A new instrument to measure wealth inequality: distributional wealth accounts

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In this study we investigate the sensitivity of different wealth measurement approaches. In this context, we analyze the alignment of Household Finance and Consumption Survey (HFCS) data with national accounts data and examine the production of distributional wealth accounts, which poses severe conceptual challenges. For a number of reasons, household surveys underestimate top wealth shares. We show that different assumptions generate a wide range of results for different wealth inequality indicators. In particular, the share of the top 1% of households in net wealth ranges from about 25% to about 50%, depending on the underlying assumption. Thus, while the true value of the wealth share held by the top 1% is unknown, all available information indicates that it is closer to 50% than to HFCS results. We call for caution in interpreting top shares as the underlying assumptions are mostly ad hoc choices made by data producers. Our study argues that we need better microdata on the top end of the net wealth distribution.

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Wealth inequality has moved center stage in economic debates today – even at central banks.[2] Thus, issues relating to wealth distribution measurement have become crucial. The well-known Stiglitz-Sen-Fitoussi Report (Stiglitz et al., 2009) already acknowledged the need for timely and adequate information on wealth inequality measurement. And for quite some time, various international institutions such as the Organisation for Economic Co-operation and Development (OECD), Eurostat, a number of research networks[3] and Thomas Piketty's World Inequality Database (WID)[4] have undertaken extensive efforts to improve wealth inequality measurement (see e.g. Chancel, 2022). These efforts yield yearly, quarterly or even real-time data on the distribution of wealth stocks.

The financial accounts are part of the System of National Accounts. In the next few years, the financial accounts will include distributional wealth information to complement the aggregate statistics in several countries. Wealth inequality measurement would then be able to draw on information on wealth ownership

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2 *See e.g. the paper by Doepke et al. (2019) presented at the ECB conference "Money Macro Workshop" in 2019 and the speech given by ECB Executive Board member Yves Mersch in Zurich in 2014, available at www.ecb.europa.eu/press/key/date/2014/html/sp141017_1.en.html.*

3 *For more information, see https://ec.europa.eu/eurostat/web/experimental-statistics/income-consumption-and-wealth.*

4 *https://wid.world/.*

with respect to specific socioeconomic groups, such as breakdowns by profession or ownership status regarding a household's main residence. The US Federal Reserve, for instance, already publishes distributional financial accounts – also as modern dashboards – on a regular basis.[5]

In this paper, we discuss the question of how reliable key statistics on distributional wealth indicators are. In the case of Austria considered in this paper, we find an extremely wide range of estimates for key indicators, depending on the underlying assumptions. We link micro- and macrodata on wealth and discuss various problems of the available data sources. We apply different procedures to correct for these problems. Essentially, we follow the literature (ECB, 2020) to generate distributional wealth accounts for Austria and assess the sensitivity of key results with respect to assumptions made during the estimation procedure.[6] The goal of our analysis is to assess the impact potential of ad hoc assumptions on results which will, in turn, be used later. We refrain from any judgment on which simulation procedure is preferable. Our focus on Austria limits the specific results of our analysis, although the more conceptual points apply more broadly. Close inspection of the statistical variability of estimates, i.e. looking at standard errors and/or variability due to imputation, sampling and estimation methods used, is left to future research.

In the EU, the quality of statistical data is regulated by the "Quality Assurance Framework of the European Statistical System."[7] According to this framework, the quality of statistical data is "measured by the extent to which the statistics are relevant, accurate and reliable, timely, coherent, comparable across regions and countries, and readily accessible by users, [...]" (European Statistical System, 2019, p. 45). Our analysis only considers the question whether statistical data are accurate and reliable. Accuracy is determined by the closeness of an estimate and its true counterpart in reality. But as the true value of an indicator is not known in practice, this criterion cannot be assessed adequately. The impact of alternative assumptions on the resulting data provides information on the reliability of data points that are eventually published.

The actual magnitude of wealth inequality is unknown. Without an external reference to "true" wealth concentration, it is not possible to judge what kind of assumptions are more or less "plausible" (Mooslechner et al., 2004). Plausibility itself is in the eye of the beholder.

An accurate Global Asset Registry would make it possible to provide the missing wealth data. In addition, such a registry could be a tool against illicit financial flows. The European Commission is currently investigating the idea of an EU Asset Registry.[8] A Global Asset Registry would centralize relevant information on assets owned by natural persons, thereby providing information on global wealth concentration and on whether wealth data correspond to income tax register data. These data would also allow for depicting distributional wealth accounts in the System of National Accounts without requiring an extensive estimation

[5] *www.federalreserve.gov/releases/z1/dataviz/dfa/.*

[6] *While we look at stocks recorded in the household balance sheet, the impact of modeling choices on flows such as income is discussed in Humer et al. (2021).*

[7] *https://ec.europa.eu/eurostat/documents/64157/4392716/ESS-QAF-V2.0-final.pdf.*

[8] *www.brusselsreport.eu/2021/08/30/european-commission-investigates-the-idea-of-an-eu-asset-registry/.*

procedure, which is necessary if results are based on survey data alone. To be effective, such a registry would need to be fully global, with measures in place to ensure compliance.

This paper is structured as follows: Section 1 introduces the data used in our study. In section 2, we refer to the related literature and present the investigated problem. We also discuss different modeling approaches as well as a selection of important assumptions. Section 3 discusses the results and section 4 draws policy conclusions.

1 Data and data sources

This section introduces the various data sources underlying our study. First and foremost, we use information from the Household Finance and Consumption Survey (HFCS) and the national accounts (NA) for Austria. Administrative microdata on wealth would improve our wealth estimates but such data do not exist in Austria, given that the wealth tax was abolished in 1994 and the inheritance tax in 2008. As capital income tax is deducted at the source, capital income tax information cannot be used, either. Moreover, because micro- and macrodata are constructed in different ways, it is important to consider how comparable the resulting data might be.

1.1 Household Finance and Consumption Survey (HFCS)

We use data from the third wave of the HFSC 2017 (www.hfcs.at) for Austria.[9] As a euro area-wide project, the HFCS gathers information on households' complete balance sheets, including detailed data on wealth, income, and expenditure, along with a rich set of socioeconomic variables. The unit of observation is the household.

The field period of the third wave ran from the end of 2016 until mid-2017 and comprised extensive quality checks, including the option to contact a household again to clarify details and/or correct deficiencies. About one-tenth of respondents (around 300 households) were recontacted to clarify or correct previously gathered information.

Missing information in the survey is multiply imputed, based on a chained Bayesian regression approach. Weighting ensures that the participating part of the gross sample represents the (targeted) household population in Austria along key demographic and geographic dimensions. Although the response rate in the Austrian HFCS 2017 is about 50% (see annex A, table A2), which is rather high compared with the rate observed in Germany and other countries, the observed sample is likely biased in ways that are not corrected by weighting adjustments. Furthermore, there is no oversampling of the affluent population in the Austrian HFCS 2017. A crucial difference between the set of survey participants and the overall population is the absence of very wealthy households in the HFCS.[10]

[9] *For the corresponding first results report, see Fessler et al. (2018), and for the methodological report containing the technical details, see Albacete et al. (2018).*

[10] *The value of the net wealth of the most affluent household participating in the HFCS comes close to EUR 70 million (in one implicate). Furthermore, there are fewer than five observations in each implicate that are above EUR 10 million.*

1.2 National accounts (NA)

The System of National Accounts has been well established for more than a century. Its newest requirements are laid down in the European System of Accounts (ESA) 2010. In its publication *"European system of accounts – ESA 2010,"*[11] the European Commission provides the details and definitions of the national accounts (NA). In this paper, we use NA data for Austria for Q1 17, which correspond to the middle of the field period of the HFCS data used.

1.3 Data alignment

In addition to aligning the reference periods of the two data sources (Q1 17), it is essential that the collected information and the definitions are comparable. The European Central Bank (ECB, 2020b) describes in detail the process of linking micro- and macrodata to produce distributional financial accounts and discusses the comparability of these data.[12]

Following the ECB's approach, the net wealth concept applied in this study differs from that used in the HFCS. Moreover, it does not follow the definition of financial wealth given in the national accounts. First, cash holdings are estimated in the NA but are not measured in the HFCS. Money owed between households nets out conceptually in the NA (as long as the related transactions take place between households in one country) but is available at the individual household level in the HFCS. Thus, both items need to be excluded from a comparable wealth definition. Additionally, other real assets such as cars or collectibles (which are included in the HFCS net wealth definition) are not considered in this exercise because they are not included in the NA figures.

Thus, for our purposes, net wealth includes the following items:

- deposits
- bonds
- shares
- funds
- entitlements from voluntary pension contributions
- business wealth
- housing wealth
- mortgages and other liabilities

Moreover, the household sector as defined in the national accounts also includes nonprofit institutions serving households (NPISHs) such as churches (for part of the household balance sheet). This definition differs from what is economically understood as being a household, and it also differs from what is referred to as households in public discussion. Thus, whenever possible, we exclude NPISHs from the NA figures used here. It is important to note that this separation is not possible for land underlying dwellings on the real asset side of households' balance sheets.[13] People living in institutions such as homes for the elderly or prisons are excluded from the target population in the HFCS. This separation differs from the NA accounting unit, which considers the entire resident population.

[11] *Available at https://ec.europa.eu/eurostat/documents/3859598/5925693/KS-02-13-269-EN.PDF.pdf/44cd9d01-bc64-40e5-bd40-d17df0c69334?t=1414781932000 .*

[12] *See also Andreasch and Lindner (2016), who show similarities and differences of micro- and macrodata.*

[13] *According to GEWINN (2019), 3 out of the 10 largest private holders of forests in Austria are monasteries.*

1.4 Other sources of information

The estimated totals derived from NA and HFCS data do not align well enough to support the straightforward joint usage of both data sources (see section 2.1). In particular, because HFCS estimates commonly fall short of NA estimates, we must look for other distributional information that may help address this shortfall. Additional information on the top tail of the wealth distribution may help improve the focus of the HFCS. To this end, we use information from several so-called *rich lists* and other sources, namely the following:

Forbes World's Billionaires list

This list is published yearly and ranks US-dollar billionaires around the world. The documentation Forbes provides on the methodology of data production is minimal.[14] Various estimations seem to be involved. Moreover, the fact that reported wealth is sometimes individual and sometimes aggregated across individuals makes correspondence to a household measure unclear. There are eight Austrians on the list, whose wealth ranges from USD 1.3 billion to USD 13.4 billion.[15]

Austrian rich list according to trend magazine

The Austrian business magazine *trend* publishes a list of the 100 richest Austrians,[16] including wealth data (partly expressed in ranges). There is no publicly available documentation of the methods applied to generate this list. A variety of sources seem to be used to compile information on net wealth. Past values are updated by recent valuations using information on stock value and economic development. The list only partly covers wealth held abroad and it includes persons no longer residing in Austria. The magazine does not make any claims for data completeness or quality, as would be the case with official statistics.

Despite its deficiencies, this list is often used to discuss issues concerning the top of the wealth distribution as it is the only nationally published rich list for Austria. In 2017, it listed 100 persons or families whose wealth ranged from EUR 150 million to EUR 35.7 billion, including 40 billionaires. Adjusting these data to the appropriate household level is impossible. Moreover, a lot of persons are listed within relatively large wealth intervals, such as between EUR 150 million and EUR 600 million. Since we do not have any additional information, we assume the level of wealth could be adequately described by the midpoints of the ranges.

[14] *With regard to the methodology used, Forbes publishes the following information on its website Forbes Billionaires 2021: The Richest People in the World (accessed on March 4, 2021): "The Forbes World's Billionaires list is a snapshot of wealth using stock prices and exchange rates from March 18, 2020. Some people become richer or poorer within days of publication. We list individuals rather than multigenerational families who share fortunes, though we include wealth belonging to a billionaire's spouse and children if that person is the founder of the fortunes. In some cases, we list siblings or couples together if the ownership breakdown among them isn't clear, but here an estimated net worth of USD 1 billion per person is needed to make the cut. We value a variety of assets, including private companies, real estate, art and more. We don't pretend to know each billionaire's private balance sheet (though some provide it). When documentation isn't supplied or available, we discount fortunes."*

[15] *As an aside, one of the surprising facts about the Forbes World's Billionaires list is that it does not contain billionaires from Luxembourg or Malta.*

[16] *Information on the latest trend rich list is available at www.trend.at/wirtschaft/ranking-oesterreicher-10848600 (accessed on October 14, 2021).*

OeNB in-house information

The Oesterreichische Nationalbank (OeNB) maintains a variety of data for internal use. The information used in this paper covers about 150 affluent individuals and/or households in Austria whose net wealth is estimated to range between EUR 500 million and EUR 45 billion. Individuals can be mapped into households (i.e. whether they are living together or not) but net wealth held in shared ownership of a company cannot be split. These data can be used to assess the quality of the published rich lists and, potentially, to model the top of the wealth distribution in Austria.

The Austrian business register database Sabina

In addition to the data introduced above, we also rely on information derived from the Austrian business register database *Sabina*. With the data available there, it is possible to create a database of about 2,600 owners of companies other than stock companies with an average market value of about EUR 30 million (with valuations ranging from a minimum of EUR 5 million, i.e. the minimum imposed to be included in the list, to about EUR 2.3 billion, including six billionaires). The estimation of a company's market value is based on the book value. A look-through approach to ownership records identifies the ultimate owner of a company, so that we can work with personal-level information instead of information at the level of individual companies. Double-counting of certain business assets is possible in the lists we use. Additionally, there are flaws as some companies are registered abroad. We do not claim that this is the best information available on companies. For us, this additional information solely serves as another example of a potential basis for modeling the top of the wealth distribution as introduced below.

2 Wealth measurement problems

This section presents the basic problems of aligning micro- and macrodata and approaches on how to tackle them. In the process, we seek to document the reasons why these two measures may differ.

2.1 Coverage rates

To jointly analyze wealth survey and NA data in a meaningful way, both data sources should cover items that are conceptually the same, as discussed above. One of the main additional obstacles in generating national distributional wealth accounts, however, is the relatively low coverage rate of certain wealth components in wealth surveys compared to the NA.

Chart 1 shows the coverage rates for aggregates of selected financial wealth categories whose definitions in the HFCS and the NA are comparable.[17] We see that the coverage rate varies substantially across financial instruments. In general, survey data tend to underestimate aggregate NA figures. However, aggregates derived from the survey can also be above 100% in relation to NA aggregates, e.g. for business wealth.[18] Linking HFCS business wealth (non-self-employment private business and self-employment business) data to NA business wealth data (F512

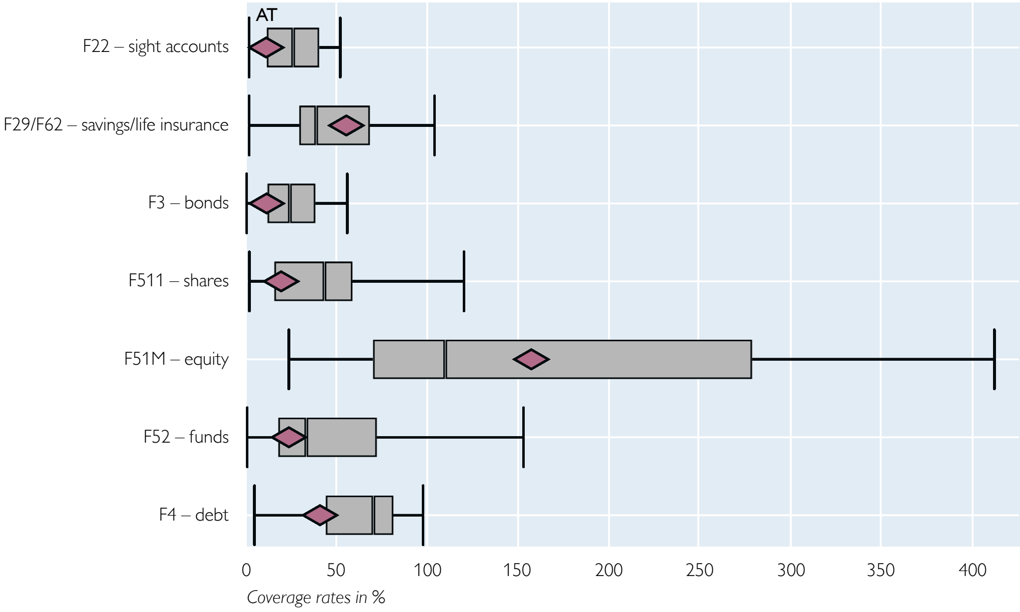
[17] *Similar information can be found e.g. in ECB (2020b) or, for Austria, in Andreasch and Linder (2016).*

[18] *The sampling variability for the estimate of total business wealth may be rather high given the low number of observations of relatively large wealth values.*

Chart 1

Coverage of NA aggregates by HFCS aggregates

Financial instruments



Source: HFCS 2020, ECB, national accounts and/or sector accounts for the middle of the reference period.

Note: This chart shows the ratio of aggregates estimated from HFCS data to NA aggregates for 20 European countries. Austria is indicated by diamonds. Boxes are defined by the 25th and 75th percentiles, with the median indicated by a bar. The whiskers at the low (high) end indicate the lowest (highest) value above the 25th percentile minus (below the 75th percentile plus) 1.5 times the interquartile range.

unlisted shares + F519 other equity + mainly nonfinancial assets) remains a key challenge.

Coverage rates in Austria (marked by the diamonds in chart 1) are comparable to those in other euro area countries.[19] Thus, we expect the exercise below to yield similar results for other countries.

2.2 Discussion of potential problems

Depending on the reasons for the discrepancies in coverage noted above, the appropriate way to adjust information on wealth will vary. Among the principal sources that explain the differences between the micro- and macrodata described above are the following:

Missing the top

Based on the results presented in the literature (see e.g. Vermeulen, 2018), it seems that extreme wealth concentration at the top of the distribution explains a substantial fraction of the undercoverage shown above. We discuss this issue in greater

[19] *In Austria, life insurance contracts are considered a saving vehicle. For this reason, we aggregated the wealth categories and/or financial instruments F29 and F62 to make coverage rates more easily comparable across countries. See Fessler et al. (2018) for details on how information on life insurance contracts is collected in Austria. We only use data on endowment insurance contracts, i.e. contracts that provide for payout at the maturity date also in case the insured person is still alive.*

detail in sections 3.2 and 3.3. The tables in annex A show the response behavior of HFCS samples. Both respondents' refusal to participate in a survey at all as well as their refusal to answer specific questions pose serious difficulties to conducting wealth surveys.[20]

Timing

Timing issues might arise because NA figures are recorded as of the end of the year or quarter, whereas the corresponding HFCS information is collected as of the time of the interview. The field period in Austria ran over three quarters from the end of 2016 to summer 2017. The bulk of the interviews took place in spring 2017, so we opted for Q1 17 in the NA as the best period for comparison. Financial assets in the NA e.g. increase from just below EUR 640 billion (Q4 16) to above EUR 670 billion (Q4 17), i.e. by around 5%.

Heaping

Heaping refers to the phenomenon of rounding in surveys. Respondents commonly round values or are asked to give approximate values. Such rounding is generally not an important issue with respect to NA data. Although rounding might explain some of the undercoverage shown above, the possibility of downward as well as upward rounding means the overall effect is, a priori, ambiguous.

Untruthful reporting

For a variety of reasons, some survey participants might fail to report or minimize certain items in their portfolio (see annex A, table A1 for item nonresponse rates), which may in turn explain part of the observed undercoverage. Unfortunately, there is very little information on the extent of insincere reporting in surveys. Since participation in the HFCS is voluntary in Austria, we might expect that participants would be less likely to waste their time in deliberately misreporting answers. Furthermore, interviewer training is considered very important in Austria. One of the few examples in the literature analyzing the deficiency of insincere reporting is Neri and Ranalli (2012). The authors directly link survey observations to bank register data for Italy, showing that, because of an underreporting of financial wealth, the measurement error can be sizable for the risky financial assets they consider. In their case, they find that, on average, reported values and register values differed by a factor of more than 5. On the other hand, Le Roux and Roma (2019) report a potential underestimation of real estate values by differing amounts across the countries included in the HFCS. Thus, the overall impact of untruthful reporting is, ex ante, unclear.

Recall bias

Some respondents may forget to report some small accounts, such as secondary sight accounts with small balances. But because the survey questionnaire is specifically designed to prompt recall of a specific set of assets and liabilities, it appears

[20] *In the Austrian HFCS, the group of households representing the very wealthy is selected by a random process that takes no account of wealth. Because of the great skewness of wealth at the top of the distribution, the resulting wealth estimates for that group would have a relatively large sampling variability even if we do not consider issues of nonresponse distortions induced by incorrect survey responses. Thus, in any given actual sample, the resulting wealth estimates for that group would often be far from the true population value.*

much less likely that a respondent would entirely forget such an item altogether. Recall of amounts, especially in cases where the respondent did not use records during the interview, may be more frequently subject to bias.[21] Additionally, the information recorded in the HFCS is the best approximation of distributional information about households' net wealth in Austria.

Estimations in the national accounts

At least in part, the NA are based on estimates. This being so, the information contained in the NA can be overestimated or underestimated, which may explain some coverage issues. For example, with regard to financial assets, cash holdings can only be estimated in the NA. The same applies to the aggregate level of real estate wealth which, given the lack of up-to-date register data on real estate, must be estimated in the NA in Austria.

Valuation of businesses

Not publicly traded businesses (i.e. those that are not listed at the stock exchange) are difficult to assess on the basis of the concept of market value. Instead, gross book values – which might differ substantially from market values – are used in the NA. By contrast, market values net of the liabilities of businesses in which at least one household member works and of which they own at least a part are recorded in the HFCS.

Problems in defining the research unit

Creating a common definition of the household sector that holds for both the HFCS and NA is far from straightforward. First, nonprofit institutions serving households (NPISHs) are considered together with private households on the real asset side in the NA. This means e.g. that in the NA, the wealth in land and structures owned by churches is included in the household sector of the real estate part of the household balance sheet. In the HFCS, NPISHs are not considered households.

In addition, assets and liabilities associated with small businesses (e.g. producer households) might be hard to classify consistently in both the NA and the HFCS. For example, a savings account registered personally to a dentist who uses it to run his or her business could be counted as business wealth or household savings, depending on the information available to classify it. The distinction made by the knowledgeable survey respondent might be more aligned with the function of said savings account, regardless of its formal nature, than a distinction made in constructing the NA.

Moreover, some individuals outside the HFCS target household population are included in, and cannot be separated from, the target population considered in the NA. Thus, the undercoverage shown above is in part attributable to differences in the target populations.

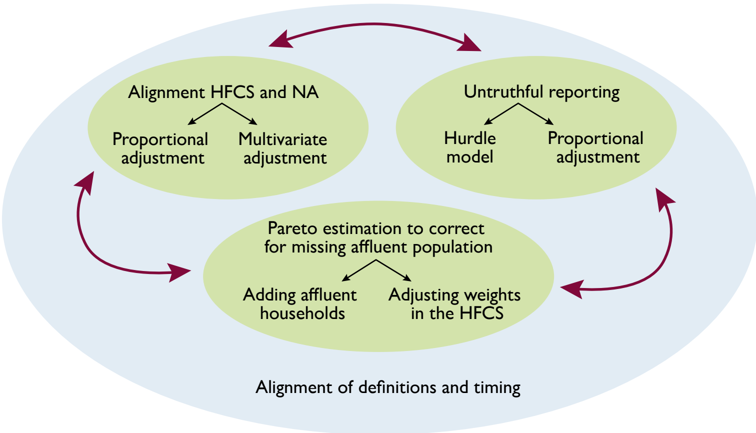
2.3 Modeling approaches – how to tackle problems

To tackle coverage issues and to align the aggregate results obtained from the micro- and macrodata, several modeling avenues can be taken. Figure 1 gives an overview of the three main types of action taken to align HFCS data with NA data:

[21] *See also Biancotti et al. (2008) for a discussion of such a measurement error in a wealth survey.*

Figure 1

Overview of adjustments performed during HFCS and NA alignment



Source: Authors' compilation.

(1) alignment of aggregate HFCS results with corresponding NA figures; (2) adjustment of HFCS responses for untruthful reporting; and (3) correction for not capturing very affluent respondents in the HFCS.

Obviously, each of the blocks shown in figure 1 is interconnected with the other blocks. Adding data on affluent households to HFCS data would e.g. reduce the need for any upward adjustment of HFCS figures during data alignment. Such adjustments can be modeled by applying a variety of approaches, any of which require assumptions that are interconnected and will influence the results. Even more assumptions and more model combinations would arise if we were to model separately the coverage problems of "timing," "recall bias," or "heaping."

We consider combinations of various data adjustments to address the sensitivity of key distributional results to these adjustments and, implicitly, to data imperfections. The sequence of modeling approaches considered in the alignment of HFCS and NA data is given in the list below:

- proportional adjustment or no proportional adjustment;
- hurdle model adjustment or no hurdle model adjustment;
- Pareto distribution (to model top of distribution by adjusting weights or simulating new households);
- final grossing-up by multivariate calibration or proportional adjustment (to achieve full alignment of HFCS and NA aggregates).

In the following, we introduce all modeling components. Technical details are provided in annex B.

The modeling procedure may start with an initial *proportional adjustment,* which means that each item of the household balance sheet is adjusted by a simple constant factor to align aggregate figures. This factor is derived by the ratio of NA starting aggregate figures to HFCS starting aggregate figures. If taken alone, this approach implicitly assumes that the entire undercoverage of wealth in the HFCS results from uniform underreporting of wealth amounts by survey respondents.

The *hurdle model adjustment* as applied here implicitly assumes that any underreporting by individual survey respondents is due entirely to their not reporting the existence of an item, but the existence and the amount of any item actually reported is taken to be correct. The model uses the observed data to calculate a propensity to hold each item and applies a randomized process to households reporting they did not have an item to assign ownership of such item to these households. In essence, it is a way of including households that appear to be relatively close to owning a specific type of asset or liability.

By considering the data adjustments performed with or without *hurdle model adjustment,* we can assess the sensitivity of these adjustments. Both adjustment procedures – *hurdle model* and *proportional adjustment* – can be considered a means of correcting for underreporting. The first approach tackles underreporting by adjusting reported values and the second by negating reported non-ownership of an asset or liability.

The central element in all these combinations of approaches is the modeling of "missing" rich households by means of a *Pareto distribution* (see annex B for more details on the related estimation).[22] Using Pareto estimates, we can adjust the weights of the richest households in the HFCS to mimic the Pareto distribution ("adjust weights") or add some particularly rich synthetic households ("add wealthy households"). This part of data adjustment addresses the possibility that the observed set of households is incorrect because some households are missing altogether or some are incorrectly characterized in terms of their ability to be representative of the population.

The *final grossing-up adjustment* aligns whatever difference remains between the aggregate figures of the HFCS and the NA. Data alignment is generally not achieved before this step is completed, no matter which of the previous steps were actually performed. Two possible approaches at this stage are *simple proportional adjustment or multivariate calibration adjustment*. The former uses a simple constant adjustment factor (again, based on the ratio of totals derived from micro- and macrodata). The latter is implemented via a generalized linear weight adjustment with bounds on the adjustment factor that minimizes a quadratic loss function subject to reaching aggregate figures for both the top of the distributions (above the Pareto threshold) and the remainder of the household population.

Each step of this modeling procedure depends on specific assumptions. Unfortunately, there is very limited theoretical foundation for the choice of these assumptions. The ad hoc approaches considered here are rather pragmatic; they are often applied as technical solutions to statistical problems. In the following section, we provide estimates of key statistics based on a variety of combined assumptions to explore the sensitivity of these statistics.

3 Results

3.1 Overall

In table 1, we report the key results on household wealth in Austria generated in the different modeling approaches described above.[23] Table 1 shows the mean, median, Gini coefficient and wealth shares for specific groups for the 16 different modeling approaches resulting from the combinations mentioned above.[24]

[22] *Kennickell (2019) shows the importance of the right tail of the net wealth distribution for the wealth distribution. Disslbacher et al. (2020) suggest a unified regression approach to estimate all parameters of a Pareto distribution jointly and extend our analysis by a more flexible three-parameter generalized Pareto estimation. They introduce a new database of national rich lists (ERLDB) as an alternative to commonly used global rich lists to combine with HFCS 2017 data. Furthermore, Kennickell (2021) proposes a new method to estimate a Pareto adjustment without relying on external information for the far end of the wealth distribution, relying only on a reliable estimate for the aggregate level of net wealth.*

[23] *We start with an arbitrary choice of a threshold of EUR 1 million above which the Pareto distribution is used to adjust the affluent part of the distribution. Below, we vary this parameter to explore the impact of our choice of threshold.*

[24] *We use these statistics because experience with almost a decade of HFCS results has shown that these statistics are most widely discussed.*

Table 1

Net wealth simulations performed to align HFCS and NA aggregates – overview

			Mean	Median	Gini coeffi-cent	Share in net wealth		
						Top 1%	Top 10%	Bottom 50%
			EUR thousand			%		
Unadjusted HFCS results			236.5	70.9	0.748	23.7	57.9	2.5
Adjustment models								
Prior proportional adjustment	Hurdle model	Pareto adjust weights, multivariate calibration	331.9	121.1	0.788	26.2	63.5	2.1
		Pareto adjust weights, proportional adjustment	331.9	123.3	0.771	25.7	59.9	2.3
		Pareto add wealthy households, multivariate calibration	331.6	113.7	0.814	32.6	66.4	1.3
		Pareto add wealthy households, proportional adjustment	331.6	115.3	0.791	32.6	62.3	1.8
No prior proportional adjustment		Pareto adjust weights, multivariate calibration	331.9	81.0	0.849	34.3	70.3	–0.5
		Pareto adjust weights, proportional adjustment	331.9	109.3	0.789	26.6	61.2	1.2
		Pareto add wealthy households, multivariate calibration	331.6	76.8	0.828	44.6	70.4	1.4
		Pareto add wealthy households, proportional adjustment	331.6	90.8	0.785	37.8	64.8	2.5
Prior proportional adjustment	No hurdle model	Pareto adjust weights, multivariate calibration	331.8	99.5	0.821	27.7	65.7	0.2
		Pareto adjust weights, proportional adjustment	331.8	102.7	0.804	27.5	62.6	0.5
		Pareto add wealthy households, multivariate calibration	331.6	90.5	0.841	33.6	68.2	–0.4
		Pareto add wealthy households, proportional adjustment	331.6	93.3	0.821	33.9	64.7	0.1
No prior proportional adjustment		Pareto adjust weights, multivariate calibration	332.0	73.2	0.873	37.9	72.1	–1.4
		Pareto adjust weights, proportional adjustment	332.0	105.7	0.799	27.8	61.7	0.6
		Pareto add wealthy households, multivariate calibration	331.6	71.0	0.837	47.5	71.3	1.0
		Pareto add wealthy households, proportional adjustment	331.6	86.3	0.787	38.2	64.9	2.5
Minimum			331.6	71.0	0.771	25.7	59.9	–1.4
Maximum			332.0	123.3	0.873	47.5	72.1	2.5

Source: HFCS Austria 2017, OeNB; trend rich list 2017; national accounts (OeNB, Statistics Austria).

Note: In absolute values, the net wealth of the top 10% (1%) of the distribution according to unadjusted HFCS results ranges from EUR 525,000 (EUR 2.1 million) to close to EUR 70 million. After the adjustment process, these figures are naturally higher.

Across all sets of adjustments, the mean of net wealth increases from EUR 237,000 in the unadjusted data to about EUR 332,000. This result and its stability are attributable to the last step of the whole modeling procedure where aggregate figures are fixed to the NA and the population is given exogenously. This determines the mean of net wealth. The median net wealth, however, varies strongly across adjustments. In the most extreme case, it almost doubles. The changes relative to the baseline (HFCS result) show an increase of about 75%. The Gini coefficients differ by about 0.1 (i.e. about 15%), depending on the choice of adjustments. Looking at the shares in net wealth, results for the bottom shares are more stable, in absolute terms, than results for the top shares. This points even more strongly toward the need to carefully model the top of the net wealth distribution. While the bottom 50% of the household population hold about 2.5% of total net wealth (HFCS results), simulated wealth levels yield a negative share of the bottom 50% in some cases of the multivariate calibration, which results from high levels of household debt.

In general, as the last step of the adjustment procedure, multivariate calibration produces higher levels of inequality. The mechanism behind this calibration method tries to achieve an alignment of aggregate NA and HFCS figures while changing household weights as little as possible. This implies increasing the weights of wealthy households to raise aggregate wealth levels in the HFCS. Thus, the mechanics of multivariate calibration in comparison with proportional adjustment –

i.e. multiplying the wealth of each household by a constant factor – are associated with higher levels of inequality.[25] Furthermore, the approach of simulating new households ("add wealthy households") yields more top-sensitive results, i.e. a higher level of estimated inequality (measured as top shares), given the scenario definition. We must keep in mind that the newly simulated households by definition own extremely high levels of net wealth and hence belong to the most affluent part of the population. Applying hurdle model and proportional adjustment before modeling the affluent population results in a less systematic impact.

Overall, the mean and the share of the bottom 50% of the population seem to be (much) more stable than the inequality indicator, median levels and top shares. This indicates how important it is to model the affluent part of the population. In the next two subsections, we take an in-depth look at measuring the top of the distribution. According to our estimations, the wealth ownership share of the top 1% of the distribution ranges between one-quarter and one-half.

3.2 Modeling the right tail of the net wealth distribution

In a next step, we look at the illustrative example of a set of adjustments that consist of an estimation of a Pareto distribution to simulate the top of the wealth distribution (by employing both versions, i.e. "adjust weights" and "add affluent households") followed by a multivariate calibration to align HFCS and NA data. Vermeulen (2018) e.g. shows that the affluent part of the wealth distribution plays an important role. Piketty et al. (2021) provide a historical contextualization of the top of the wealth distribution. With our example, we take the analysis one step further by concentrating only on important assumptions when it comes to modeling the top of the wealth distribution. In choosing this approach, we implicitly assume truthful reporting in the HFCS (i.e. we neither perform a proportional adjustment nor a hurdle model adjustment).

Table 2 shows key statistics, i.e the mean, median and inequality measures and shares for specific groups of net wealth. We show the results for unadjusted HFCS 2017 data and 12 different variants of modeling the top of the wealth distribution. Table 2 also shows the minimum and maximum values resulting from the different modeling variants to allow for direct comparison.

[25] *We should like to thank our referee for pointing out this line of thought.*

Table 2

Sensitivity of key results to modeling top of distribution while keeping external rich list constant

		Mean	Median	Gini coefficient	Share in net wealth		
					Top 1%	Top 10%	Bottom 50%
		EUR thousand			%		
Unadjusted HFCS results		236.5	70.9	0.748	23.67	57.87	2.48
Adjustment models							
Adjust weight							
Threshold EUR 1 million	xx% of debt[1]	332.0	73.2	0.873	37.9	72.1	–1.4
Threshold EUR 2.5 million		331.8	69.5	0.873	48.0	72.8	–0.9
Threshold automatic		331.2	74.2	0.858	30.6	70.3	–1.1
Threshold EUR 0.5 million		331.4	73.9	0.860	31.4	70.7	–1.1
Add wealthy households							
Threshold EUR 1 million	75% of debt[2]	331.6	71.0	0.837	47.5	71.3	1.0
Threshold EUR 2.5 million	75% of debt	×[3]	×	×	×	×	×
Threshold EUR 1 million	30% of debt	331.6	66.7	0.849	48.0	72.1	0.5
Threshold EUR 1 million	1% of debt	331.6	60.0	0.909	50.7	75.5	–2.4
Threshold automatic	75% of debt	331.6	71.9	0.845	44.7	71.5	0.5
Threshold EUR 0.5 million	75% of debt	331.6	72.2	0.845	45.1	71.7	0.6
Minimum		331.2	60.0	0.837	30.6	70.3	–2.4
Maximum		332.0	74.2	0.909	50.7	75.5	1.0

Source: HFCS Austria 2017, OeNB; trend rich list 2017; national accounts (OeNB, Statistics Austria).

[1] *The portfolio allocation, and thus also the extent of debt holdings, of the affluent part of the population is given by survey responses. Additional assumptions regarding debt holdings (and other portfolio choices) only need to be made for the "add wealthy households" approach.*

[2] *As the affluent part of the distribution is modeled in terms of net wealth (i.e. gross wealth minus debt), we need an assumption about the share of "missing" aggregate debt held by the simulated households ("add wealthy households"). Thus, we vary this parameter to see its impact.*

[3] *Model does not converge.*

Before starting the estimation, we need to define the threshold w_0 above which the Pareto estimation takes place. We can set this threshold arbitrarily, e.g. at EUR 0.5 million, EUR 1 million or EUR 2.5 million. Changing the threshold from EUR 1 million to EUR 2.5 million either increases the top 1% share from about 38% to 48% of net wealth (if we adjust weights) or makes it impossible to run the model at all (if we add wealthy households). The lack of convergence observed in the multivariate calibration can be explained by the fact that it is impossible to achieve an alignment of aggregate NA and HFCS data while maintaining the household structure as defined in the HFCS.

Thus, a seemingly small change in the internal assumptions used in modeling the top of the distribution has huge implications. By leaving the choice of threshold to an automatic internal procedure, the modeler can generate a net wealth share of 30% or 45% for the top 1%.[26] Overall, increasing (in the range under investigation) the threshold at which the Pareto distribution starts implies that more wealth is concentrated at the extreme levels of the distribution and that the net wealth share of the top 1% increases accordingly.

Leaving the threshold at EUR 1 million but changing the extent by which the undercoverage of outstanding debt is attributed to the top of the net wealth

[26] *If we set the choice of the threshold w_0 to "auto," the model automatically selects the threshold that maximizes the fit of the Pareto distribution. This is done via a mean residual life plot. For Austria, the threshold values selected by this "auto" approach tend to be lower than EUR 1 million and close to EUR 500,000.*

distribution – considering three different ad hoc levels of 75%, 30% and 1% – only has an effect in the method "add wealthy households" because in the "adjust weights" method, the portfolio allocation is given by the households in the HFCS. The Gini coefficient e.g. changes from 0.84 to 0.91 and is getting close to maximum inequality. Also the median level of net wealth could substantially decrease under these conditions. In general, the more debt is held by the top, the lower the inequality measured by the Gini coefficient and the top 1% share.

3.3 Information on the right tail of the net wealth distribution

So-called rich lists are important data sources in modeling the top of the net wealth distribution. However, these lists exhibit serious problems of data quality and lack transparency (see section 2). In the following estimation procedure, we use various sources of information to analyze their respective impact on the results. This approach may shed light on what happens if one country uses one type of information while other countries opt for a different type – choices that may e.g. depend on data availability per country. We use information from a rich list for Austria provided by an Austrian business magazine (*trend* list), data on wealthy Austrians included in the *Forbes* rich list, some corresponding OeNB in-house information as well as information obtained from the *Sabina* business register. We use the latter because wealth and business wealth are highly correlated.[27]

Table 3 follows the same structure as table 2. For this exercise, we leave all the other modeling assumptions constant, meaning that again we start from the approach of employing no initial proportional adjustment and no hurdle model adjustment.

Table 3

Sensitivity of key results to modeling the top of the distribution by employing various rich lists

	Mean	Median	Gini coefficient	Share in net wealth		
				Top 1%	Top 10%	Bottom 50%
	EUR thousand			%		
Unadjusted HFCS results	236.5	70.9	0.748	23.67	57.87	2.48
Adjustment models						
Adjust weight, threshold EUR 1 million						
trend rich list	*332.0*	*73.2*	*0.873*	*37.9*	*72.1*	*–1.4*
Forbes rich list	*331.9*	*79.1*	*0.849*	*32.3*	*67.9*	*–1.2*
OeNB in-house information	332.0	74.5	0.867	36.4	70.9	–1.4
Business equity holdings	331.8	80.7	0.842	30.6	66.6	–1.1
Add wealthy households, threshold EUR 1 million, 75% of debt						
trend rich list	*331.6*	*71.0*	*0.837*	*47.5*	*71.3*	*1.0*
Forbes rich list	*331.7*	*81.8*	*0.788*	*35.6*	*65.0*	*2.2*
OeNB in-house information	331.6	72.9	0.824	44.7	69.8	1.4
Business equity holdings	331.7	83.5	0.784	32.2	64.0	2.1
Minimum	332	71	0.784	30.6	64.0	–1.4
Maximum	332	84	0.873	47.5	72.1	2.2

Source: HFCS Austria 2017, OeNB; various rich lists for 2017; national accounts (OeNB, Statistics Austria).

[27] *See e.g. the new sampling strategy employed in the German Socio-Economic Panel (SOEP), (Schröder et al., 2020).*

Especially for the net wealth shares of the top of the distribution and for the Gini coefficient we find that the specific choice of a rich list has a strong impact. The Gini coefficient varies within a range of close to 10 points, depending on the choice of list. Furthermore, the net wealth share of the top 1% varies between about 30% and almost 50%. The median of wealth varies sizably across different rich lists.

Which information yields what type of results is difficult to discern. For the Gini coefficient and the net wealth shares of the top 1% and top 10%, there seems to be a consistent pattern, with the approach using the business register database *(Sabina)* list resulting in the lowest values and that using the *Forbes* list in the second lowest, while the results of the approaches employing OeNB in-house information and the *trend* list are reasonably close. One might have expected the *Sabina*-based values to be lowest since *Sabina* data exclude wealth other than business wealth. Still, the overall impact of the choice of external information on the top of the distribution cannot be denied. Thus, we use these results to argue for a cautious approach to cross-country comparisons that use different data sources in Pareto adjustments to estimated wealth distributions (Fessler and Schürz, 2013).

3.4 Modeling the top and its impact on the distribution

The sensitivity of the overall distribution of net wealth to changes made to the top of the distribution can be analyzed by decomposing the overall distribution into subgroups defined by their position within the distribution. Cowell at al. (2017) showed that the Gini coefficient can be decomposed as follows:

$$GC = p_{top}sh_{top}GC_{top} + p_{bottom}sh_{bottom}GC_{bottom} + BI$$

where GC is the Gini coefficient, sh_g denotes the share of net wealth held by group $g \in (bottom\ [95\%]; top\ [5\%])$ and p_g is the population share of group g. The remaining term *(BI)* is the between-inequality of both groups; this is the GC if each member of the two groups has the group-specific mean net wealth level.

Table 4 displays the results of this exercise. We show a group breakdown by percentiles (top 5% vs. remainder) as well as a breakdown by threshold used in the Pareto estimation. It is of particular importance that the largest contribution to inequality stems from between-inequality.

The choice of how to model the affluent population – that is the decision to use a rich list or not – has a huge impact on the GC of the subpopulations

Table 4

Decomposing the Gini coefficient of net wealth

	trend rich list		No specific adjustment of top of distribution[1]	
	Top 5%	Pareto threshold EUR 1 million	Top 5%	EUR 1 million
Gini coefficient	0.837	0.837	0.837	0.837
Population share: affluent households in %	5	4	5	7
Within inequality: affluent households	0.698	0.700	0.475	0.470
Population share: other households in %	95	96	95	93
Within inequality: other households	0.678	0.682	0.781	0.787
Between-inequality	0.573	0.553	0.465	0.513
	%			
Contribution to inequality				
Total (1+2+3)	100	100	100	100
of which: affluent population (1)	*3*	*2*	*1*	*2*
rest of population (2)	*29*	*32*	*43*	*36*
between-inequality (3)	*68*	*66*	*56*	*61*

Source: HFCS Austria 2017, OeNB; trend rich list 2017; national accounts (OeNB, Statistics Austria).

[1] *In the two columns below, we do not model the affluent part of the net wealth distribution with the Pareto distribution, but instead achieve alignment with NA data only through multivariate adjustment.*

and on the resulting between-inequality. This holds despite an almost exact equality of the overall *GC*.

4 Conclusions

This study focuses on important caveats in aligning micro- and macrodata on household wealth in Austria. A thorough analysis of households' assets and liabilities requires detailed microdata and improved macrodata, i.e. national accounts (NA) data. Peoples' reported perceptions of the value of their assets, overall, do not align well with corresponding aggregate market values recorded in the NA.

We use various standard modeling approaches to align data stemming from two data sources, namely the Household Finance and Consumption Survey (HFCS) and the NA. Our results on top wealth shares in Austria are highly sensitive to the modeling assumptions. Given huge discrepancies in the obtained results, we find the information content of wealth inequality data to be rather limited. Given the present data limitations, it is difficult to calculate policy models, e.g. for wealth taxes or inheritance taxes. Overall, we therefore argue that the information contained in the newly developed distributional wealth accounts should be analyzed with caution. Based on the results of our modeling exercise for Austria, our conjecture is that international comparisons – but also the development of national wealth inequality indicators over time – might be flawed by differences in modeling assumptions or the availability of underlying data that are used in the background.

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Annex A

Additional tables

Table A1 as in Albacete et al. (2018); table A2 as in the ECB's methodological documentation for the HFCS (ECB, 2020a).

Table A1

Item nonresponse for selected variables (unweighted)

	Household has item		Responses by households that have the item			
	Yes	Un-known	Amount	Range	"Don't know"/ "No answer"	Other missing values[1]
	(1)	(2)	(3)	(4)	(5)	(6)
	%					
Value of main residence[2]	37.4	0.0	82.0	14.9	2.8	0.3
HMR mortgage 1: amount still owed	12.5	0.2	81.8	8.6	8.6	1.0
Monthly amount paid as rent	56.6	0.0	59.7	39.8	0.5	0.0
Other property 1: current value	12.7	0.1	77.9	16.2	4.9	1.0
Other property mortgage 1: amount still owed	1.4	0.1	79.1	2.3	14.0	4.7
Value of sight accounts	99.4	0.0	83.8	8.0	8.1	0.1
Value of saving accounts	98.7	1.3	81.0	9.0	5.3	4.7
Value of publicly traded shares	4.7	0.5	82.5	11.9	5.6	0.0
Amount owed to household	6.6	0.2	94.6	3.4	2.0	0.0
Employment status (main activity) (person 1)	100.0	0.0	100.0	0.0	0.0	0.0
Gross employee income (person 1)	53.3	0.0	91.3	6.6	1.9	0.2
Gross income from unemployment benefits (person 1)	6.6	0.0	87.2	9.9	3.0	0.0
Gross income from financial investments	63.8	11.7	54.8	34.5	9.3	1.4
Gift/inheritance 1: value	27.2	1.2	84.6	7.3	5.4	2.8
Amount spent on food at home	100.0	0.0	95.9	4.0	0.1	0.0

Source: HFCS Austria 2017, OeNB.

Note: HMR = household main residence.

[1] *Missing values due to editing measures and exits from loops.*
[2] *Based on the HB0900 variable.*

Table A2

Response behavior in the HFCS

Country	Gross sample size	Net sample size	Response rate[1]	Response rate[2] (including panel)	Refusal rate	Cooperation rate	Contact rate	Eligibility rate
Belgium	7,613	2,329	28.9	37.6	46.6	38.9	96.5	81.4
Germany	16,375	4,942	16.1	31.5	48	31.5	85.5	95.8
Estonia	3,816	2,679	60.7	72.8	17.8	76.3	95.4	96.5
Ireland	13,200	4,793	38.5		26.2	56.8	67.9	94.2
Greece	7,980	3,007	39.4		50.5	41.8	94.3	95.6
Spain	N/A	6,413	N/A	N/A	N/A	N/A	N/A	N/A
France[3]	21,484	13,685	64.2	68.1	11.3	76.9	76.9	93.6
Croatia	4,055	1,357	35.8		49.2	41.7	41.7	93.5
Italy	15,379	7,420	36.6	50.3	28.6	62.1	81	93.9
Cyprus	2,218	1,303	N/A	60.8	28.9	62.6	97.4	96.6
Latvia	2,894	1,249	N/A	45.3	24.7	64.1	70.7	95.3
Lithuania	3,774	1,664	45.3		26.3	56.5	80.2	98.1
Luxembourg	7,100	1,616	24.6		53.7	28.6	86	92
Hungary	15,006	5,968	44.2		25	59.8	73.9	89.9
Malta	1,590	1,004	53.5	64.8	25.3	71.2	91.3	97.4
Netherlands	3,760	2,556	N/A	68	28.9	68	N/A	N/A
Austria	6,280	3,072	49.8		45.3	50.6	98.5	98.2
Poland	12,038	5,858	45.7	52.5	31.8	53.6	98	92.6
Portugal[3]	8,000	5,924	85.5		3.5	93.5	91.4	86.7
Slovenia	5,505	2,014	37.7		45.5	42.7	88.3	97.1
Slovakia	4,017	2,179	N/A	56.1	26.4	67.2	83.5	96.7
Finland	13,396	10,210	60.1	77.4	15.3	81.6	94.9	98.4

Source: ECB – HFCS metadata.

Notes: M stands for missing value – comparable information not available from the metadata. Gross sample includes panel households that have responded to previous waves of the same survey. N/A = information not available.

[1] *For comparability, response rates are shown for households interviewed for the first time.*

[2] *Response rates for the whole sample in countries that have a panel component. In Finland, the panel component consists of households interviewed in the three previous waves of the income and living conditions survey.*

[3] *In France and Portugal, survey participation is compulsory for households.*

Annex B

Technical introduction to the modeling approaches applied in this study

As described in the main text, households' net wealth contains various assets and liabilities. Adjustments can be made for a specific asset or liability or for net wealth itself, depending on the data sources available. If adjustments are made for net wealth itself and if we wish to obtain results on asset classes at the same time, we need to split the change across asset classes afterward. Proportional adjustment and hurdle model adjustment are often performed on a specific item while Pareto adjustment is implemented for the net wealth of households.

Proportional adjustment

The simplest approach to align aggregate figures A from the HFCS and the NA is to calculate the factor m_c for each asset and liability component c by dividing aggregate values, i.e.

$$m_c = \frac{A_{cNA}}{A_{cHFCS}}.$$

Multiplying each individuals' holding of each asset and liability by m_c ensures alignment of the two data sources. This approach assumes, however, that all responses in the HFCS are wrong and are off by relatively the same amount, which is very unlikely to be the case.

Another difficulty arises from the (implicit) assumption at which step in the modeling procedure which proportional adjustment is performed. In our study, we illustrate cases where we perform proportional adjustment at the beginning and at the end of the procedure, respectively. We will show below that proportional adjustment is an alternative to multivariate calibration when it comes to aligning aggregate figures.

Hurdle model

In the HFCS, responding households are asked, for each item of their balance sheet, whether they hold this specific item (yes/no). If they answer "yes," they are asked to specify the corresponding amount. In the type of adjustment considered here, the "no" response is assumed to be incorrect for part of the group reporting not to hold a specific asset. Information on the share of wrongly collected "no" answers is rarely available. However, we can estimate a logit model to simulate the likelihood of respondents holding a specific balance sheet item C, given the observed data and letting C be the choice variable of holding an item and C the value of this item. The logit model can be written as

$$P(C = 1|x_1, \dots, x_k) = f(x_1, \dots, x_k)$$

where $(x_1, \dots, x_k) \in X$ are several explanatory factors. The function *f()* is the logistic distribution function so that the model can be written as

$$P(C = 1|x_1, \dots, x_k) = \frac{\exp(\beta_0 + \beta_1 x_1 + \dots + \beta_k x_k)}{1 + \exp(\beta_0 + \beta_1 x_1 + \dots + \beta_k x_k)}.$$

This model can be estimated with a generalized linear method.[28] It is used to predict the likelihood of holding a particular item of a household's balance sheet. Taking a random draw from the uniform distribution within the interval of zero and one, one can determine whether a negative answer can be assumed to be false. If the prediction obtained from the logit model is higher than the random draw, a particular household is simulated to hold the particular item (i.e. we set the "no" answer [false negative] to "yes").

Once it has been decided which "no" answer was falsely recorded and thus had to be changed to "yes," we need to impute the actual value of the respective item that is held by a household. For this step, an OLS regression is estimated in the following form

$$c = \beta_0' + \beta_1' x_1 + \cdots + \beta_k' x_k + \varepsilon.$$

Derived coefficients are used to impute the missing values.

In principle, there is no theoretical reason why the logit model and the OLS regression should have an identical or a similar set of explanatory variables *X*. Albacete (2014) and Kennickell (2017a and 2017b) provide a more in-depth discussion of explanatory variables that should be used in such an imputation procedure. To keep it simple, as the best selection of explanatory variables *X* is not the focus of our paper, we use the same set of explanatory variables. It contains income, the number of household members, employment status, position of the household in the wealth distribution as originally determined in the HFCS (wealth decile) and level of education. Only the information on income is used as a continuous variable. All the other variables are categorical or dummies.

All balance sheet items can be adjusted by employing this procedure. The impact of adjustments on results varies. Balance sheet items such as deposits, which almost every household owns, are affected only slightly by employing this procedure, whereas other items that are held be fewer households might be affected more heavily.

Pareto adjustment

As discussed in the main text, wealth surveys typically have difficulties in reaching the top end of the wealth distribution. For this reason, the literature suggests using a Pareto distribution in the adjustment procedure. This suggestion is based on the generally accepted assumption that the top of the net wealth distribution follows a power law. Denote net wealth by *w*. The pdf [*f(w)*] and cdf [*F(w)*] of the Pareto distribution are defined by

$$f(w) = \begin{cases} \alpha \dfrac{w_o^{\alpha}}{w^{\alpha+1}} & for\ w \geq w_o \\ 0 & for\ w < w_o \end{cases}$$

$$F(w) = \begin{cases} 1 - \left(\dfrac{w}{w_o}\right)^{-\alpha} & for\ w \geq w_o \\ 0 & for\ w < w_o \end{cases}$$

[28] *In R, the package "svyglm" is used to take weighting into account.*

Thus, the distribution is defined by two parameters: w_o, a threshold above which the distribution is assumed to apply, and α, a "shape" parameter. We vary w_o in our exercise to see the effect of the choice of this assumption on the results. α is estimated via an OLS regression based on the complementary cumulative distribution function, incorporating a bias correction (Vermeulen, 2018; Gabaix and Ibragimov, 2011) for the survey results. As discussed in the main text, to estimate the Pareto distribution, we supplement the observed HFCS data with data from several so-called rich lists. These added observations are included with a weight of one.

Once the specific form of the Pareto distribution is estimated, we need to either adjust the weights of households in such a way that the right tail follows this distribution or impute new households that follow this distribution.[29] In the first approach, "adjust weight," the Pareto's α is estimated for the data from the HFCS as well as for observations from the rich lists (denoted $\hat{a}$) and separately for the HFCS alone (denoted α'). Denoting the weight of a household i by ψ_i, we can adjust the weights of households above w_o by the factor

$$\psi_i' = \psi_i \frac{f(w|w_0,\alpha\prime)}{f(w|w_0,\widehat{\alpha})},$$

so that the top follows the estimated Pareto distribution including the information obtained from the rich lists. This procedure does not impact the net wealth levels held by individual households but only the household weight attached to it. This implies, however, that this modeling approach does not only change balance sheet information but also all other information, e.g. the estimates on sociodemographic characteristics. To avoid this second effect, we use a calibration method based on a quadradic loss function[30] to retain the original distribution of sociodemographic information (age, education, gender, labor status, household size and total household population). To achieve both the top of the distribution that follows the Pareto distribution and maintain the original sociodemographic information, an iterative procedure of the Pareto estimation and calibration is implemented until α' (incorporating the previous iteration's adjustments) and $\hat{a}$ converge.

Instead of adjusting household weights, we can also simulate synthetic households from the estimated Pareto distribution. To do so, we subdivide the potential wealth range above w_o into three parts: the part above w_o and below (and including) the maximum value observed in the HFCS ($w^{\alpha}_{maxHFCS}$), the range between the maximum HFCS value and below the lowest observation in the rich list ($w^{\alpha}_{minRich}$), and the part above $w^{\alpha}_{minRich}$. We only simulate households in the middle range. Given the number of households in the first part (denoted S_{HFCS}) and the i.i.d. assumption, the number of households S_{top} to be simulated is

$$S_{top} = S_{HFCS} \frac{w_0^{\alpha} w_{minRich}^{\alpha} - w_0^{\alpha} w_{maxHFCS}^{\alpha}}{w_{minRich}^{\alpha} w_{maxHFCS}^{\alpha} - w_0^{\alpha} w_{minRich}^{\alpha}}.$$

Given the number of synthetic households to be simulated, their net wealth levels can be drawn from the Pareto distribution with the estimated α and the assumed w_o. These households enter the data with a weight of one. Note, however, that the

[29] *We could also implement a hybrid approach by adjusting weights and imputing new households. In this paper, we refrain from this possibility, however.*

[30] *Similar to the multivariate calibration method described in more detail below.*

portfolio allocation of these households and their sociodemographic characteristics are not known. In particular, an additional assumption must be made concerning liability holdings and thus implicitly determining the coverage rates of the HFCS with regard to the NA data. We simulated various possible values to see how sensitive the results are with respect to this assumption.

Multivariate calibration

As a final step, we apply a calibration method to achieve alignment with NA totals.[31] We estimate a generalized linear calibration on the weights, with bounds for both the parts above and below the exogenously assumed threshold w_o for the Pareto distribution. This calibration minimizes a quadratic loss function

$$\min_{k} \sum_{i=1}^{N} \frac{(k_i * \psi_i - \psi_i)^2}{w_i} ,$$

subject to the share of wealth above and below w_o not being changed and aggregated into the NA totals. Recall that we denote household weight ψ_i and net wealth w_i for all individual households i in the survey. The basic idea of this approach is simple: This step adjusts the weights of each household separately in such a way that the total wealth levels obtained from the NA can be achieved and that the structure with respect to socioeconomic characteristics is maintained. The bounds on the adjustment factor k are generally set to 0.003 and 1,000. In some models described in our paper, these bounds are too restrictive for a solution to be achieved.

This calibration approach ensures alignment of the aggregate levels of portfolio items in the HFCS and the national accounts. As such, it is an alternative to the proportional adjustment presented above.

[31] *We use the "gencalib" function of the sampling package in R. We make use of the option "truncated" to implement the bounds. For technical details, please refer to the documentation of the "gencalib" function and the literature provided therein. Alternatively, as explained above, a simple proportional adjustment could be used as well.*