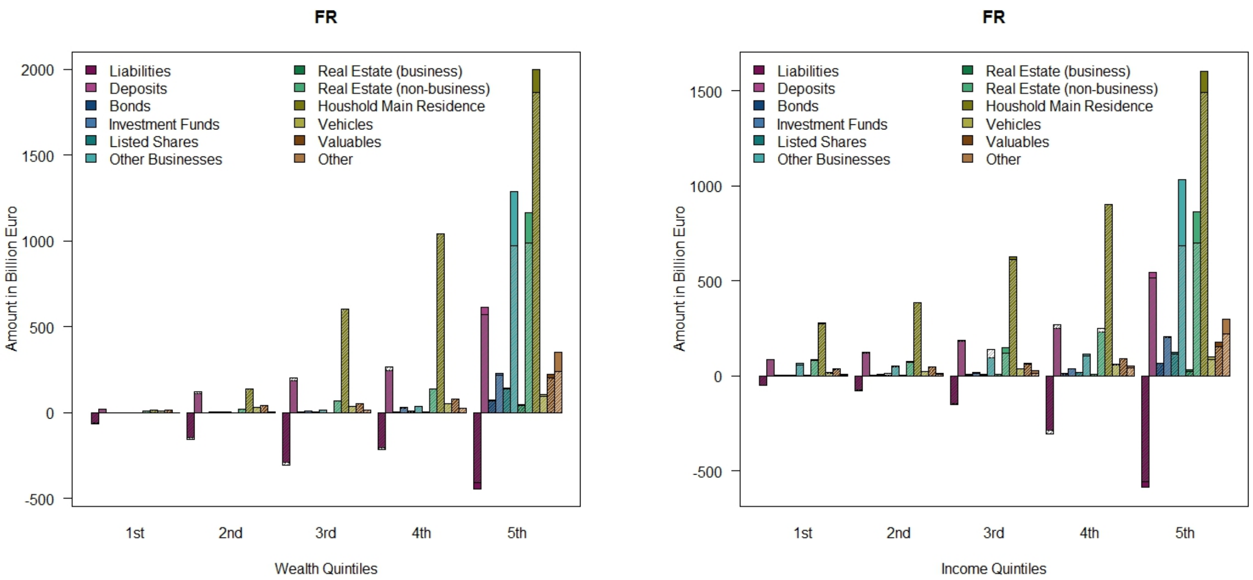
5.3 Hybrid DINA

Figure 6 shows some DINA results for France. The full set of results for Austria, Finland, France, Germany and Spain are reported in Appendix D.

Wealth is very concentrated at the very top: the top wealth group possesses substantial shares of total wealth (AT: 81.4%, FI: 66.4%, FR: 70.9%, DE: 81.5%, ES: 66.6%), whereas the poorest group have negative wealth in Austria, Finland and Germany. In France and Spain, the amount is positive but very small.

[49] The harmonized HFCD only contains *gross income*. Income contains employee income, self-employment income, rental income from real estate property, income from financial assets, income from private businesses other than self-employment, pension income (public, occupational and private), income from regular social transfers, unemployment benefits, and any other sources. I use total household income.

Figure 6: DINA.



Notes: The figures show Hybrid DINA. Amounts are in billion euro and are broken down by net worth quintiles. Dashed bars show amounts before the Pareto adjustment and full bars after Pareto adjustment.

Average net worth among the wealthiest 20% is more than 200 times higher than among the bottom 40% in Austria. This ratio is approximately 70 in Finland, 50 in France and 25 in Spain. In Germany, average net worth among the bottom 40% is still negative.

When assessed against income groups, the concentration is lower, i.e., there is a strong but no perfect correlation between income and wealth: the 20% highest income households respectively possess “only” 57.9% (AT), 48.2% (FI), 54.4% (FR), 59.8% (DE) and 48.8% (ES) of total wealth. The lowest-income group holds small but consistently positive shares of total wealth (AT: 3.3%, FI: 6.5%, FR: 6.5%, DE: 4.3%, ES: 8.6%). Again wealth inequality is highest in Austria and Germany, and lowest in Finland and Spain: the 20% income-richest households are on average 5 to 6 times wealthier than the 40% lowest-income households in Finland and Spain. This measure is approximately 11 in Austria, 8 in France and 9 in Germany.

Housing wealth constitutes the most important asset class in all countries. Thereof, owner-occupied housing wealth contributes the largest share. Owner-occupied housing wealth indeed dominates other housing wealth in all wealth and income groups and all countries. Note that due to differential misreporting, the distribution of owner-occupied housing wealth may in fact be more skewed when measured again income groups than reported here. Residential housing wealth excluding owner-occupied housing is relatively most important in Spain. Non-owner-occupied housing assets become relatively more important in households’ portfolios when moving up the distribution (see also Figure 14).

Differences in the degree of inequality within housing wealth is largely determined by differences in home-ownership rates, which are substantially lower in Germany and Austria than in other countries (see footnote 40 and Figure 15). Thus, the first and second wealth groups in these two countries possess only low amounts of housing assets.

In all countries, housing wealth at the very bottom of the distribution is larger than when moving up few quantiles, which is usually paired with larger debts (see Figure 14). This pattern is particularly pronounced in Austria and Germany, and thus also reproduced in the per quintile DINA data.

Business wealth and holdings in investment funds and bonds is heavily concentrated among the wealthiest households. The top wealth group owns the lion's share of these assets. For instance, in Austria and Germany the wealthiest 20% households possess 97.7% and 96.9% of total business wealth (listed shares, other businesses and real estate for business use). This share is lower but still substantial in France (95.0%), Finland (92.4%) and Spain (91.25%). Again the concentration is less dramatic but still substantial when looking at the highest income group (AT: 76.0%, FI: 78.2%, FR: 76.0%, DE: 82.1%, ES: 69.7%).

The fundamental differences in the spread of holdings in financial and housing wealth may also help explaining different magnitudes of the macroeconomic wealth effect: Case et al. (2005) and Bostic et al. (2009) document a much larger effect of changes in housing prices on aggregate consumption as compared to changes in stock market prices or financial wealth in general.

The distribution of debts stands out for Spain, where they are large and evenly spread across wealth groups. Average debts among the wealthiest 20% is just 1.3 times average debts among the poorest households. One explanation is the extraordinary housing boom at the beginning of the century that motivated many people to invest in real estate. After the bust, many were left with substantial mortgage debts. Thus, the share of owners with mortgages is large across all wealth groups (see Figure 14 and Figure 15).

Deposits constitute the only type of financial assets possessed by large sections of society. Although the absolute holdings in deposits increases when moving up the wealth distribution, in relative terms deposits are the most important asset type at the bottom of the distribution (see also Figure 14).

Aggregates for vehicles are close to holdings in listed shares or investment funds and rage between 2% and 3% of total wealth (in Finland this share is slightly larger: 5%). Vehicles are, however, less unequally distributed across wealth or income groups. In fact, their relative importance in households' portfolios is substantial for the two lowest wealth groups (see Figure 14). Including vehicles into a wealth measure thus leads to lower levels of measured inequality than when focusing on financial assets only.

Valuables typically contribute with roughly 1% to total wealth. Only in France, with 5% this share is substantially larger. There, more than 50% of valuables are owned by the top wealth group.

6 Conclusions

This paper compiles Distributional National Accounts (DINA) by breaking down net worth and several components thereof by wealth and income groups. Therefore, I combine survey (HFCS) and national accounts (NA) data. As response to the insufficient representation of the top tail, I perform a top tail correction making use of rich list data and for France also top wealth shares compiled from income tax data. This additional information is used to estimate a Pareto or Generalized Pareto distribution that substitutes the top tail in the survey.

It turns out that the reliability of the top tail varies substantially across countries: in countries that apply a sophisticated oversampling strategy based on personal wealth or income data, the top tail adjustment has much less impact. For reasons of comparability, a top tail adjustment thus appears to be essential.

The article suggests a partial integration of distributional information into the System of National Accounts, but points out the importance of extending the list of variables to reach a comprehensive measure of total wealth. This partial integration is called *Hybrid DINA*. This approach is also feasible when links between micro and macro data are not (yet) well established for all variables.

The article discusses in detail the link between micro and macro data for housing wealth. The national accounts concept of recording structures and land separately counteracts a meaningful link with distributional data, which usually treats housing wealth as a bundle of goods. The comparability is further complicated by data gaps regarding land and the joint recording of housing wealth owned by private households and Non-Profit Institutions Serving Households (NPISHs) in the NA. Thus, I establish a pseudo-link between the NA and the HFCS by interpreting the residual of residential housing wealth recorded in the HFCS and the value of residential structures recorded in the NA as the value of land.

The article further discusses the reliability of self-reported housing wealth in the HFCS. It turns out that collectively households seem to be able to track changes in residential property prices well. I construct subjective price indices for owner-occupied housing implied by the HFCS. The resulting indices also provide indication about how property prices evolved in the long term – a missing piece of information for many countries.

Comparing acquisition prices with self-estimated current prices yields an implicit measure of net depreciation. Depreciation rates vary across the income and wealth distribution. Patterns are in-line with findings from transaction data and theoretical arguments.

Nonetheless, I find that totals tend to be overstated in the HFCS, which is in-line with findings based on other surveys. This may be explained by an owner-pride factor or endowment effect. Explicitly modelling this factor finds large positive effects. I also find that low-income households tend to report relatively higher amounts than high-income households.

The missing top tail in the HFCS leads to too low aggregates for all components of wealth including housing wealth. The overly optimistic estimates of housing wealth provided by owner-occupiers, in contrast, leads to an overstated aggregate for this component. Further research is needed to understand which of the two effects dominates for housing wealth.

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Appendix

A The Conceptual Link between HFCS and NA data

A.1 Financial Assets and Liabilities

Financial assets and liabilities are recorded in the *Financial Accounts (FA)* that form part of the NA. Large parts of FA data is based on counterpart reporting data, i.e., the primary source originates from data reported by banks, investment funds, insurance corporations and pension funds.

Thus, the general data quality on loans (liabilities), deposits, debt securities (bonds), investment fund shares and listed shares is high:

> Highest accuracy is achieved for the data on deposits held and loans received as they are reported by banks in the euro area under ECB Regulation ECB/2013/33, which ensures a fully harmonised and almost complete monthly reporting of household deposits held with Monetary Financial Institutions (MFIs), and of loans granted by MFIs. Those are the main sources for the FA. Statistical information on the holdings of money market funds, other investment fund shares, listed shares and debt securities [bonds] are obtained through the new securities holdings statistics (ECB/2012/24) and/or the domain specific statistics for money market and other investment funds (ECB/2013/33 and ECB/2013/38). These data are considered complete and of overall good quality, though the sectoral delineation of holdings is not always straightforward, particularly when the country of residence of the holder and issuer differs. (EG-LMM, 2017, paragraph 26)

The FA instruments *F.4 Loans (liabilities)*, *F.22 Transferable deposits* and *F.29 Other deposits*, *F.3 Debt securities*, and *F.52 Investment fund shares or units* do have a conceptually highly-comparable counterpart in the HFCS (see Table 2). Given the high data quality in the FA for these variables, they enter the integrated part of DINA.

Despite the conceptually well-established link, comparing HFCS to FA aggregates, usually reveals much lower values in the HFCS. Due to the high confidence in the FA data, one can speak of *under-coverage* in the HFCS (see EG-LMM, 2017, for coverage ratios and a discussion). Under-coverage may be the result of all survey-related issues discussed in subsection 2.3. In particular, missing wealth at the top of the distribution may explain parts of the gap although Chakraborty and Waltl (2018) find that the proportion of the gap explained by the so-called "missing wealthy" is rather small in Austria and Germany.

A.2 Business Wealth

The FA record business wealth in the instruments *F.511 Listed shares*, *F.512 Unlisted shares* and *F.519 Other equity*: Listed and unlisted shares are equity securities listed or unlisted on an exchange. Other equity compromises all other types of equity including, for example, equity in limited liability companies whose owners are partners but not shareholders or real estate assets located in a different country. Dwellings and land used for business purposes are not identifiable in the NA.

The HFCS records the variables *self-employed businesses*, *non-self-employed businesses* and *publicly traded shares*. Additionally, real estate assets used for business purposes could be considered as part of business wealth.

For listed shares, the conceptual link between the FA and HFCS is strong. For all other items, the link is problematic. The EG-LMM proposes several re-classifications and split-ups necessary (both in the HFCS and the NA) to establish a reliable link (see EG-LMM, 2017, paragraphs 55 to 60) as summarized below.

A particular problem arises from the national accounts' distinction between *producer households* and *quasi-corporations*. Producer households are not considered as separate institutional unit, and associated assets and liabilities are thus spread over all instruments in the household sector. They cannot be distinguished from holdings by non-producer households. In contrast, when a business is considered as a separate institutional unit, it is labelled a quasi-corporation, and a net value of assets and liabilities is recorded as other equity. Such a distinction is not possible in the HFCS counteracting an unambiguous link.

The distribution of wealth held by producer households across all instruments constitutes a fundamental problem in the comparison of NA and HFCS data. The household sector (S.14) consists of several sub-sectors including employers (S.141) and own-account workers (S.142). If it was possible to separately identify assets forming part of either one of these two sub-sectors, a consistent link could be established.

Similarly, in the HFCS more detailed information about the legal forms of businesses would facilitate comparison.

In contrast to other financial assets, the quality of FA data on unlisted shares and other equity is low. Valuation of unlisted shares and other equity is complicated as market values are – in contrast to listed share – not observable. Also, these instruments tend to be affected by vertical balancing (the process of aligning financial and non-financial accounts balancing items) and thus may not be very accurate (see EG-LMM, 2017, paragraph 27).

Thus, integrating components of business wealth other than listed shares is problematic. For the sake of a comprehensive measure for net worth across different groups (a horizontal reading of DINA as shown in Table 13) requires these components to be put in a supplement account. Finer recording of business wealth in both, the NA and HFCS, potentially facilitates a reallocation to the integrated account in the future.

A.3 Consumer Durables and Valuables

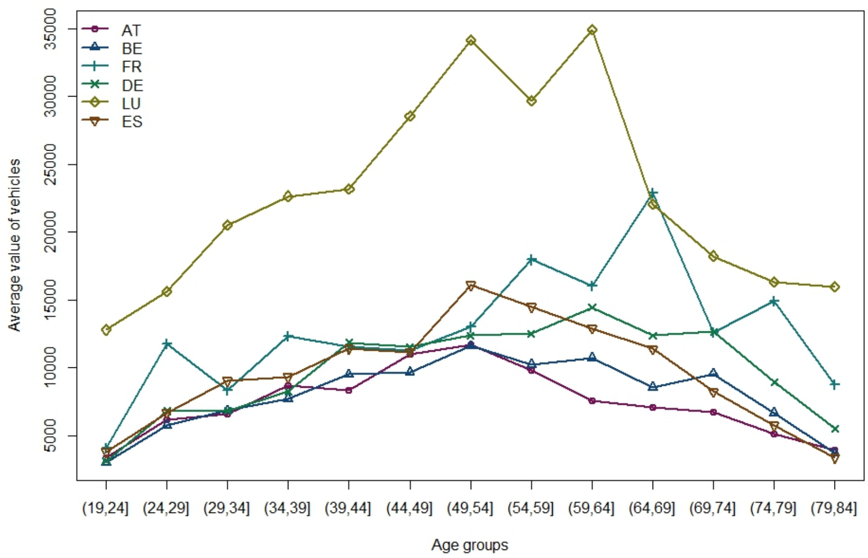
Consumer durables are excluded from NA balance sheets. This means that valuables such as household appliances, furniture, consumer electronics, but also vehicles like cars, yachts and jets, that could well be considered important for an overall measure of wealth do not appear in the definition of net worth coming from the NA.

Eliminating consumer durables from total wealth lets the sector as a whole appear to be poorer than it actually is. It is very likely that these missing assets are not equally distributed within society. Indeed, one would expect rather wealthy or high-income households to possess on average more in number and/or more expensive household appliances, furniture, and vehicles.

Additionally, holdings in consumer durables are known to differ across the life-cycle. Fernandez-Villaverde and Krueger (2011) find that consumption expenditures on both durable and non-durable goods are hump-shaped, and that young households keep very few liquid assets and hold most of their wealth in consumer durables. The same pattern is observed in the HFCS for vehicles (see Figure 7), the only consumer durable recorded in the HFCS. Thus, excluding these assets will bias break-downs by age groups, and, due co-movement over the life-cycle, also income and wealth groups.

To serve the second function of DINA, comprehensive (horizontal) wealth inequality measures, suggest the inclusion of vehicles in the supplement account. The recording of additional consumer durables in the HFCS would increase the comprehensiveness of the total wealth measure.

Figure 7: Average Value of Vehicles by Age Group.



Notes: The figure shows the average value of vehicles per household by age group for selected countries. Age is defined as the age of the reference person. *Source:* (2nd wave) HFCS

Valuables, in contrast, fall within the scope of the national accounts *(AN.13 Valuables)* and are also recorded in the HFCS. The HFCS asks for valuables in general and names jewellery, works of art, and antiques as examples. In the NA, valuables include produced assets that are not primarily used for production or consumption, that are expected to appreciate or at least not to decline in real value, do not deteriorate over time under normal conditions and that are acquired and held primarily as stores of value. They consist of works of art, antiques, jewellery, precious stones, non-monetary gold and other metals, and the like (see ESA, 2010).

Conceptually, the definitions seem to match well. However, currently NA data is only available for four countries in the euro area (Finland, France, Portugal and Latvia). The Finnish HFCS lacks this question. HFCS aggregates are considerably larger: coverage ratios (HFCS over NA aggregates) range between 1.5 in Portugal, 2.9 in France and 4.5 in Latvia for 2014 thus indicating under-coverage in the NA.

Given the scarce data availability in the national accounts, valuables are hence not integrated but allocated to the supplement account.

B Subjective and objective RPPIs

The objective RPPIs are predominantly taken from the BIS data warehouse, that includes RPPIs for a long list of countries. I give preference to indices representing the entire country and including all types of dwellings (apartments and houses). For some countries more than one index fulfils these criteria whereas for other countries no index exists at all that has such a broad coverage. Table 9 summarizes details about all objective RPPIs used in this article.

Figure 3 and Figure 8 graphically compare objective and subjective indices. Table 10 reports the full set of subjective index series.

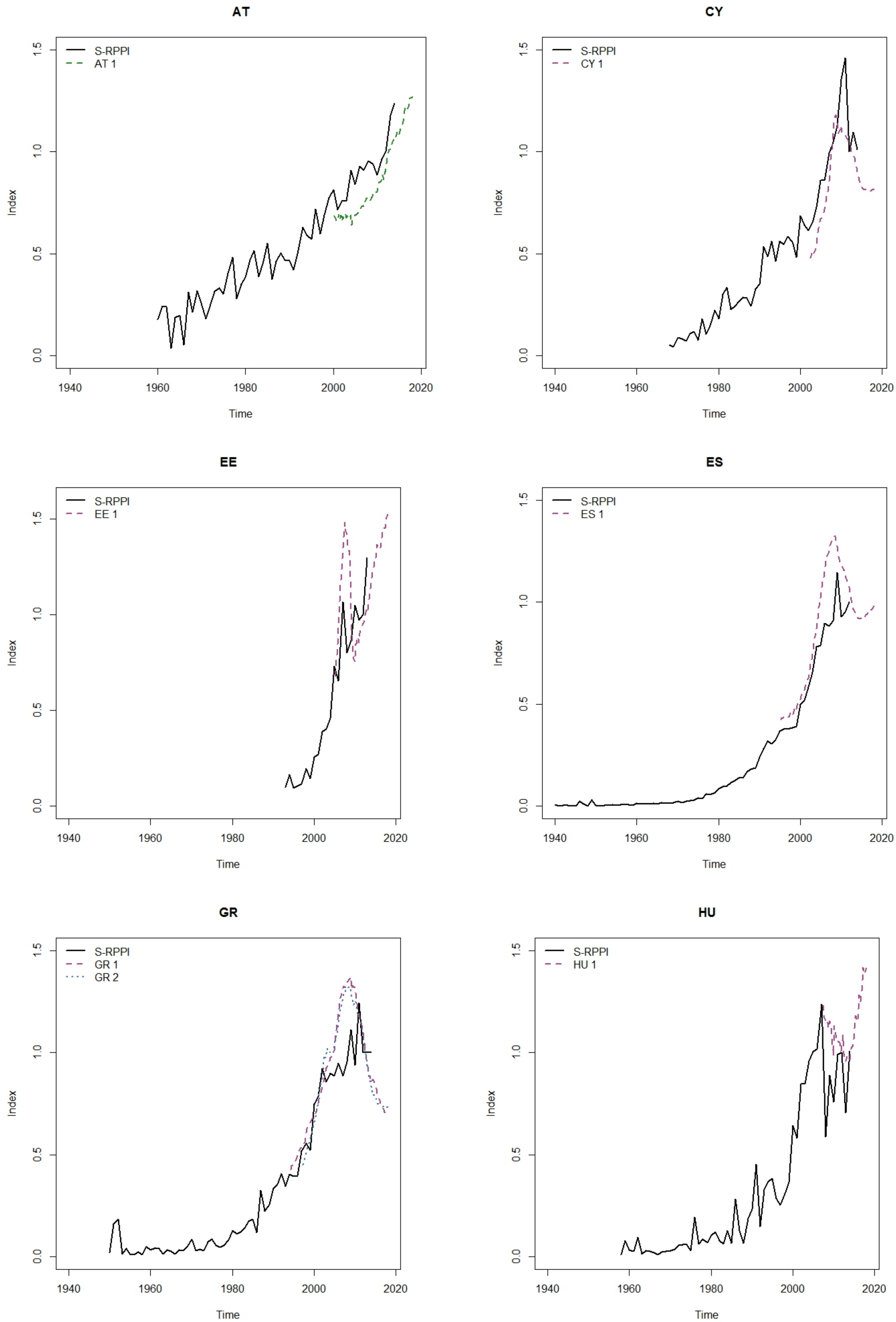
Table 9: Objective residential property price indices.

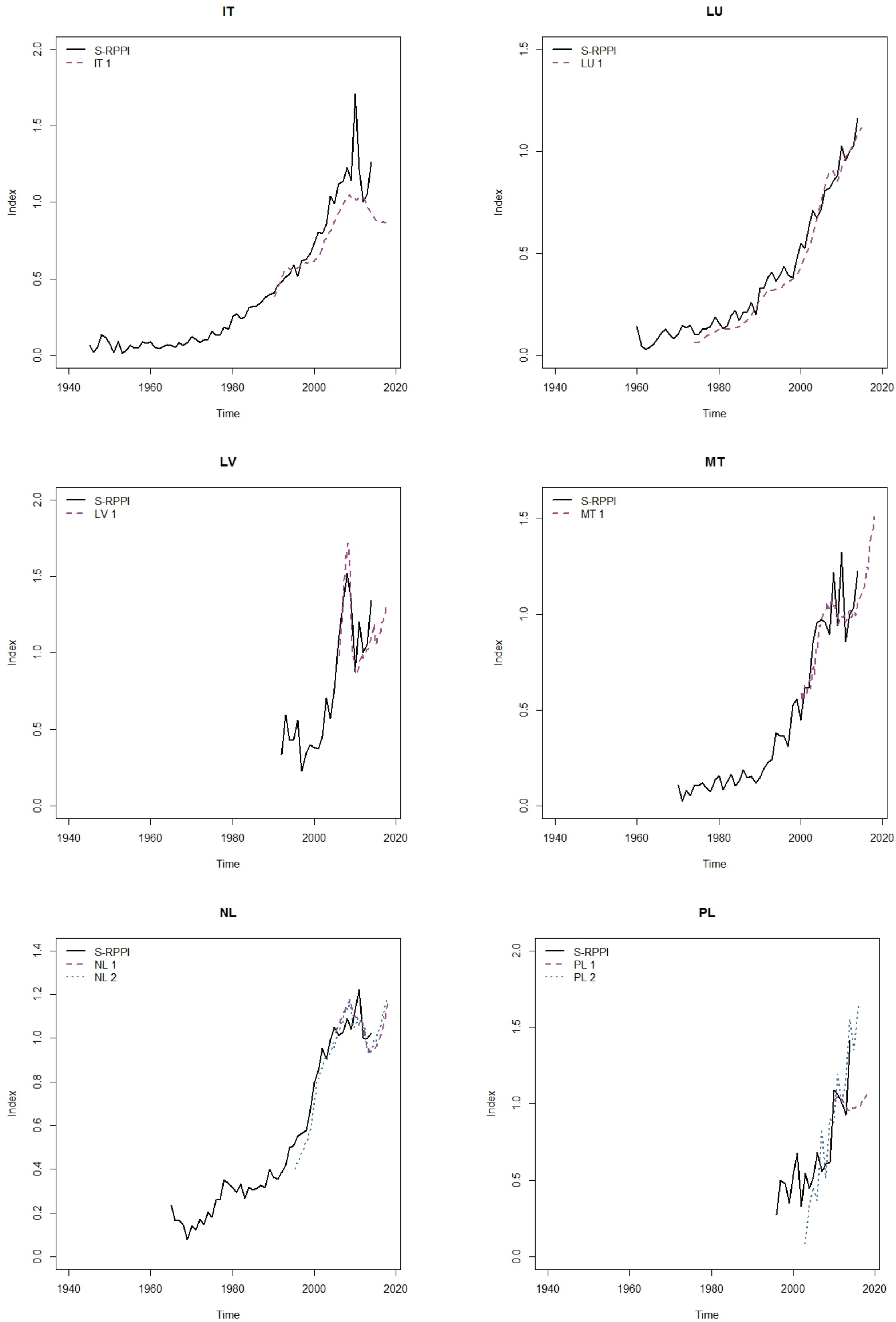
ID	Country	Coverage	Frequency	Time frame	Quality Adjustment	Compiler	Source (if source different to compiler)	Source ID
AT 1	Austria	All dwellings; Whole country	Quarterly	2000 – 2017	Hedonic	NCB	BIS	Q:AT:0:1:0:0:6:0
BE 1	Belgium	All dwellings; Whole country	Quarterly	2005 – 2017	Hedonic	NSI	BIS	Q:BE:0:1:0:1:6:0
BE 2	Belgium	Existing dwellings; Whole country	Quarterly	1973 – 2017	Geographical stratification	NCB	BIS	Q:BE:0:1:1:0:0:0
BE 3	Belgium	Diverse	Annual	1878 – 2012	Diverse	Knoll et al. (2017)		
CY 1	Cyprus	All dwellings; Whole country	Quarterly	2002 – 2017	Hedonic	NCB	BIS	Q:CY:0:1:0:0:6:0
DE 1	Germany	All owner-occupied dwellings; Whole country	Annual	1975 – 2015	Diverse	NCB	BIS	A:DE:0:1:0:0:6:0
DE 2	Germany	All dwellings; Whole country	Quarterly	2000 – 2017	Hedonic	NSI	BIS	Q:DE:0:1:0:1:6:0
DE 3	Germany	Diverse	Annual	1870–1938, 1962 – 2012	Diverse	Knoll et al. (2017)		
EE 1	Estonia	All Dwellings; Whole country	Quarterly	2005 – 2017	Stratification	NSI	BIS	Q:EE:0:1:0:1:1:0
ES 1	Spain	All dwellings; Whole country	Quarterly	1995 – 2018	Stratification	General Government	BIS	Q:ES:0:1:0:3:1:0
FR 1	France	All dwellings; Whole country	Quarterly	2006 – 2017	Hedonic	NSI	BIS	Q:FR:0:1:0:1:6:0
FR 2	France	Diverse	Annual	1870 – 2012	Diverse; Mainly Repeat-sales	Knoll et al. (2017)		
GR 1	Greece	All dwellings; Whole country excl. capital	Quarterly	1994 – 2017	No	NCB	BIS	Q:GR:1:1:0:0:1:0
GR 2	Greece	Flats; Capital city and suburbs	Quarterly	1997 – 2017	No	NCB	BIS	Q:GR:3:8:0:0:1:0
HU 1	Hungary	All dwellings; Whole country	Quarterly	2007 – 2017	Hedonic	NSI	BIS	Q:HU:0:1:0:1:1:0
IE 1	Ireland	All dwellings Whole country	Monthly	2005 – Feb 2018	Hedonic	NSI	BIS	M:IE:0:1:0:1:0:0

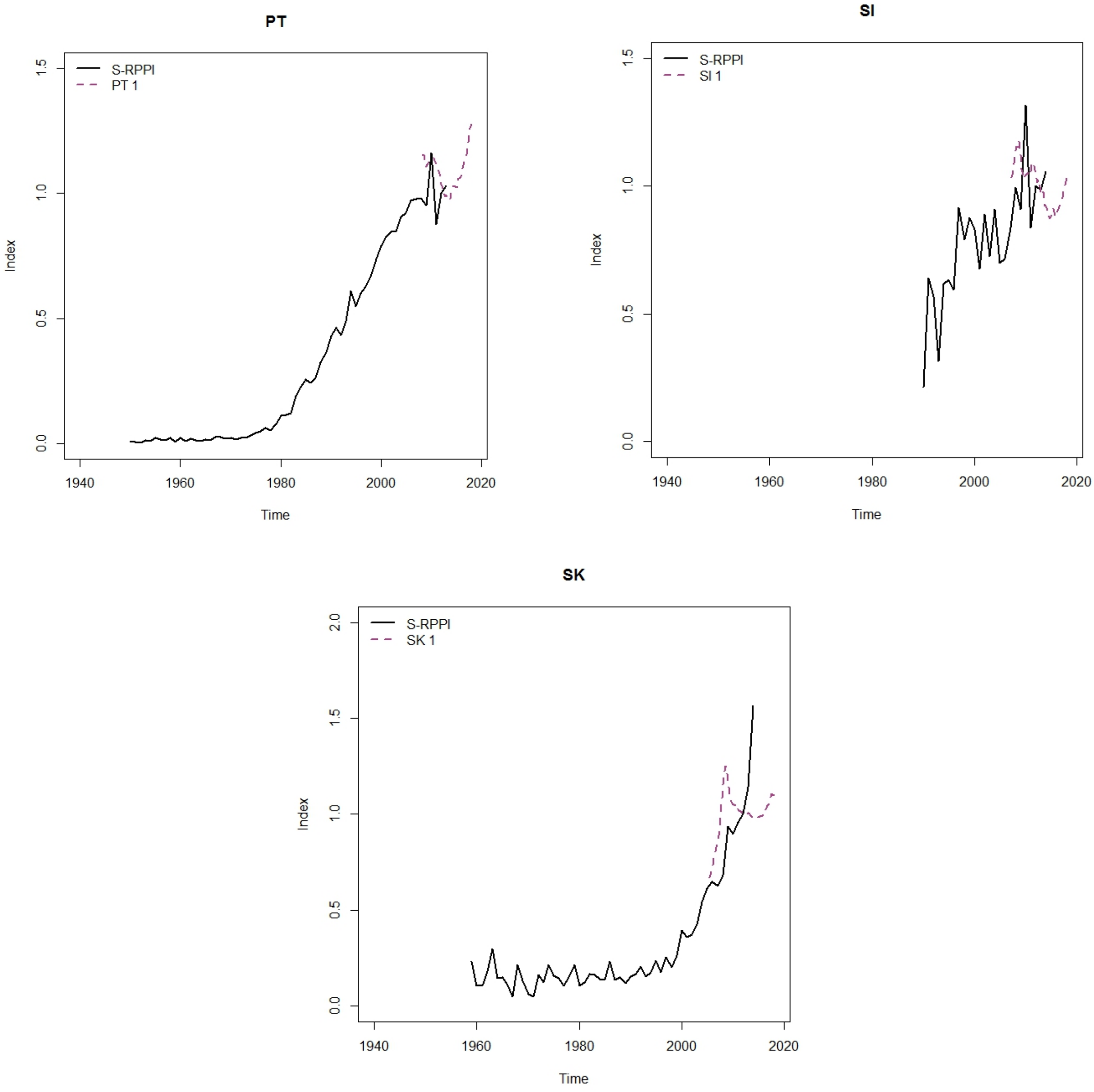
IE 2	Ireland	Dublin only;	Annual	1950 – 2014	Hedonic	Lyons (2018)		
IT 1	Italy	All dwellings; Whole country	Quarterly	1990 – 2017		NCB	BIS	Q:IT:0:1:0:0:6:0
LU 1	Luxembourg	All dwellings; Whole country	Annual	1974 – 2015		NSI	BIS	A:LU:0:1:0:1:0:0
LV 1	Latvia	All dwellings; Whole country	Quarterly	2006 – 2017	Hedonic	NSI	BIS	Q:LV:0:1:0:1:6:0
MT 1	Malta	All dwellings; Whole country	Quarterly	2000 – 2017	No	NCB	BIS	Q:MT:0:1:0:0:0:0
NL 1	Netherlands	All dwellings; Whole country	Quarterly	2005 – 2017		NSI	BIS	Q:NL:0:1:0:1:6:0
NL 2	Netherlands	Existing single-family; houses; Whole country	Quarterly	1995 – 2017		NSI	BIS	Q:NL:0:2:1:1:0:0
PL 1	Poland	Flats; Whole country	Quarterly	2010 – 2017	Stratification	NSI	BIS	Q:PL:0:8:0:1:6:0
PL 2	Poland	Single-family houses Whole country	Annual	2003 – 2016	Average price	NSI	BIS	A:PL:0:2:0:1:1:0
PT 1	Portugal	All dwellings; Whole country	Quarterly	2008 – 2017	Hedonic	NSI	BIS	Q:PT:0:1:0:1:6:0
SI 1	Slovenia	All dwellings; Whole country	Quarterly	2007 – 2017	Hedonic	NSI	BIS	Q:SI:0:1:0:1:6:0
SK 1	Slovakia	All dwellings; Whole country	Quarterly	2005 – 2017	Per Square meter prices	NCB	BIS	Q:SK:0:1:0:2:1:0
EA 1	Euro Area	EA-17; Average over national indices	Quarterly	1980 – 2018	Diverse	ECB		RPP.Q.I6.N.TD.00.3.00

Notes: The table provides overview information about the objective indices used in this article. Long series usually include structural breaks due to changes in methodologies and/or data sources. In-depth methodological descriptions are provided by the respective index compilers. NSI refers to *National Statistical Office* and NCB to *National Central Bank*. In the case of several indices, preference has been given to long series with the broadest coverage in terms of types of dwellings and geographical coverage.

Figure 8: Subjective versus objective indices.




IT
S-RPPI
IT 1
LU
S-RPPI
LU 1
LV
S-RPPI
LV 1
MT
S-RPPI
MT 1
NL
S-RPPI
NL 1
NL 2
PL
S-RPPI
PL 1
PL 2
Index
Time



Notes: Subjective (S-RPPI) versus objective indices. All indices are nominal and normalized with respect to the year 2012 or, in case of quarterly data, the average in 2012. Details about the objective indices are reported in Table 9. More country results are shown in Figure 3.

Table 10: Subjective residential property price indices (S-RPPI).

Year	AT	BE	CY	DE	ES	FR	GR	IT	LU	MT	NL	PT	SI	SK	EE	HU	IE	LV	PL
1940					0.7														
1941					0.2														
1942					0.4														
1943					0.4														
1944					0.1														
1945					0.2			6.7											
1946					2.5			2.2											
1947					1.1			5.2											
1948					0.0			13.5											
1949					2.9			11.7											
1950					0.4		2.0	8.0				1.0							
1951					0.2		16.3	1.8				0.8							
1952					0.5		18.3	9.4				0.6							
1953		10.1			0.5		1.3	1.3				1.4							
1954		5.4			0.6		4.0	3.7				1.0							
1955		6.3			0.3		1.1	6.6				2.3				3.1			
1956		8.7			0.6		1.0	5.0				1.6					1.7		
1957		8.2			0.8		2.3	4.7				1.5					1.0		
1958		6.5			0.8		1.1	8.8				2.3				1.2	1.2		
1959		5.7			0.5		4.9	8.1				0.8		23.2		7.8	1.4		
1960	17.8	10.8			1.3		3.5	8.7	14.2			2.2		10.6		3.5	0.9		
1961	24.4	11.2			1.0		4.4	5.3	4.7			1.1		10.8		2.7	1.0		
1962	24.0	10.0		25.9	1.2		4.1	4.4	3.0			2.0		18.2		9.7	1.1		
1963	3.8	7.2		22.2	1.0		1.5	5.6	3.9			1.5		30.0		1.5	1.4		
1964	18.8	10.4		36.3	1.4		3.2	7.2	5.5			1.0		14.4		2.9	1.6		
1965	19.9	12.9		33.6	1.1		2.7	6.5	8.2		23.7	1.7		14.9		2.8	1.5		
1966	5.3	7.6		36.2	1.8		1.3	5.2	11.2		16.6	1.5		11.2		2.0	2.9		
1967	31.2	13.4		34.0	1.6		3.3	8.4	12.9		16.7	2.8		5.0		1.1	1.7		
1968	21.2	11.2	5.3	38.8	1.4		3.0	6.7	10.3		14.7	2.7		21.4		2.3	2.5		
1969	31.8	11.0	4.2	29.1	1.8		5.0	8.4	8.4		8.1	2.1		13.1		2.6	2.6		
1970	24.5	12.0	8.9	37.0	2.3	7.0	8.6	12.5	10.5	10.9	14.3	2.4		6.4		3.0	3.4		
1971	18.1	13.7	8.4	41.3	1.9	11.6	3.1	10.7	14.7	2.7	12.4	1.8		4.8		3.8	3.9		

1972	25.3	14.2	7.3	48.5	2.4	17.2	3.6	8.3	13.4	8.2	17.1	2.2		16.4		5.6	3.5		
1973	31.5	17.3	10.9	48.0	2.7	10.3	3.1	10.3	14.9	5.3	14.8	2.5		12.4		5.9	3.9		
1974	33.2	18.8	11.8	40.7	3.1	9.2	7.3	10.4	10.6	11.1	20.6	3.4		21.7		6.1	4.4		
1975	30.1	18.4	7.8	48.2	3.9	15.2	8.6	15.6	10.2	10.5	18.1	4.3		16.0		3.1	6.1		
1976	40.4	20.2	18.0	45.3	3.7	14.1	5.5	13.1	12.8	11.9	25.9	5.0		14.5		19.5	7.6		
1977	48.3	22.3	10.6	46.9	6.0	11.5	4.7	13.3	13.2	9.4	26.1	6.3		10.6		6.3	7.0		
1978	27.8	25.8	15.0	48.2	5.6	16.3	5.7	18.3	14.3	7.4	35.1	5.4		15.1		8.6	9.2		
1979	35.1	25.4	22.3	62.5	6.8	17.9	8.2	17.2	18.9	13.7	33.3	8.0		21.4		6.8	13.8		
1980	38.3	26.8	18.2	71.5	8.6	27.9	12.9	25.6	15.9	15.7	31.5	11.3		10.8		10.4	14.1		
1981	47.1	26.1	30.3	64.8	9.7	29.0	11.1	27.0	13.1	8.6	29.5	11.6		12.4		12.2	18.4		
1982	51.6	22.5	33.5	57.1	10.0	13.5	12.1	24.2	14.6	12.8	33.3	12.3		16.8		7.9	20.2		
1983	38.9	26.3	22.9	69.6	11.7	35.3	14.1	25.0	19.8	16.6	26.6	19.1		16.4		6.2	15.8		
1984	46.3	27.6	24.3	67.1	12.6	29.6	17.4	31.0	22.0	10.6	31.8	22.7		14.1		12.7	21.6		
1985	55.2	24.6	26.5	62.7	13.9	20.1	18.3	32.0	17.2	13.0	30.7	25.5		13.5		6.6	19.5		
1986	37.6	33.8	28.7	68.3	13.9	31.1	11.7	32.4	20.9	19.0	31.1	24.3		23.4		28.2	19.3		
1987	46.4	28.7	28.1	67.7	16.8	28.8	32.5	34.6	21.3	14.7	32.9	26.2		13.7		13.0	20.9		
1988	50.1	31.0	24.4	72.5	18.2	48.2	22.5	37.8	26.0	15.4	31.5	32.6		14.9		6.6	19.7		
1989	46.9	34.8	32.8	79.3	18.8	38.5	25.5	39.9	20.1	12.1	39.8	36.3		11.9		18.6	22.3		
1990	46.5	35.6	35.1	66.7	24.1	28.0	33.5	40.6	33.0	14.9	36.6	43.2	21.4	15.6		23.5	28.0		
1991	42.0	41.2	53.3	77.7	28.3	34.9	35.3	45.4	33.3	19.5	35.5	46.2	63.9	16.6		45.4	29.4		
1992	51.5	40.3	48.5	70.3	31.7	23.8	40.7	48.3	38.6	22.9	38.5	43.4	56.7	20.6		14.8	36.1	33.8	
1993	63.0	39.3	56.2	85.7	30.6	40.6	34.4	51.2	40.8	24.1	41.6	49.0	31.4	15.6	10.0	33.0	33.4	59.6	
1994	58.9	43.1	46.2	86.0	32.7	30.4	40.5	53.0	36.5	38.3	50.0	61.0	61.7	17.6	16.5	36.7	33.5	42.8	
1995	57.2	45.0	56.0	90.1	36.8	54.6	39.3	59.0	39.3	37.0	50.7	54.9	63.5	23.8	9.6	38.4	35.9	43.4	
1996	72.0	42.8	54.3	94.5	37.7	35.6	39.9	51.6	43.7	36.3	55.0	60.1	59.4	17.4	10.7	28.7	43.2	56.1	27.5
1997	59.8	47.2	58.5	85.6	37.8	43.3	51.8	61.8	39.6	31.1	56.4	62.6	91.6	25.5	11.5	25.3	44.7	22.8	49.7
1998	69.0	51.5	55.8	96.7	38.5	38.1	55.5	63.1	38.1	52.6	58.0	67.7	78.9	20.2	19.8	30.8	61.4	34.8	47.6
1999	77.3	52.9	48.2	94.6	38.9	41.8	52.3	66.7	47.3	55.9	67.4	73.8	87.5	26.3	14.5	36.4	74.7	39.8	35.2
2000	81.3	57.8	68.6	103.0	50.0	54.7	74.8	73.5	54.9	45.0	79.7	79.1	82.9	39.3	25.7	64.3	84.5	38.2	54.0
2001	71.6	57.9	64.0	92.0	51.9	56.2	78.3	80.7	52.7	61.9	85.2	82.6	67.6	35.9	27.0	58.1	101.4	37.2	67.9
2002	76.1	62.7	61.3	90.6	58.5	55.1	92.1	79.6	63.1	61.6	95.2	84.6	88.8	37.3	39.0	84.6	97.4	45.7	32.9
2003	75.9	63.6	65.3	100.8	65.8	54.9	85.5	85.7	71.1	85.0	90.5	84.6	72.7	42.4	40.4	84.6	119.1	70.7	54.6
2004	90.8	73.4	72.9	95.7	78.0	63.3	89.9	104.2	67.1	95.7	99.2	90.6	90.9	54.1	45.7	95.8	133.4	57.2	44.9
2005	84.1	80.5	85.9	99.0	78.8	77.1	88.6	99.3	71.3	97.2	105.1	92.1	69.7	61.2	73.2	100.3	153.3	76.6	52.1
2006	92.8	81.3	86.0	98.5	89.5	87.8	94.9	111.8	80.7	96.1	101.0	97.2	71.6	64.8	65.6	101.8	171.9	108.2	68.4

2007	91.0	91.3	99.5	101.2	88.1	98.3	88.4	113.9	82.0	89.5	102.9	97.9	83.6	62.5	106.9	123.8	176.6	133.3	55.5
2008	95.4	97.9	104.5	92.7	90.9	88.7	95.4	123.1	85.5	121.9	109.0	97.7	99.3	68.4	80.2	58.8	172.0	152.2	61.0
2009	93.7	100.2	112.8	100.4	114.5	94.3	111.2	114.1	88.3	94.0	104.2	95.2	91.0	93.8	86.5	88.9	133.3	133.7	61.7
2010	88.6	117.2	135.5	101.0	92.9	92.0	93.8	170.9	102.8	132.5	112.9	116.0	131.5	89.5	104.8	75.6	111.3	87.7	108.9
2011	96.3	97.7	146.0	109.5	95.0	87.3	124.3	121.7	95.3	85.6	122.1	87.7	83.7	95.9	97.2	99.1	107.7	120.4	105.7
2012	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
2013	117.9	103.0	109.4	107.5		98.5	100.1	105.2	102.7	103.6	99.7	103.1	98.3	114.3	129.9	70.6	99.0	106.0	92.7
2014	123.7	120.1	101.2	121.4		106.8	100.1	126.3	116.2	122.8	102.3		105.8	156.3		100.8		134.2	141.3

Table 11: Selected RPPIs.

Country	Combination of indices
Belgium	BE 3 until 2012 and BE 1 for 2013–2014
Germany	DE 3 until 2012 and DE 1 for 2013–2014
France	FR 2 until 2012 and FR 1 for 2013–2014
Ireland	IE 2

Notes: The table reports the objective indices selected to estimate implicit net depreciation rates.

C A Generalized Pareto Adjustment of the Top Tail

France has been a major focus for research on income and wealth inequality, and thus ample information is available. Long series of top wealth shares are available in the WID.world database (Alvaredo et al., 2017). These shares are mainly based on income tax files (see Garbinti et al., 2016). This extra source of information can be used to test the appropriateness of top tail adjustments based on rich list data.

The WID.world database reports that the share of total wealth held by the top 1% (3%) equals 23.4% (35.5%) in 2014, whereas the HFCS finds a ratio of 18.6% (29.6%) only.[50] Under the assumption that this share is correct, I estimate the missing wealth in the French HFCS. The procedure described in the following can be applied whenever there is an additional piece of information available describing the wealth at the top.[51]

The following procedure is based on two major assumptions: first, the survey is successful in measuring assets and liabilities for the entire distribution except the wealthiest p%. Second, the distribution of wealth within the top tail follows a *Generalized Pareto Distribution* (GPD). GPDs are a family of heavy-tail distributions including the standard Pareto distribution as a special case. Thus, the distributional assumptions are less strict than for the other top tail adjustments performed in this article.

C.1 From Shares to Total Wealth

I assume that the survey measures the wealth of the bottom $(100 - p)$% of the population correctly, but misses crucial parts at the very top. Furthermore, I assume that the wealth share held by the top p% is accurately measured in the WID.world database.

Let α denote the "true" (WID.world) wealth share of the top p% and α^* the observed share according the HFCS. Let furthermore w_p denote the wealth of the top p% of the population, e.g., w_{100} refers to total wealth and w_1 to the wealth of the top 1%. Likewise I denote the observed total wealth as reported in the HFCS by w_p^*. Furthermore, I assume that the survey gets the corresponding quantile right.[52]

The assumption that the HFCS is a reliable source for the bottom $(100-p)$% of the population yields

$$w_{100} - w_p = w_{100}^* - w_p^*. \tag{6}$$

Furthermore, the assumption that the top tail is incomplete in the HFCS implies $w_p > w_p^*$, or equivalently

$$\exists\, \varepsilon > 0 : \quad w_p = w_p^* + \varepsilon,$$

which together with (6) yields $w_{100} = w_{100}^* + \varepsilon$.

While w_p, w_{100} and ε are unobserved, one does observe w_p^*, w_{100}^*, α and α^*. Since

$$\alpha^* = \frac{w_p^*}{w_{100}^*} \quad \text{and} \quad \alpha = \frac{w_p}{w_{100}} = \frac{w_p^* + \varepsilon}{w_{100}^* + \varepsilon}$$

[50] Garbinti et al. (2016) follow an individual ("equal-splits") rather than the HFCS household concept. The top 3% approximately represent the group of millionaires.

[51] In theory, one could also use rich lists to calculate average wealth at the very top and proceed as described here. However, the usual large gap between the lowest observation on a rich list and the top observation in the HFCS makes this approach infeasible.

[52] Chakraborty and Waltl (2018) find that their adjustment for the "missing wealthy" leads to changes in quantiles from roughly the 98%th or 99%th quantile onwards in Austria and Germany.

one can write
$$\frac{\alpha}{\alpha^*} = \frac{w^*_{100}(w^*_p + \varepsilon)}{w^*_p(w^*_{100} + \varepsilon)} \quad \text{which yields} \quad \varepsilon = \frac{(\alpha^* - \alpha) \cdot w^*_p w^*_{100}}{\alpha w^*_p - \alpha^* w^*_{100}}.$$

Using the population total ($n = 29,017,678$ households) obtained from the HFCS, the adjusted average wealth among the top $p\%$ is given by:

$$AVG(p) = \frac{w^*_p + \varepsilon}{p\% \cdot n} \quad \text{and} \quad AVG(3) = 2,972,263.$$

The average wealth among the top 3% increased substantially by roughly 700,000 EUR.

C.2 From Total Wealth to Instrument-Specific Aggregates

The total wealth of the top $p\%$ is changed, which needs to be broken down on instrument-level: As Chakraborty and Waltl (2018) show, applying average portfolio shares when aiming for such a break-down is not enough. Stratifying the tail into, say, four strata defined as quartiles of the tail distribution and applying stratum-specific shares, which can be observed from the HFCS, is a feasible strategy.

As there is no distributional information within the top $p\%$, one needs to impose a parametric model to retain this information. This is done by employing a *Generalized Pareto Inter- and Extrapolation*. This method was proposed by Blanchet et al. (2017) and was originally designed to recover historic wealth and income distributions from tabulated data. Historic data is rarely available in the form of micro data, but often brackets, such as the average wealth for certain quantile ranges, is available. The interpolation method based on quintic Hermite splines recovers an entire distribution from this information.

For the top bracket, say the top 3%, interpolation is not feasible as no upper bound is known. For this last bracket, Blanchet et al. (2017) propose an extrapolation using a GPD. The parameters are estimated to match the average wealth in the top bracket but also match the interpolated distribution from the bracket before, i.e., it is additionally guaranteed that the distribution has a continuously differentiable quantile functions and matches the last observed quantile.

The family of GPDs is defined as

$$GPD_{\mu,\sigma,\xi}(x) = \begin{cases} 1 - \left(1 + \frac{\xi(x-\mu)}{\sigma}\right)^{-1/\xi}, & \text{for } \xi \neq 0, \\ 1 - e^{-(x-\mu)/\sigma}, & \text{for } \xi = 0, \end{cases}$$

where $\mu \in \mathbb{R}$, $\sigma \in (0, \infty)$ and $\xi \in \mathbb{R}$. The distribution is defined for all $x \geq \mu$ (in the case of $\xi \geq 0$) or $\mu \leq x \leq \mu - \sigma/\xi$ (in the case of $\xi < 0$). The family is very general and includes the standard Pareto distribution ($\xi > 0$ and $\mu = \sigma/\xi$), the (shifted) exponential distribution ($\xi = 0$) and the uniform distribution ($\xi = -1$) as special cases.

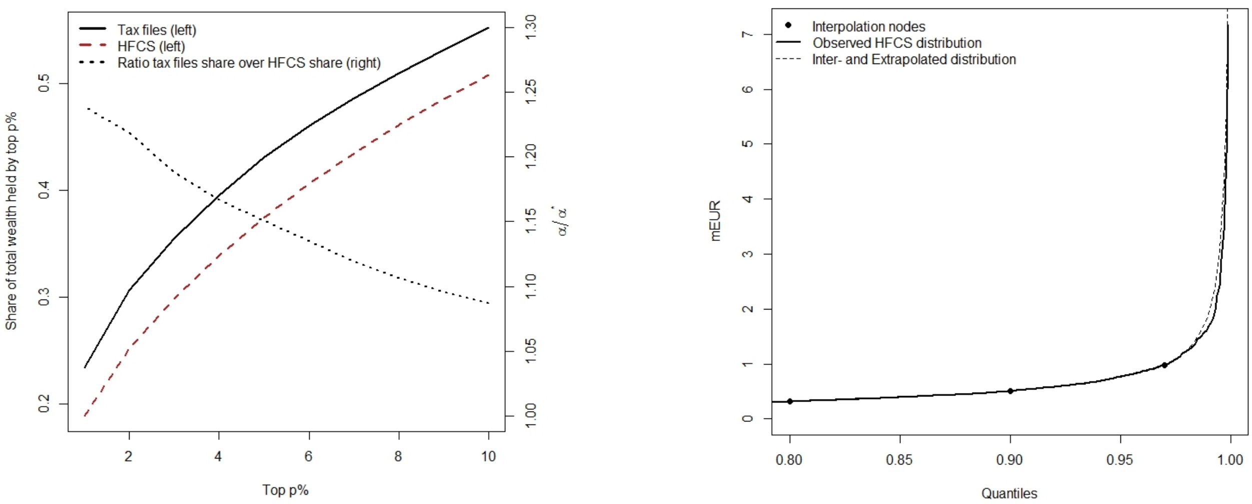
Following Blanchet et al. (2017), I focus on the cases $0 < \xi < 1$, which guarantees that the estimated distribution is in the limit a power law and has finite expectation.

I apply the interpolation on the brackets $(10\%; 25\%)$, $(25\%; 50\%)$, $(50\%; 75\%)$, $(75\%; 80\%)$, $(80\%; 90\%)$ and $(90\%; p\%)$ using average wealth for each bracket and quantiles calculated from the HFCS. The upper tail $(p\%, 100\%)$ is modelled by a GPD extrapolation. The average wealth in the top bracket hence is not the average measured by the HFCS but the adjusted average $AVG(p)$!

Using only these few pieces of information, the interpolation method is able to recover the full HFCS distribution almost perfectly. The top part of the distribution becomes steeper as a result of the top tail adjustment[53] (see the right panel of Figure 9). The estimated GPD at the top is smoothly matched with the empirical HFCS distribution. No artificial break is created that may be the case in a standard Pareto adjustment.

The left panel of Figure 9 compares information on wealth between the HFCS and tax files. The share of the top $p\%$ for $p \in [1, 10]$ is generally larger when measured from tax files than when measured from the HFCS indicating that the HFCS underestimates the heavy skewness at the top of the wealth distribution. When matching the top $p\%$ share between tax files and the HFCS thus yields to an increase in total wealth in the HFCS (i.e., $\varepsilon > 0$). The increase is larger when a larger share is matched.

Figure 9: HFCS versus Tax-files implied Wealth Share.



Notes: The figures compare wealth shares reported in WID.world and implied by the HFCS. The left panel shows the share held by the top $p\%$ measured from either source as well as the ratio of the two denoted by α/α^* measuring the distance between the two sources. $\alpha/\alpha^* = 1$ would indicate a perfect match. The right panel plots the quantile function measured from the HFCS and the result from the inter- and extrapolation for $p = 3$, i.e., the adjustment starts at the 97% quantile. Below the 97% quantile, the observed and interpolated distributions match almost perfectly. The top tail adjustment leads to a steeper quantile function above the 97% quantile.

To break down tail wealth into its components, I follow the so-called analytical approach in Chakraborty and Waltl (2018) but adapt the methodology so that it does not only work for a standard Pareto distribution but also for a GPD.

For that, I need to calculate the expected mean for each stratum. Mirroring the set-up in Chakraborty and Waltl (2018), I will eventually calculate the conditional expectation for four strata defined as quartiles of the tail distribution, i.e., the GPD.

For that endeavour, the quantile function $F^{-1}(p)$ of the GPD is needed, which is obtained by

[53] For the top tail and $p = 97\%$, the estimation procedure yields the parameters

$$\hat{\mu} = 983,641, \quad \hat{\xi} = 0.7171, \quad \text{and} \quad \hat{\sigma} = 562,657.$$

Thus, $\hat{\xi} > 0$ and $\hat{\sigma}/\hat{\xi} = 784,670 < \hat{\mu}$. The standard Pareto distribution requires $\xi > 0$ and $\frac{\sigma}{\xi} = \mu$. So the estimated distribution is not a standard Pareto distribution.

solving $F(x) = p$:

$$F^{-1}(p) = \mu + \frac{\sigma}{\xi} \cdot \left[(1-p)^{-\xi} - 1\right].$$

Average wealth within stratum $Q = [F^{-1}(p_1); F^{-1}(p_2)]$ is then given by

$$\begin{aligned} E(Y|Y \in Q) &= \frac{1}{p_2 - p_1} \int_{p_1}^{p_2} F^{-1}(q) \, \mathrm{d}q \\ &= \mu - \frac{\sigma}{\xi} + \frac{\sigma}{\xi(\xi-1)(p_2-p_1)} \cdot \left[(1-p_2)^{1-\xi} - (1-p_1)^{1-\xi}\right]. \end{aligned}$$

Average tail wealth is obtained by setting $p_1 = 0$ and $p_2 = 1$,

$$E(Y) = \mu - \frac{\sigma}{\xi} + \frac{\sigma}{\xi \cdot (1-\xi)}.$$

Per construction, $E(Y) = AVG(p)$.

For a standard Pareto distribution with threshold parameter y_0 and shape parameter ϑ, one substitutes $y_0 = \mu = {}^{\sigma}/_{\xi}$ and $\vartheta = {}^{1}/_{\xi}$, and obtains

$$E_{Pareto}(Y|Y \in Q) = \frac{\vartheta y_0}{(1-\vartheta) \cdot (p_2 - p_1)} \cdot \left[(1-p_2)^{1-{}^{1}/_{\vartheta}} - (1-p_1)^{1-{}^{1}/_{\vartheta}}\right]$$

as derived in Chakraborty and Waltl (2018), appendix D.

For each wealth stratum (i.e., each quartile of the tail distribution), the total wealth is calculated by multiplying the respective conditional expectation by the number of households belonging to the wealth stratum. The resulting stratum-specific wealth is broken down on instrument-level by multiplying it by an average portfolio structure observed for the respective quarter in the HFCS yielding aggregates for the tail and eventually also total instrument-specific aggregates.

Given the large increase in total wealth, consequently also instrument-specific aggregates rise. Table 12 reports changes in aggregates after the top tail adjustment. Changes are compared to those implied when adjusting the top tail using rich list data, the regression method proposed by Vermeulen (2016) and the analytical approach proposed by Chakraborty and Waltl (2018). I make use of observations from the Forbes World's Billionaires list and a national rich list (Capital). The table reports findings for the top 3% share as this corresponds best to the adjustment based on the rich list data.[54]

Adjustments relying on observed wealth shares are very similar to the adjustments using the Forbes World's billionaires list or the CAPITAL list as an external data source to quantify the impact of the "missing wealthy." When using the Forbes list, increases are largest, whereas relying on the wealth share reported in the WID.world database yields the lowest adjustment. Results from the CAPITAL list lie in between but are very close to the Forbes results.

The fact that the exact choice of rich list does not seem to matter a lot increases confidence in the approach. The Forbes list is substantially shorter than the Capital list (43 as compared to 100 in 2014).

Alstadsæter et al. (2017, 2018) document large holdings of wealth stored in off-shore tax havens. They conclude that the top shares estimated from tax files alone thus constitute a lower bound of the true wealth share.

[54] When relying on rich lists, the empirical tail estimated from the HFCS is replaced for all millionaires, which corresponds in France approximately to the 97.1% percentile (or equivalently the top 2.9%).

Thus, relying on a top tail adjustment based on rich lists appears reasonable. But it needs to be acknowledged that top tail corrections are just estimations. The missing wealth at the top is, however, substantial according to any data source taking as benchmark. Ignoring these shortcomings are hence more problematic than the insecurity arising from picking the one or other data source and estimation techniques to adjust for it.

Table 12: Change in HFCS aggregates.

		Change in Aggregates		
		Top 3% share	Forbes list	CAPITAL list
1	Liabilities	3.70	5.44	5.23
2	Deposits	6.11	8.18	7.81
3	Bonds	47.72	62.69	58.58
4	Investment Funds	16.72	24.01	22.52
5	Listed Shares	36.66	49.09	46.87
6	Other Businesses	21.70	33.77	30.76
7	Real Estate (business)	6.43	11.47	10.46
8	Real Estate (non-business)	9.96	14.86	14.52
9	Household's Main Residence	2.30	3.76	3.63
10	Vehicles	4.05	5.88	5.66
11	Valuables	3.24	6.21	5.56
12	Other	30.15	40.21	37.83
	Total	7.94	11.87	11.18

Notes: The table reports changes in aggregates in % after applying top tail adjustments. "Top 3% share" refers to the adjustment when relying on the WID.world wealth shares. "Forbes list" and "CAPITAL list" refer to the methodology by Chakraborty and Waltl (2018).

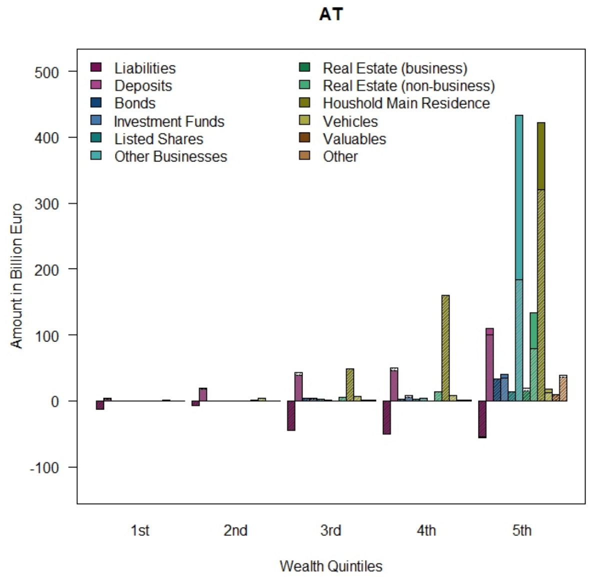
Besides the external data source used, the two top-tail-adjustments differ in two ways: first, the methodology relying on rich list observations explicitly corrects for the missing wealthy only. The estimation is not affected by the rest of the distribution. Relying on wealth shares as done here relies on the correct measurement of the rest of the distribution. For instance, the measured share held by the top could be too low because the lower part of the distribution is overestimated, the upper part of the distribution is underestimated, or both effects occur at the same time. Second, the approach by Chakraborty and Waltl (2018) relies on a more restrictive parametric model, namely the standard Pareto distribution, when estimating the top tail, whereas the methodology applied here estimates a GPD, which is a large family of distributions including the Pareto distribution as a special case. This is advantageous as the exact shape of the distribution is not determined by the econometrician but chosen by the data.

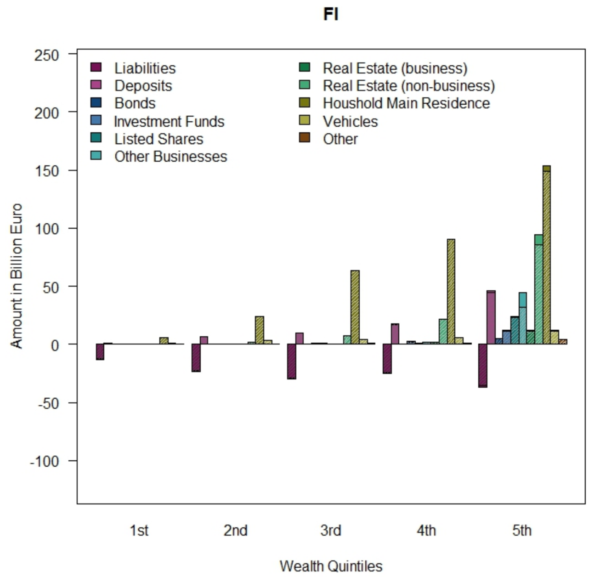
D Hybrid DINA

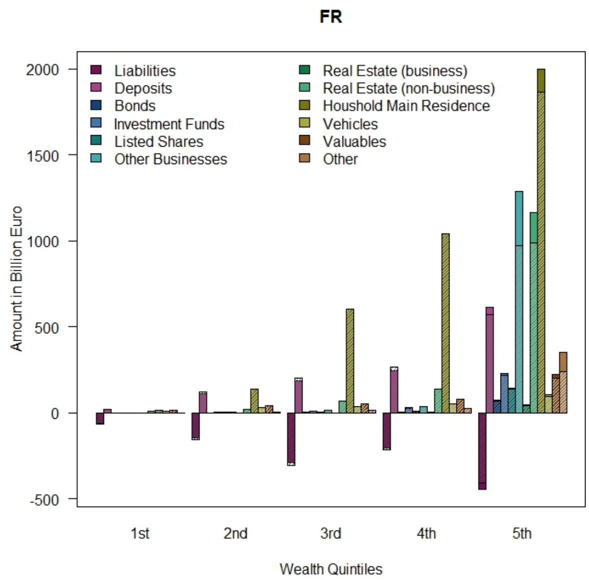
This appendix provides the full set of DINA results for Austria, Finland, France, Germany and Spain. Figure 12 and Figure 11 show break-downs by wealth groups with and without top-tail adjustment. Table 13 reports the corresponding numbers.

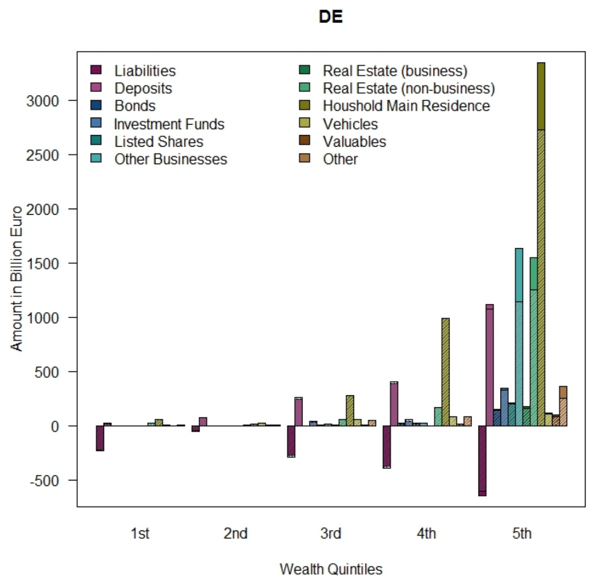
Figure 12 and Figure 13 show break-downs by income groups. Table 14 present again the corresponding numbers.

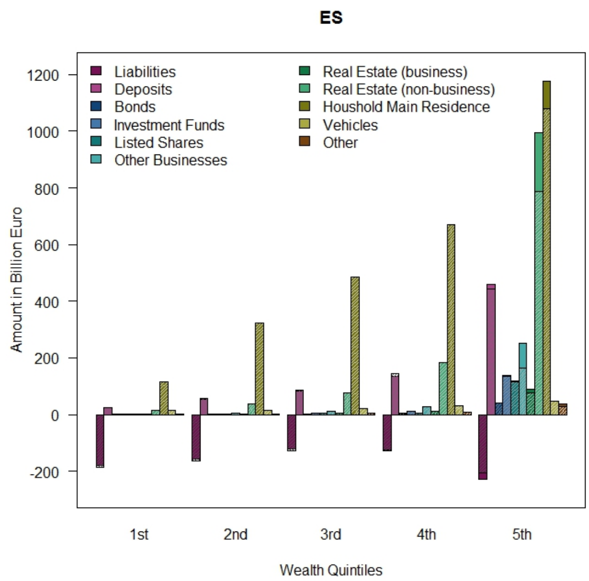
Figure 10: DINA for Wealth Groups: Aggregates.





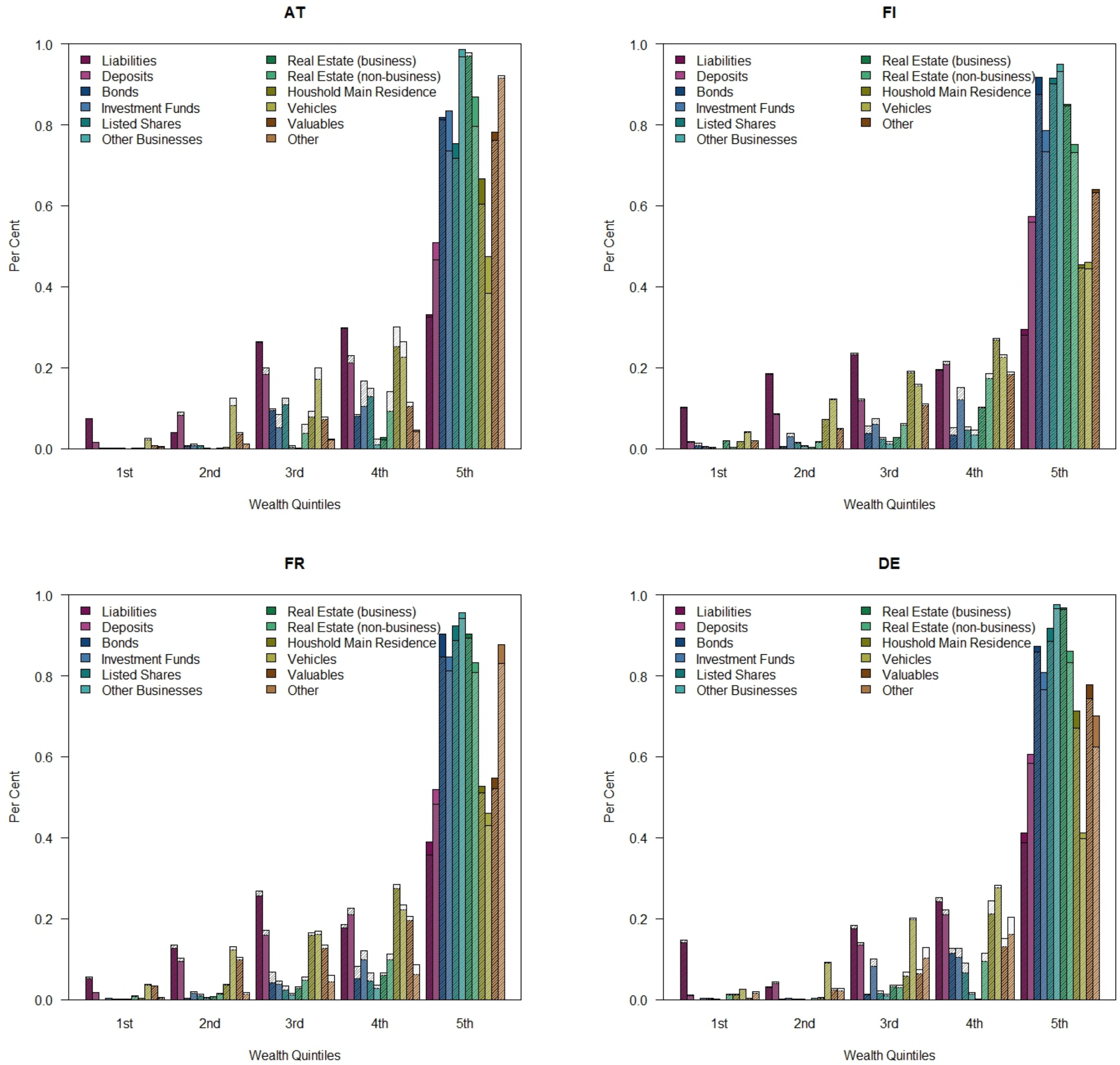


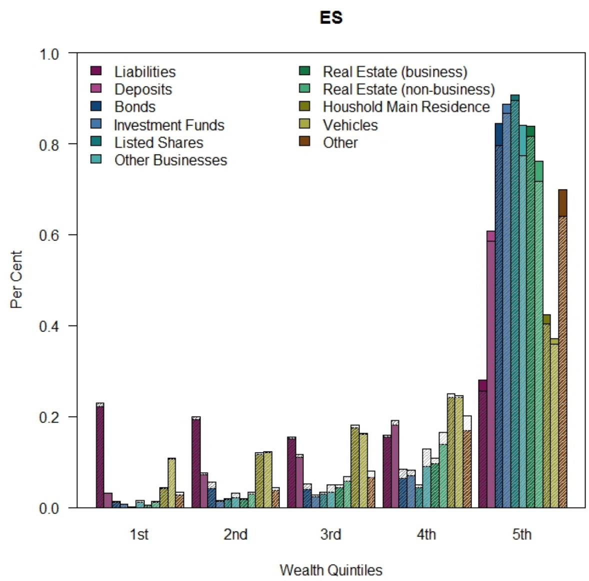




Notes: The figures show Hybrid DINA. Amounts are in billion euro and are broken down by net worth quintiles. Dashed bars show amounts before the Pareto adjustment and full bars after Pareto adjustment.

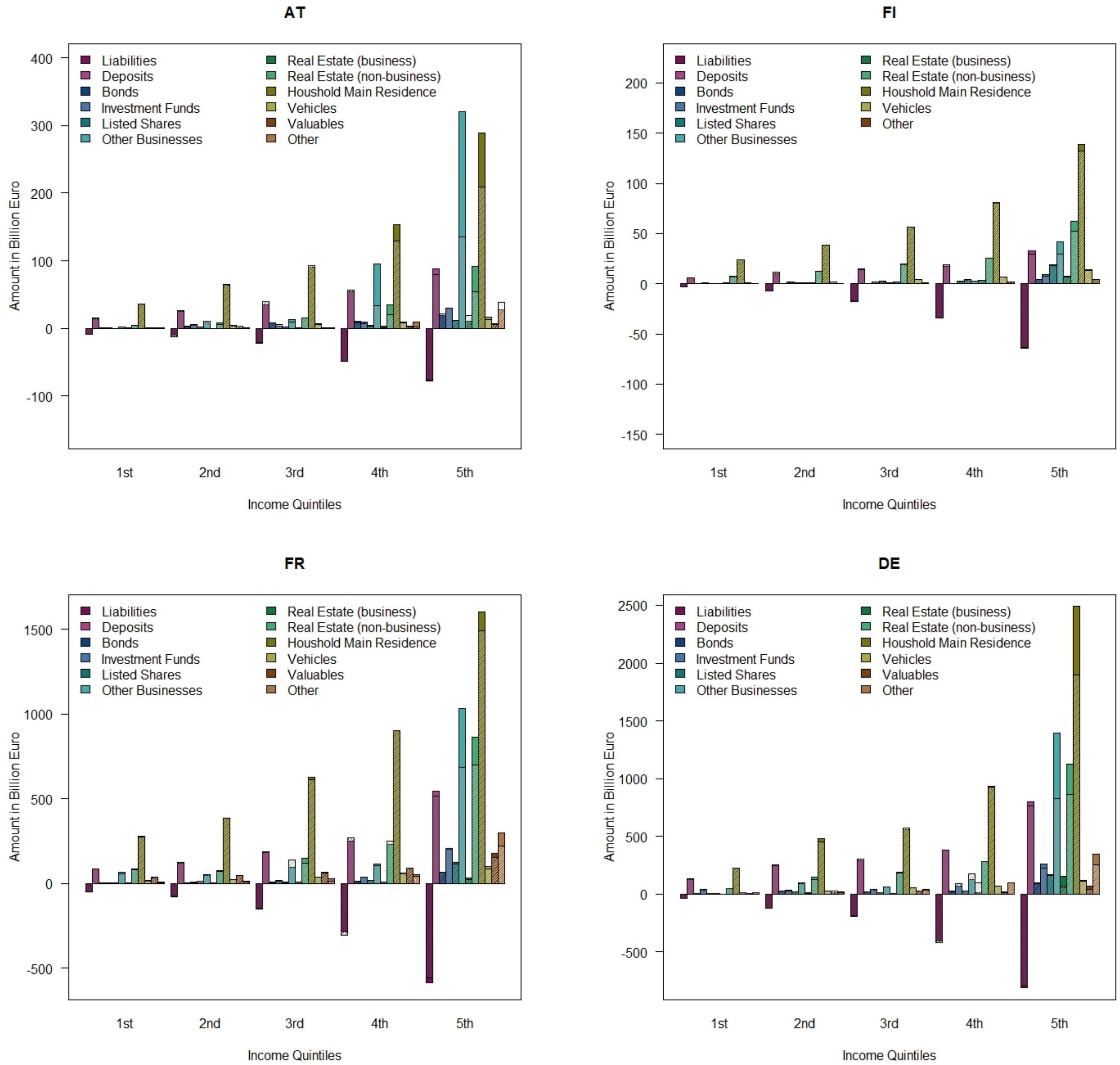
Figure 11: DINA for Wealth Groups: Shares.

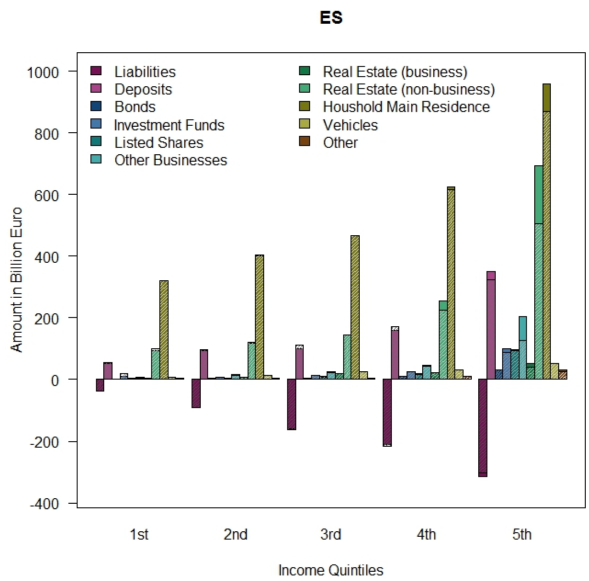




Notes: The figures show shares of different assets/liabilities held by each net worth quintile. Dashed bars show shares before the Pareto adjustment and full bars after Pareto adjustment.

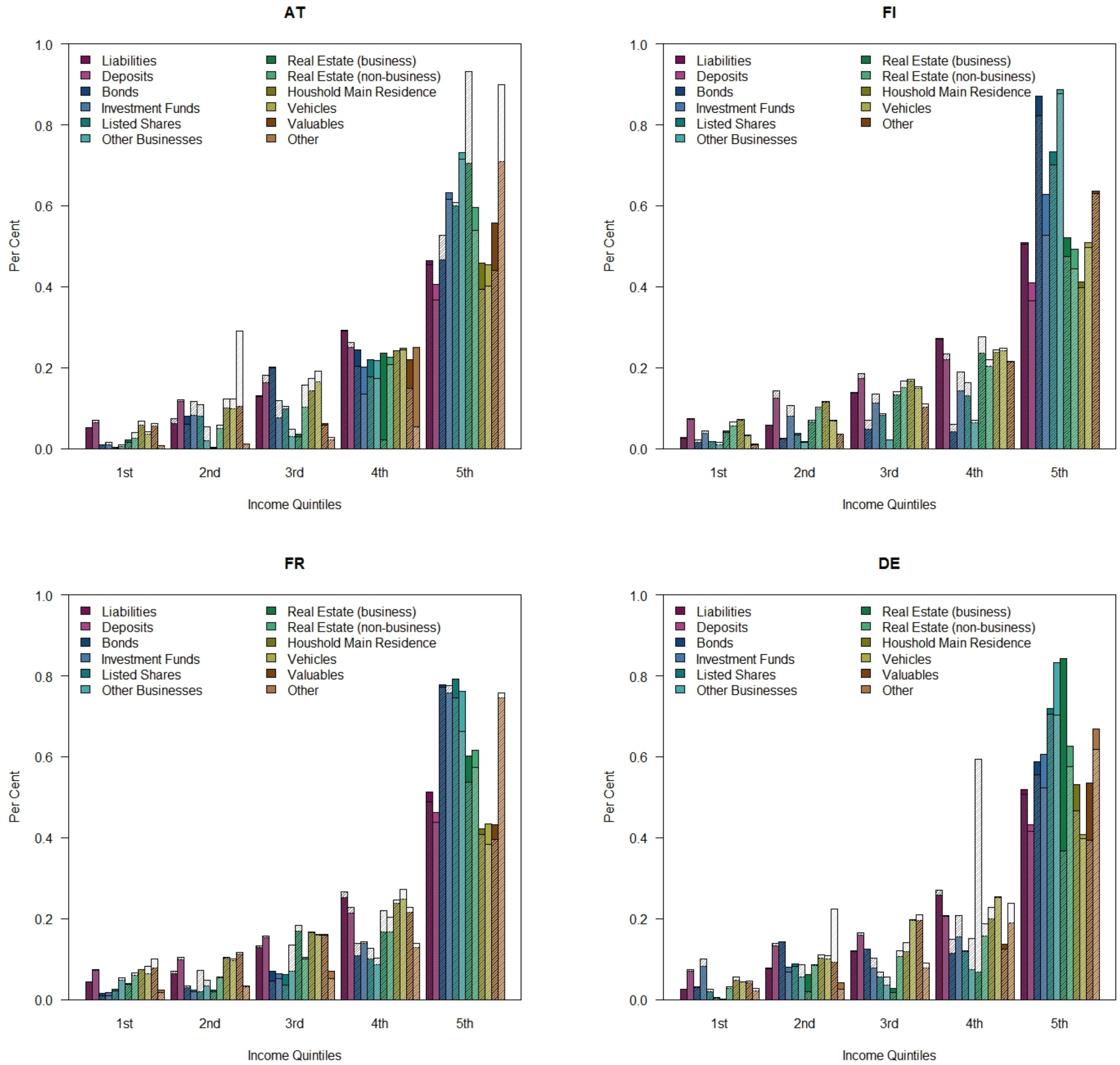
Figure 12: DINA for Income Groups: Aggregates.

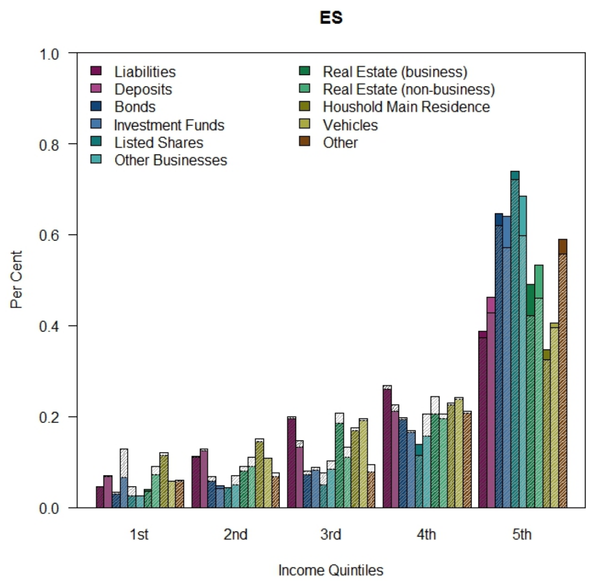




Notes: The figures show Hybrid DINA. Amounts are in billion euro and are broken down by gross income quintiles. Dashed bars show amounts before the Pareto adjustment and full bars after Pareto adjustment.

Figure 13: DINA for Income Groups: Shares.





Notes: The figures show shares of different assets/liabilities held by each gross income quintile. Dashed bars show shares before the Pareto adjustment and full bars after Pareto adjustment.

Table 13: DINA for Wealth Groups.

Austria (Wealth Groups)

							Housing Wealth						
					Business Wealth								
	Liabilities	Deposits	Bonds	Inv. Funds	Listed Shares	Other Businesses	Real estate (business)	Real estate (non-business)	HMR	Vehicles	Valuables	Other	Net Worth
I	-12.33	3.20	0.04	0.04	0.03	0.12	0.00	0.21	0.46	0.84	0.09	0.17	-7.13
II	-6.53	17.70	0.25	0.33	0.12	0.07	0.00	0.10	1.59	4.01	0.46	0.46	18.55
III	-44.01	39.53	3.85	2.52	2.07	1.40	0.03	5.90	48.98	6.42	0.92	0.88	68.49
IV	-49.87	45.56	3.29	5.03	2.45	4.28	0.42	14.08	159.55	8.52	1.35	1.77	196.43
V	-55.52	109.91	33.44	40.10	14.28	433.20	14.98	133.41	422.19	17.83	10.08	35.48	1209.38
Σ	-168.27	215.89	40.87	48.02	18.95	439.06	15.43	153.71	632.77	37.61	12.90	38.76	1485.70
$s80/s20$	4.50	34.40	933.25	900.76	544.07	3498.01	–	621.48	911.20	21.31	110.50	211.65	–
$s80/s40$	5.89	10.52	230.47	211.52	193.09	4529.20	–	861.50	412.09	7.36	36.67	113.26	211.89
$\lvert s80 - s20 \rvert$	2236	5526	1730	2074	738	22424	776	6897	21837	880	517	1829	62990
$\lvert s80 - s40 \rvert$	921	3528	1702	2037	724	22411	776	6876	21648	422	465	1772	61439

Finland (Wealth Groups)

							Housing Wealth						
					Business Wealth								
	Liabilities	Deposits	Bonds	Inv. Funds	Listed Shares	Other Businesses	Real estate (business)	Real estate (non-business)	HMR	Vehicles	Valuables	Other	Net Worth
I	-12.61	1.29	0.04	0.06	0.06	-0.01	0.27	0.37	5.53	1.06	–	0.13	-3.81
II	-22.98	6.68	0.02	0.45	0.35	0.24	0.04	2.03	24.28	3.20	–	0.32	14.64
III	-29.08	9.55	0.20	0.89	0.60	0.56	0.38	7.30	63.61	4.16	–	0.71	58.88
IV	-24.27	16.74	0.18	1.79	1.18	1.53	1.41	21.70	90.63	6.03	–	1.22	118.14
V	-37.00	46.10	4.88	11.71	23.55	44.30	12.00	94.57	153.81	12.29	–	4.26	370.48
Σ	-125.94	80.37	5.32	14.90	25.74	46.61	14.11	125.97	337.86	26.74	–	6.64	558.33
$s80/s20$	2.93	35.78	111.18	199.40	425.17	–	43.73	252.81	27.83	11.56	–	33.11	–
$s80/s40$	2.08	11.57	156.12	46.15	115.47	387.71	76.40	78.74	10.32	5.77	–	18.97	68.43
$\lvert s80 - s20 \rvert$	1860	3418	369	888	1792	3379	894	7184	11309	856	–	315	28544
$\lvert s80 - s40 \rvert$	2607	2300	363	815	1734	3344	867	6846	7183	287	–	256	26603

France (Wealth Groups)

								Housing Wealth					
					Business Wealth								
	Liabilities	Deposits	Bonds	Inv. Funds	Listed Shares	Other Businesses	Real estate (business)	Real estate (non-business)	HMR	Vehicles	Valuables	Other	Net Worth
I	-59.71	19.71	0.00	0.73	0.06	1.79	0.03	10.09	15.16	8.26	13.33	1.55	11.01
II	-145.79	111.82	0.21	4.19	1.34	4.83	0.36	18.30	136.38	28.91	40.43	5.29	206.28
III	-291.61	188.18	3.52	9.80	3.52	16.24	1.40	67.88	601.68	37.59	51.97	17.31	707.48
IV	-201.67	247.80	4.26	26.10	7.06	37.72	3.00	137.61	1041.14	51.95	79.77	24.81	1459.54
V	-444.24	613.64	75.06	226.63	144.14	1290.90	44.87	1163.64	2000.23	108.02	224.02	350.33	5797.24
Σ	-1143.01	1181.16	83.05	267.46	156.11	1351.47	49.65	1397.52	3794.60	234.73	409.53	399.29	8181.56
$s80/s20$	7.44	31.13	–	309.97	2399.30	721.08	1791.04	115.36	131.93	13.07	16.81	225.52	526.74
$s80/s40$	4.32	9.33	726.07	92.02	205.88	390.18	230.81	81.98	26.40	5.81	8.33	102.45	53.36
$\|s80 - s20\|$	2650	4094	517	1557	993	8885	309	7951	13682	688	1452	2404	39881
$\|s80 - s40\|$	229	2416	514	1494	974	8806	304	7629	11697	232	803	2320	36961

Germany (Wealth Groups)

								Housing Wealth					
					Business Wealth								
	Liabilities	Deposits	Bonds	Inv. Funds	Listed Shares	Other Businesses	Real estate (business)	Real estate (non-business)	HMR	Vehicles	Valuables	Other	Net Worth
I	-220.98	18.73	0.01	1.22	0.42	0.87	0.00	20.00	56.65	7.39	0.41	8.02	-107.25
II	-46.73	74.43	0.08	1.13	0.09	1.30	0.00	5.26	18.65	26.28	2.98	10.87	94.35
III	-275.11	247.27	2.06	35.54	3.61	16.85	5.86	54.75	274.47	57.20	8.29	52.35	483.16
IV	-377.12	385.67	19.52	44.47	15.08	21.12	0.06	171.32	992.52	79.73	17.04	83.01	1452.42
V	-643.65	1113.09	148.34	347.86	211.07	1632.16	179.95	1548.22	3345.47	118.99	100.84	361.24	8463.58
Σ	-1563.57	1839.20	170.02	430.23	230.26	1672.31	185.87	1799.55	4687.75	289.59	129.57	515.48	10386.27
$s80/s20$	2.91	59.42	10522.73	284.13	505.94	1867.38	–	77.40	59.05	16.10	245.72	45.07	–
$s80/s40$	4.81	23.90	3220.83	294.96	835.77	1501.02	89315.70	122.56	88.86	7.07	59.41	38.26	–
$\|s80 - s20\|$	2131	5517	748	1748	1062	8224	907	7704	16580	563	506	1781	43208
$\|s80 - s40\|$	546	4672	747	1730	1059	8206	907	7550	16106	260	474	1631	42798

Spain (Wealth Groups)

						Business Wealth		Housing Wealth					
	Liabilities	Deposits	Bonds	Inv. Funds	Listed Shares	Other Businesses	Real estate (business)	Real estate (non-business)	HMR	Vehicles	Valuables	Other	Net Worth
I	-179.97	23.17	0.52	1.00	0.24	4.98	0.52	14.71	116.31	13.93	1.50	3.28	0.19
II	-157.12	54.51	2.10	2.09	2.17	6.01	1.81	37.71	324.46	15.85	1.99	6.67	298.25
III	-122.34	82.98	1.93	3.65	3.81	9.75	4.64	75.41	485.61	21.07	3.57	10.27	580.35
IV	-125.12	136.50	3.15	11.03	5.76	27.72	10.21	182.07	670.01	31.78	9.06	27.23	989.39
V	-227.74	459.92	41.92	138.87	118.59	601.59	89.91	993.57	1176.36	48.75	37.34	252.14	3731.22
Σ	-812.30	757.07	49.61	156.64	130.59	650.06	107.08	1303.46	2772.76	131.37	53.47	299.59	5599.41
$S80/S20$	1.27	19.85	81.34	138.77	484.10	120.86	172.78	67.55	10.11	3.50	24.86	76.77	19236.48
$S80/S40$	1.35	11.84	32.10	89.89	98.06	109.48	77.24	37.91	5.34	3.27	21.37	50.64	25.00
$\|S80-S20\|$	548	5012	475	1582	1358	6846	1026	11232	12164	400	411	2856	42812
$\|S80-S40\|$	5123	3495	421	1523	1305	6651	978	10198	3383	124	348	2665	35965

Notes: The table reports DINA figures for wealth broken down by wealth groups (quintiles of the net worth distribution). Numbers are in billion euro and top tail adjusted. Pink cells form the integrated account: numbers are thus scaled to match national accounts totals. Blue cells are pseudo-integrated: the sum of the real estate (non-business) and HMR is interpreted as households' housing wealth excl. NPISH – a split-up that is currently not reported in the NA. The inequality measure $S80/S20$ refers to the ratio of average holdings by the top 20% over the average holdings of the bottom 20% (in terms of wealth). Additionally, the ratio of average holdings of the bottom 40% as compared to the holdings of the top 20% is reported ($S80/S40$). The absolute difference in average holdings between the bottom 20%/40% and the top 20% is reported in euro ($|S80-S20|$ and $|S80-S40|$).

Table 14: DINA for Income Groups.

Austria (Income Groups)

							Housing Wealth						
					Business Wealth								
	Liabilities	Deposits	Bonds	Inv. Funds	Listed Shares	Other Businesses	Real estate (business)	Real estate (non-business)	HMR	Vehicles	Valuables	Other	Net Worth
I	-8.41	14.02	0.57	1.01	0.10	1.14	0.33	4.38	33.53	1.25	0.58	0.32	48.83
II	-10.79	24.44	3.05	3.40	1.45	4.68	0.05	7.70	63.42	3.64	1.49	0.45	102.98
III	-21.37	34.94	8.17	3.77	1.85	17.74	0.54	16.00	90.58	6.17	0.88	1.04	160.30
IV	-51.43	55.61	10.52	8.28	4.45	78.21	2.97	32.87	152.18	9.43	2.68	7.83	313.60
V	-76.28	86.89	18.56	31.56	11.09	337.29	11.55	92.75	293.07	17.13	7.28	29.11	859.99
Σ	-168.27	215.89	40.87	48.02	18.95	439.06	15.43	153.71	632.77	37.61	12.90	38.76	1485.70
$s80/s20$	9.07	6.20	32.50	31.19	107.39	295.23	34.91	21.17	8.74	13.74	12.49	90.93	17.61
$s80/s40$	7.95	4.52	10.24	14.31	14.31	115.88	61.23	15.35	6.05	7.01	7.02	75.74	11.33
$\lvert s80 - s20\rvert$	3514	3774	931	1582	569	17405	581	4576	13439	822	347	1491	42002
$\lvert s80 - s40\rvert$	1962	517	585	1177	414	16862	559	3551	5136	381	162	1428	28809

Finland (Income Groups)

							Housing Wealth						
					Business Wealth								
	Liabilities	Deposits	Bonds	Inv. Funds	Listed Shares	Other Businesses	Real estate (business)	Real estate (non-business)	HMR	Vehicles	Valuables	Other	Net Worth
I	-3.25	5.83	0.08	0.56	0.43	0.42	0.61	6.92	23.77	0.84	–	0.07	36.29
II	-7.28	10.01	0.13	1.19	0.95	0.82	0.94	12.31	38.58	1.84	–	0.24	59.72
III	-17.21	13.98	0.26	1.68	2.09	1.01	1.89	18.94	56.53	3.98	–	0.68	83.82
IV	-34.00	17.58	0.22	2.13	3.38	3.01	3.33	25.67	80.10	6.46	–	1.42	109.30
V	-64.21	32.96	4.64	9.35	18.89	41.36	7.34	62.12	138.88	13.63	–	4.23	269.20
Σ	-125.94	80.37	5.32	14.90	25.74	46.61	14.11	125.97	337.86	26.74	–	6.64	558.33
$s80/s20$	19.74	5.66	56.10	16.71	43.88	98.00	12.04	8.97	5.84	16.22	–	57.98	7.42
$s80/s40$	12.20	4.16	44.67	10.69	27.37	66.84	9.47	6.46	4.46	10.19	–	27.14	5.61
$\lvert s80 - s20\rvert$	4649	2069	347	670	1408	3122	514	4210	8779	975	–	317	17763
$\lvert s80 - s40\rvert$	3291	97	322	446	1230	2966	324	1804	1082	631	–	275	5886

France (Income Groups)

							Housing Wealth						
					Business Wealth								
	Liabilities	Deposits	Bonds	Inv. Funds	Listed Shares	Other Businesses	Real estate (business)	Real estate (non-business)	HMR	Vehicles	Valuables	Other	Net Worth
I	-49.91	84.74	1.34	4.59	4.01	65.06	1.97	83.50	279.49	14.80	32.07	9.70	531.34
II	-72.90	117.16	2.51	6.12	3.17	44.48	1.15	74.18	386.43	22.68	46.13	12.40	643.52
III	-145.95	180.55	5.73	17.25	9.68	95.44	8.41	145.86	624.45	37.12	66.25	28.11	1072.90
IV	-288.23	251.77	8.94	36.93	15.75	116.09	8.25	232.44	900.64	58.21	88.10	51.27	1480.17
V	-586.01	546.95	64.52	202.56	123.50	1030.40	29.87	861.54	1603.58	101.92	176.97	297.82	4453.63
Σ	-1143.01	1181.16	83.05	267.46	156.11	1351.47	49.65	1397.52	3794.60	234.73	409.53	399.29	8181.56
$s80/s20$	11.74	6.45	48.26	44.16	30.80	15.84	15.20	10.32	5.74	6.89	5.52	30.70	8.38
$s80/s40$	9.54	5.42	33.51	37.83	34.39	18.81	19.19	10.93	4.82	5.44	4.53	26.95	7.58
$\|s80-s20\|$	3695	3186	435	1365	824	6654	192	5363	9126	600	999	1986	27034
$\|s80-s40\|$	2346	987	392	1249	752	5592	163	3765	1873	186	142	1748	14501

Germany (Income Groups)

							Housing Wealth						
					Business Wealth								
	Liabilities	Deposits	Bonds	Inv. Funds	Listed Shares	Other Businesses	Real estate (business)	Real estate (non-business)	HMR	Vehicles	Valuables	Other	Net Worth
I	-39.42	128.15	5.05	35.37	4.30	5.52	0.08	49.40	225.89	12.39	5.35	11.51	443.58
II	-121.90	243.83	24.32	34.24	20.39	92.97	11.39	151.05	481.97	29.27	11.95	21.74	1001.20
III	-186.06	292.77	21.26	33.76	12.90	59.28	5.13	190.05	555.14	56.61	25.35	40.33	1106.53
IV	-403.84	378.15	19.58	66.57	27.27	122.80	12.58	283.84	934.26	73.03	17.65	97.60	1629.49
V	-812.35	796.29	99.80	260.29	165.40	1391.74	156.70	1125.22	2490.50	118.30	69.29	344.30	6205.47
Σ	-1563.57	1839.20	170.02	430.23	230.26	1672.31	185.87	1799.55	4687.75	289.59	129.57	515.48	10386.27
$s80/s20$	20.61	6.21	19.74	7.36	38.48	251.94	1969.61	22.78	11.03	9.55	12.96	29.91	13.99
$s80/s40$	10.07	4.28	6.79	7.48	13.40	28.26	27.33	11.23	7.04	5.68	8.01	20.71	8.59
$\|s80-s20\|$	3897	3368	478	1134	812	6988	790	5424	11417	534	322	1678	29048
$\|s80-s40\|$	2469	264	207	610	585	6023	674	3652	5418	176	175	1401	16717

Spain (Income Groups)

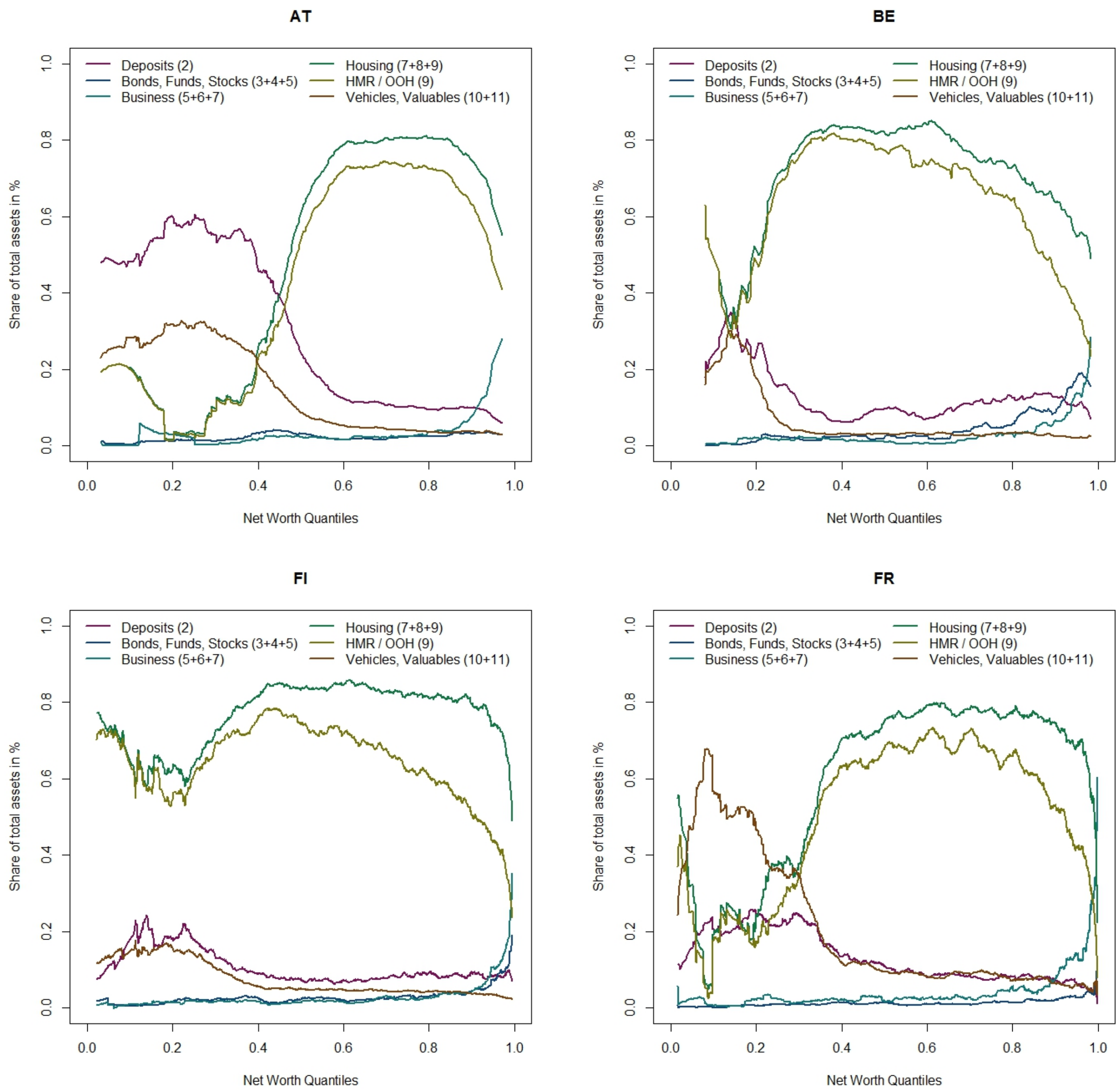
						Business Wealth		*Housing Wealth*					
	Liabilities	Deposits	Bonds	Inv. Funds	Listed Shares	Other Businesses	Real estate (business)	Real estate (non-business)	HMR	Vehicles	Valuables	Other	Net Worth
I	-37.57	51.75	1.50	10.23	3.44	14.75	4.16	94.56	319.61	7.62	3.07	7.54	480.67
II	-90.06	94.13	2.82	7.40	5.79	26.66	8.66	116.58	401.19	14.11	3.68	14.93	605.89
III	-158.46	100.68	3.61	12.81	6.54	40.12	19.83	143.55	466.30	25.18	4.13	25.14	689.43
IV	-211.29	160.33	9.64	25.80	18.22	99.16	21.97	254.84	625.86	31.23	11.08	47.08	1093.92
V	-314.93	350.18	32.04	100.40	96.60	469.36	52.46	693.94	959.80	53.23	31.51	204.91	2729.50
Σ	-812.30	757.07	49.61	156.64	130.59	650.06	107.08	1303.46	2772.76	131.37	53.47	299.59	5599.41
$S80/S20$	8.38	6.77	21.41	9.81	28.06	31.82	12.60	7.34	3.00	6.98	10.28	27.19	5.68
$S80/S40$	4.94	4.80	14.85	11.39	20.93	22.67	8.18	6.57	2.66	4.90	9.34	18.24	5.02
$\|S80-S20\|$	3183	3424	351	1035	1069	5216	554	6878	7346	523	326	2265	25804
$\|S80-S40\|$	685	670	269	748	897	4435	308	3117	5528	112	207	1836	6384

Notes: The table reports DINA figures for wealth broken down by income groups (quintiles of the gross household income distribution). Numbers are in billion euro and top tail adjusted. Pink cells form the integrated account: numbers are thus scaled to match national accounts totals. Blue cells are pseudo-integrated: the sum of the real estate (non-business) and HMR is interpreted as households' housing wealth excl. NPISH – a split-up that is currently not reported in the NA. The inequality measure $S80/S20$ refers to the ratio of average holdings by the top 20% over the average holdings of the bottom 20% (in terms of income). Additionally, the ratio of average holdings of the bottom 40% as compared to the holdings of the top 20% is reported ($S80/S40$). The absolute difference in average holdings between the bottom 20%/40% and the top 20% is reported in euro ($|S80-S20|$ and $|S80-S40|$).

E Relative Importance of Different Asset Classes Over the Distribution

Figure 14 shows the relative importance of different asset classes (as per cent of total assets) over the wealth distribution as a moving average. Figure 15 depicts the tenure status by wealth group. All figures use unadjusted data from the second wave of the HFCS.

Figure 14: Relative Importance of Different Asset Classes.



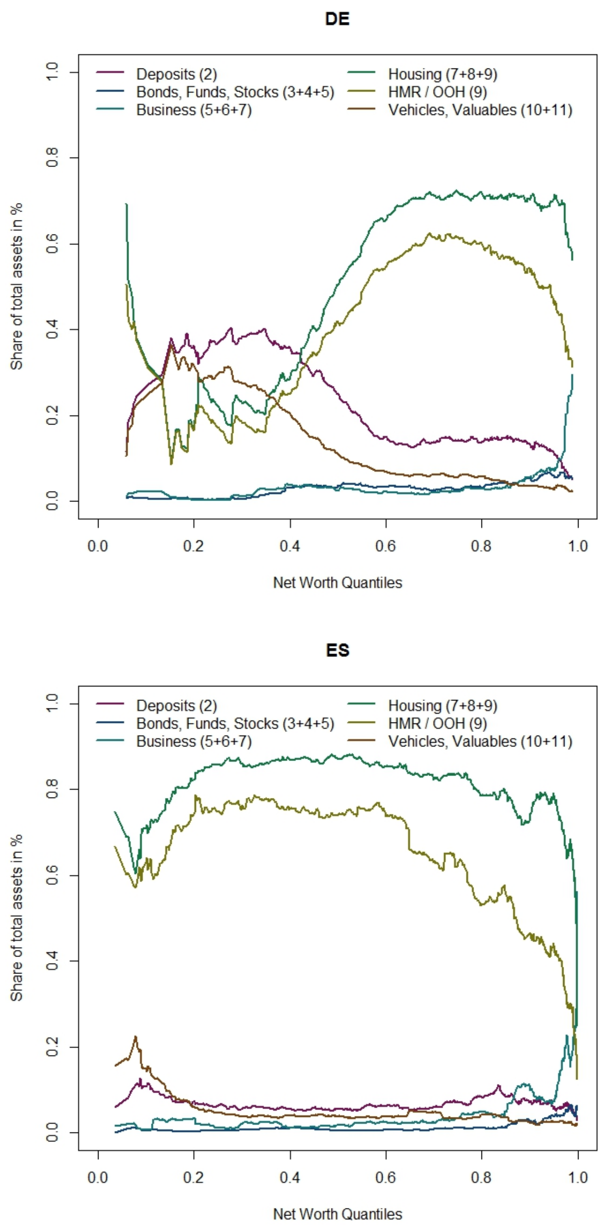


Figure 15: Tenure Status by Wealth Group.