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Roadmap to Wealth: Analyzing Wealth as a Micro-level Outcome Variable

1. Philipp M. Lersch; DIW Berlin/SOEP & Humboldt-Universität zu Berlin
2. Marion Leturcq; INED
3. Franziska Sesser; Humboldt-Universität zu Berlin

Abstract

Researchers analyzing wealth inequality at the micro-level of households see themselves confronted with a multitude of issues in operationalizing and measuring wealth and often make *ad hoc* choices in response. We present a systematic overview of decisions researchers must take when measuring wealth. As an empirical illustration, we conduct a multiverse analysis of the wealth return to tertiary education, where wealth is constructed following all combinations of decisions. We document the large empirical variance in estimated associations due to different empirical decisions. The association between wealth and tertiary education is highly affected by the definition of wealth (only housing assets or total wealth) and the transformation applied to the dependent variable (untransformed vs. rank or IHS transformation). We call for a transparent documentation of all empirical decisions as the absolute minimum for improving research practice in the field.

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1. Introduction

Stark and increasing economic wealth inequalities in many affluent societies have received much attention in recent years from social scientists across different disciplines because wealth inequality can cause immense societal harm and is a defining social challenge of our times (Killewald, Pfeffer, and Schachner 2017; Zucman 2019; Lersch, Struffolino, and Vitali 2022). Researchers are concerned with the potential causes and consequences of wealth inequalities at the micro-level of individuals and households. For instance, they study how race, gender, and class is related to wealth (Killewald and Bryan 2018; Frémeaux and Leturcq 2020; Hansen and Toft 2021), and they examine the relationship between wealth and health, education, and subjective well-being (Semyonov, Lewin-Epstein, and Maskileyson 2013; Headey and Wooden 2004; Pfeffer 2018).

The literature on wealth is still in an early phase (Killewald, Pfeffer, and Schachner 2017). While the data quality and availability for wealth has dramatically improved in recent years with clear recommendations regarding data collection (OECD 2013), research practice in examining these data lacks behind. In contrast to the study of income, where the Canberra consensus (UNECE 2011) established clear recommendations for the measurement of income, no clear recommendations of best research practice exists for wealth (Brady 2022). Researchers see themselves confronted with a multitude of issues in operationalizing and measuring wealth (Figure 1) and often make *ad hoc* choices in response. The many analytical options create a "garden of forking paths" (Gelman and Loken 2014, 464) in which analysts, including the authors of this article, too often follow one arbitrary and insufficiently documented path violating fundamental norms of (open) science. In particular, insufficient documentation violates standards of transparent and open science and raises hurdles for replicating and extending on prior research. Consequently, we argue that progress in the field is critically hampered.

To illustrate the range of analytical choices found in the literature, we looked at recent articles published in the Review of Income and Wealth between 2017 and 2022. For example, regarding the adjustment for household composition, (Fisher et al. 2022) uses the square root of family size to adjust household wealth, (Knight, Shi, and Haiyuan 2022) uses per-capita household wealth, (Kuypers et al. 2022) use household wealth without adjustment, (Schneebaum et al. 2018) use wealth data at the household level for single households only, and (Bönke et al. 2019) uses individual net worth. Regarding transformations, (Schröder et al. 2020) uses log-transformed wealth only with positive values, (Bourdieu et al. 2019) uses a log-transformation replacing those without wealth with 0, (Schneebaum et al. 2018) uses an inverse hyperbolic sine transformation, and (Karagiannaki 2017) uses untransformed wealth but applies a median regression in some analyses. Overall, these variations highlight the diverse approaches researchers take to measure wealth in different contexts.

Against this background, we have three primary objectives in the current study. First, we present a systematic overview of the empirical decisions researchers must make when measuring wealth. Here, we mainly aim for sensitizing researchers for the many different possibilities for measuring and operationalizing wealth. Second, we discuss the underlying assumptions and potential implications of these decisions, which are often passed over in applied research. For many decisions, general recommendations for best practice are not possible and concrete decisions need to be made in light of specific research questions and relevant theory. Where possible, however, we give general recommendations. Third, drawing on an empirical example, we document the large empirical variance in estimated associations due to different empirical decisions using a multiverse analysis. For this, we examine the relationship between education and wealth. For the empirical application, we draw on high-quality survey data from the German Socio-economic Panel (SOEP) Study.

In our empirical application, we consider the typical research case in which wealth is the outcome variable in a multivariable regression analysis where we study the relationship between wealth and tertiary education. Education is an interesting driver of wealth: it is mostly time-invariant for adults, and reflects individual choices and constraints. Education is itself related to many other processes as a determinant and as a driver of wealth accumulation. Education is directly associated with income, consumption, and financial knowledge. But education also reflects social and family background, which is also directly associated with wealth accumulation through gifts and bequests. While sociological and economic theory suggests a strong positive link between education and wealth, empirical evidence on this link remains preliminary.

We conduct a multiverse analysis, that is we consider 1,536 different ways of measuring and operationalizing wealth, and examine how wealth is associated with tertiary education in each case. Our results show considerable variance in the association between tertiary education and wealth, depending on measuring and operationalizing decisions. On average, education is associated with an increase of 0.349 of a standard deviation in wealth, with a minimal estimate of 0.139 and a maximal value of 0.53. Our results indicate that the association is highly affected by the definition of wealth (only housing assets or total wealth) and the transformation applied to the dependent variable (rank transformation or IHS transformation). It is moderately associated with the imputation method.

In light of our discussion and results, we, first, strongly caution analysts to carefully consider their research questions and objectives, particularities of their data, and context of wealth measurement in making analytical choices. Second, we advise researchers to check the sensitivity of the results to particular decisions. Our multiverse analysis suggests that variation in estimated relationships can be vast and the direction of changes in coefficients often cannot be determined on theoretical grounds. If researchers would decide differently, their results may change in unexpected ways. If there is one lesson to be learned from our article, it is that analysts' decisions matter. Third, we call for a transparent documentation of all empirical decisions as the absolute minimum for improving research practice in the field. We primarily consider wealth as measured in survey data, but most decisions we discuss below equally apply when wealth is measured in administrative register data.

The paper is structured as follows: section 2 presents the main sources of wealth accumulation. Section 3 provides a presentation and discussion on the many choices made to operationalize wealth related to measurement, level of analysis and edition of the data. Section 4 presents an empirical example of the impact of operationalization choices, based on a multiverse analysis of wealth return to education. Section 5 discusses the results and concludes.

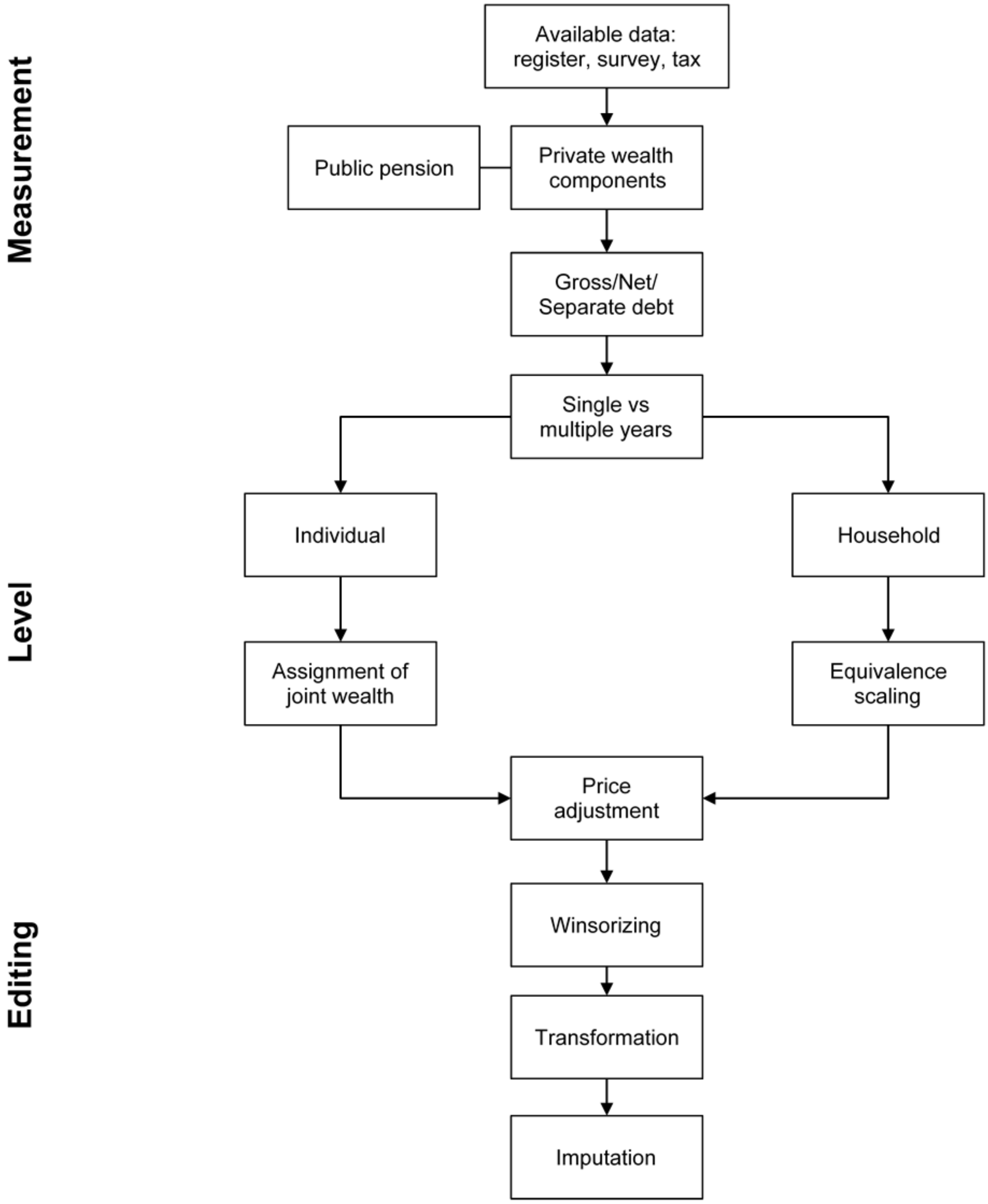

Figure 1: Central decisions in operationalizing and measuring wealth

2. Sources of Wealth Accumulation

Economic wealth is composed of assets that can be of different types such as housing, financial, and business, for which a property title can be established and transferred. The property title is held by one or several members of the household. Debts and liability can be subtracted to achieve net wealth. Wealth can be important for people in many ways. For one, it can provide a sense of security and financial stability, allowing individuals to better manage unexpected expenses or emergencies. It can also provide opportunities for individuals to invest in their future, such as funding education, starting a business, or purchasing a home. It can also provide a higher standard of living by offering consumption potential.

In this section, we examine the drivers of wealth accumulation identified in the literature.

Wealth is a cumulative process and a key determinant of wealth is age. Other determinants of wealth include gender, social origins or race, ethnicity, nativity; they are mostly exogenous factors. Education can be considered as time-invariant at adult age, thus when individuals accumulate wealth. Family structure is an important time-varying and endogenous driver of wealth. Couples typically have higher saving capacity than singles, but families with children also have higher consumption levels than couples with no kids. The legal structure of the family also matters. Marriage, as well as other types of registered partnership (such as civil unions) are associated with higher levels of wealth (Frémeaux and Leturcq 2020). The causal relationship between marriage and wealth is unclear, because of selection into marriage. Richer couples are more likely to be married rather than cohabiting, but it is unclear whether marriage has a causal impact on wealth or if couples anticipating higher levels of wealth (for instance, stable couples) are more likely to get formally married. Using German longitudinal data, Lersch (2017) shows that marriage is associated with a significant marriage premium, suggesting a causal impact of marriage on wealth.

Other time-varying determinants of wealth include the macro-level context (such as economic stability) or policy incentivizing wealth accumulation, such as policy promoting inter-vivos gifts.

As a cumulative process, wealth is determined by past and contemporary behaviors, which complicates the analysis of its main determinants. Most drivers of wealth, both endogenous and exogenous, would take time to materialize into accumulated wealth. For instance, Kapelle and Lersch (2020) show that the marriage premium tends to increase over time in Germany.

Which mechanisms link wealth to the above mentioned characteristics? It is widely recognized that wealth accumulation follows the dynamic:

$$W_{it} - W_{it-1} = r_{it} W_{it-1} + S_{it} + B_{it} \quad (1)$$

Where W_{it} represents wealth of individual *i* at the end of period *t*, r_{it} represents the return of wealth during period *t*. S_{it} represents savings (potentially negative), and B_{it} represents inter-vivos gift and bequest (potentially negative). Equation (1) describes an accounting model, but it helps to understand how determinants affect wealth accumulation. Its underlying processes have social, cultural and economic roots.

Savings reflect contemporary income and consumption. Thus, wealth, through savings, is related to all components that have been shown to be correlated with income and consumption. These components include age, education, social origins, race or ethnicity, gender, family structure, marital decisions, etc. The association between wealth and income is stronger at higher levels of income, as wealth generates income flows which are larger among richer households. The causal association between wealth and income goes in both directions, pointing to an inverse causality issue (Barsky et al. 2002, Killewald 2013).

Inter-vivos gifts and bequests are strongly associated with social origins (Hansen and Wiborg 2019) or other family characteristics such as sibship size (Perozek 1998). Inter-vivos gifts and bequests are facilitated (or impeded) by local policies and social norms, thus reflecting the political and cultural context (Beckert 2022).

The return of wealth is determined by the wealth portfolio, i.e. the asset composition of wealth. Some assets provide higher, but often more volatile returns. Significant heterogeneity in asset portfolios across households has been observed in the literature (Curcuru et al. 2010). The heterogeneity in asset portfolios reflect differences in observable characteristics such as household composition (for instance, couples hold more housing wealth than singles), the type of occupation (self-employed hold more business assets than employees). It also depends on unobserved characteristics such as risk preferences or financial knowledge (Lusardi, Michaud, and Mitchell 2017; Abreu and Mendes 2010), which have been found to be associated with education and family background (Lusardi and Mitchell 2011). Richer households tend to exhibit higher returns of wealth (Bach, Calvet, and Sodini 2020). As for savings, the causal relationship goes in both directions. Higher returns generate wealth, but a higher level of wealth offers more asset diversification opportunities.

Most determinants of wealth are related to several components of wealth accumulation as described by equation (1) through different channels. For instance, gender is associated with savings as women have typically lower savings capacity than men because of the gender gap in earnings (Goldin 2014). Gender is also associated with inter-vivos gifts and assets portfolios as daughters tend to receive assets of lower value and different nature than sons (Gollac and Bessière 2020). Equation (1) thus provides a framework that helps structure a discussion of the mechanisms behind the relationship between wealth and its demographic and social determinants.

3. Operationalizing wealth

Measurement

Data on wealth

Measuring wealth is not an easy task. Wealth is a stock, and individuals or households do not make an inventory of their assets on a regular basis. There are broadly three ways to measure wealth, which are usually applied on different sources of data: 1) inventories established in surveys; 2) inventories established for tax purposes; and 3) capitalization of income flows generated by wealth observed in fiscal data. These three ways of measuring wealth all have advantages and disadvantages. They complement each other, but they are rarely combined (for an example of a combined approach, see Garbinti et al. (2021)).

Wealth surveys

Surveying wealth consists of guiding households in making an inventory of (all or most of) assets held by the household at the time of the survey. Wealth surveys typically include additional detailed questions on the life and trajectory of individuals. Wealth surveys are best suited for analyzing the relationship between wealth and personal and household characteristics, as they provide information of personal and family characteristics and trajectories that other sources of data don’t provide.

Wealth surveys differ on two dimensions, which pose specific issues. First, a wealth survey is either a module based on a larger survey, such as the German SOEP or the U.S. PSID; or a specific survey such as the French wealth survey. For both cases, criteria of inclusion of surveyed population should be discussed. For instance, most wealth surveys exclude persons living in group quarters, and institutional households e.g., the elderly living in nursing homes (even if entering a nursing home is associated with important changes in wealth portfolio; Poterba et al. (2011)), prisoners or young adults in boarding schools.

It is necessary to make inclusion criteria clear, as they are important to gauge to what extent the sample is representative of the population. An important difference between a module based on a larger survey and a specific survey is the treatment of total non-response. When households refuse to participate in a specific module, information from the rest of the survey may be used to impute the value of wealth, but this may be more difficult for specific surveys.

A second important dimension regarding wealth surveys is the way wealth is surveyed. Households are often asked to give an overall valuation of their wealth (generally using fixed brackets). This overall valuation is a loose measure of wealth. A more precise way of surveying wealth consists in first doing an inventory of all assets, and then asking respondents to give a valuation of each asset (as done by the French wealth survey, or the wealth module of the German SOEP survey). The valuation is often the market value of the asset, but the purchase value is also often included. It is important to pay attention to which of the market or purchase value is provided by the survey, and to make it clear to the reader.

In wealth surveys, assets' valuation is generally self-reported. As men and women have different levels of financial literacy (Lusardi and Mitchell 2008) and because partners do not necessarily pool their assets within couples (Frémeaux and Leturcq 2020), it is important to pay attention to the identity of the respondent(s) in multi-adult households. Using French data, Frémeaux (2023) shows the gender of the respondent matters, and men tend to report higher value of wealth than women. A change in the respondent across waves may affect the consistency of the data.

All survey data rely on the survey design, and wealth surveys are no exception. The measure of wealth using survey data relies on the precise implementation of the questionnaire, on the way modules are connected to each other, the way questions are connected to each other within modules, or the categorization of answers. Small changes in the questionnaire may affect consistency in the data.

Wealth surveys often contain large measurement errors on wealth. People tend to underreport (some assets are not included in the inventory) and undervalue their wealth (individuals are not fully aware of the value of their assets, in particular regarding current market values in dynamic market contexts) in surveys. Comparing National Account (NA) to Household Finance and Consumption Surveys (HFCS), the European Commission (2013) shows significant differences between the mean net wealth per person in national accounts and in the HFCS: the mean net wealth estimated from the NA is roughly 50% higher than the mean net wealth estimated in the HFCS in France or in Germany. Sampling design may also explain the discrepancy between National Account and surveys: wealth distribution is highly skewed, which means that more affluent households need to be oversampled to describe effectively the wealth distribution. Survey data offer limited information of the population at the top of the distribution of wealth, as they cover a small part of this population. Oversampling rich households reduces this issue, as done by the French wealth survey. Survey data requires some top coding or transformation to lower the impact of outliers (see below).

In this paper, we are interested in applications focusing on individual-level outcomes, using survey data. We briefly present the other two methods of measuring wealth, highlighting the advantages and disadvantages of the three methods.

Register data

Register data are administrative data keeping track of all assets. They are usually established for fiscal reasons, when wealth is directly taxed. Wealth registers are a valuable source of data as they provide the most accurate measure of wealth.

Few countries establish registers of all assets up to date of living individuals (some notable exceptions include Norway and Denmark). Register data of wealth exists in countries implementing a wealth tax, so information collected crucially depends on the definition of the wealth tax. For instance, France implemented a wealth tax from 1988 to 2018. All households with a wealth larger than 800,000€ were eligible, so wealth registered were limited to wealthy households subject to the wealth tax. In 2018, it has been replaced by a wealth tax on housing assets only, thus the inventory only includes housing assets of rich households.

Many countries compile inventories of assets of deceased persons, for inheritance purposes. These data can be used to estimate the wealth of the living, using the mortality multiplier method to adjust the population of the deceased to the population of the living (see for instance Piketty et al. (2006)). Inventories of assets of deceased persons present three main caveats: they are not representative of the living population, they give a biased picture of wealth when deceased people transmitted bequests before dying, and they provide only limited information on individual characteristics.

Register data on wealth are uncommon data, and their consistency crucially depends on the fiscal legislation on wealth and wealth transmissions, which tends to vary across time.

Fiscal data

Another method to measure wealth is to capitalize flows of income generated by wealth, reported by taxpayers (such as rents or dividends) (Saez and Zucman 2016). Flows of income are divided by the average return of the type of asset (for instance, rents are divided by the average rate of return of housing wealth), thus giving an estimated value of wealth generating observed income. This method is usually implemented on fiscal data, which offers comprehensive information on all sources of income of all taxpayers in a population.

Fiscal data are best suited to observe the top of the distribution of wealth as they offer information on the whole population including the richest individuals, and they are often the standard to document wealth inequality. Fiscal data crucially depends on the fiscal legislation on income tax. As most countries implement some type of income tax, fiscal data gives the opportunity to construct measures of wealth inequality consistent across time and across countries.[1] Fiscal data provides little information on individual characteristics and trajectories.

[1] See for instance the series of the World Inequality Database https://wid.world/

Private wealth components

The operationalization of wealth measurement is country-specific: which components of wealth are transferable assets may differ across countries, as well as the possibility to hold separate wealth within the household. These points are developed below.

Wealth portfolio is composed of several assets that can be broadly classified as four main categories, which can also be divided into subcategories.

- Housing assets: this category of assets includes the owner-occupied primary residence, other owner-occupied residences and productive real-estate assets. Owner-occupied primary residence is the most important asset in the asset portfolio of households, and the category "housing asset" often refers to the owner-occupied primary residence only (this is the definition of housing asset in our empirical example below). Other owner-occupied residences include secondary houses, which are mostly owned by affluent households (André and Meslin 2021). Productive real-estate assets generate income flows through rents.
- Financial assets: they are composed of deposits and other (mostly productive) financial assets such as bonds (including loans) and stocks, life insurance, private pension plans.
- Professional assets: they are composed of intangible and tangible assets that have a professional use. Intangible assets are typically shares of firms, while intangible assets are land and plots, buildings, machinery used by a firm.
- Durable goods, such as vehicles, are sometimes considered as part of wealth. Non-professional tangible assets, such as art pieces and jewelry are also commonly accepted as components of wealth, but information on art works may not be included in all wealth data.

Pension plans require specific attention. Pension plans are public in some countries, where Pay-as-you-go pension plans are implemented (such as in France or Germany). In these countries, pension plans are typically not included in wealth. Their value is difficult to evaluate (see Cordova et al. (2022)), for inclusion of pension plans in Germany and its impact on the gender wealth gap). They can hardly be considered as assets: they are not accessible until retirement age and they are distributed as pensions, and they cannot be transferred (to the notable exception of the surviving spouse, at death). In other countries, such as the US, pension plans are private. Private pension plans are typically included in the value of wealth, as they share most features of other assets. In countries where a public pension system is implemented, individuals can save on a complementary private pension plan, which can be considered as financial assets. In a more conceptual discussion, Menduca (2022) argues that the definition of wealth depends on the research questions, and assets to be included in the definition of wealth should be "assets that can be used for the purpose [researchers] are interested in".

Wealth portfolio may also be composed of debts that can broadly be classified as four main types. They are not necessarily covered by all wealth data.

- Mortgages: they are debt associated with investment in real-estate assets, often self-occupied housing. They are secured loans, meaning the home which is bought with the mortgage serves as collateral for the debt. They are fixed-term, usually long-term loans, with fixed payments.
- Personal loans: they are debt associated with investment, which are not necessarily real-estate (student loan, professional loan, auto loan). They are usually (but not necessarily) collateralized, and they may be collateralized with other assets. They are usually fixed-tem loans, but may be flexible.

- Consumer debts: they offer a way to borrow funds for any expense. They are fixed-term with regular payments. They are not collateralized.
- Credit card debt: they are revolving credit that give a borrower access to funds as needed, and can be used for everyday expenses or shopping.

Assets and debts constitute the wealth portfolio of households. Their values can be summarized in a single index: the value of all assets taken together gives the gross wealth of the household, while the value of all assets minus all debts gives the net wealth of the household. Different components of wealth (housing, financial and professional assets) may also be considered separately, and the portfolio composition could be the outcome of interest. Predictors can have different impacts on different components of wealth. When feasible, studying separately wealth components might shed light on the underlying mechanisms linking a predictor to wealth.

Recommendation: We recommend providing a comprehensive list of the types of assets that are counted into household wealth, by broad categories. If some assets were observed but not included in household wealth, make it clear as well. A list of all categories of assets may not be necessary in the body of the text, but including in the appendix a complete list of all assets counted as wealth might be useful for replication purposes. Specific attention should be given to pension plans, as the inclusion or exclusion of pension plans may hinder international comparisons.

Gross/Net/Separate debt

Gross wealth measures the value of all assets held by the household (or the individual, see below for a discussion on the unit of analysis), irrespective of liabilities. Net wealth measures the value of all assets held by the household, minus the value of all debts. Gross and net wealth can also be computed for each component of wealth. Computing the *gross* value of different components of wealth is pretty straightforward, as it consists of taking the value of all assets of a certain type, e.g. gross housing wealth. Computing the *net* value of different components of wealth is more complicated, as debt cannot always be matched with a component of wealth. Computing net housing wealth is often feasible, as housing debts (mortgages) are usually identified in the data.

Net wealth provides key information about how affluent a household is at the time wealth is measured: a household holding a net wealth of 500k€ can be considered as more affluent than a household holding a gross wealth of 500k€ and 300k€ debt. Gross wealth provides key information about potential future wealth. A household holding a gross wealth of 500k€ and 300k€ debt is expected to have greater wealth in the future than a household holding 200k€ gross wealth with no debt. Net wealth tends to mix assets and debts, as if they were similar objects with opposite signs (Dräger, Pforr, and Müller 2023).

A recent literature highlights the difference between net worth and gross wealth, because debt is an investment strategy. As such, debt reflects strategic financial knowledge of households and capacity to access credit. Financial knowledge is associated with gender, age, higher educational attainment and socioeconomic background (Lusardi and Mitchell 2014). Access to bank loans might be restricted to stable households—which tend to be more advantaged households. The uneven access to credit has been extensively documented with systematic differences between races (Charles and Hurst 2002; Jappelli 1990), gender (De Mel, McKenzie, and Woodruff 2009; Moro, Wisniewski, and Mantovani 2017) and social origin (Hansen and Toft 2021).

While wealth is positively associated with higher subjective wellbeing, debt has an ambiguous impact on individual satisfaction. For instance, Dew (2007) showed that that can be detrimental when economic pressure is not taken into account, but associated with lower levels of depression once economic pressure is controlled for. An important difference comes from secured (collateralized debt) vs. unsecured debt (uncollateralized debt). While secured debt is positively correlated with children's educational outcomes, unsecured debt is negatively correlated with these outcomes (Zhan and Sherraden 2011). Similarly, Dräger et al. (2021) finds that children's educational attainment is better explained by gross wealth than net wealth.

Both gross and net wealth convey interesting -and different- information regarding household wealth. When feasible, both gross and net wealth should be analyzed, with one measure being the main specification and using the other as a companion analysis. The comparison of gross and net wealth should be made with caution. Financial decisions related to wealth have radically different impacts on net and gross wealth. For instance, the transition to homeownership would show up as a gradual increase in net wealth as people pay down their mortgage, but as an immediate jump in gross wealth. The choice of which of gross or net wealth is the main measure depends on the research question, and the possibility to compute net wealth. Computing net wealth may be infeasible when debt is not or partially observed, or when debt is observed at the household level and the analysis focuses on personal wealth (see below discussion on the unit of analysis).

Single vs. multiple years

Most data of wealth are cross-sectional data, and give a picture of wealth distribution and composition in the population over one year. In cross-sectional data, the identification of the association between individual characteristics and wealth relies on interpersonal variations. For instance the association between marriage and wealth is identified on a comparison of unmarried to married individuals. Individual characteristics are either time-varying (family composition, professional outcomes) or time-invariant (race, gender, educational attainment, social background, sibship size, etc.).

Cross-sectional data are well-suited for the analysis of the association between time-invariant characteristics and personal wealth. Longitudinal data are better suited for the analysis of the association between time-varying characteristics and personal wealth, because they enable using intra-personal variation as a source of identifying variation (e.g., Lersch 2017). Using tools designed for panel data analysis, the identification studies how wealth changes at the individual level when a time-varying characteristic changes (for instance, when it switches from 0 to 1). Longitudinal data covering a large time-span allows the identification of dynamic effects, that is the impact of a change in a time-varying characteristic on wealth 0, 2, 4 or more years after the event. Dynamic analysis is highly relevant for the study of wealth, as wealth is a cumulative process—an event may take time to show its effect on wealth.

We would generally advise to use longitudinal data if available and adequately consider within-individual variation in wealth. However, in some applications it may be advisable to reduce longitudinal data to one wealth measurement point when the analysis focuses on time-invariant characteristics to predict wealth. This can be done, first, by considering only one particularly informative wave of the data, e.g., in literature on the gender wealth gap, the most recent wealth measurement is used (e.g., Grabka, Marcus, and Sierminska 2015). An alternative practice is to take the average over multiple years. This practice may be helpful to cancel out—or at least reduce—measurement errors. The latter approach is used, for instance, in studies of the intergenerational reproduction in wealth (Pfeffer and Killewald 2018). However, using this approach comes with particular problems which need to be addressed by the researcher. For instance, adequately weighting such averaged wealth data is difficult because the underlying population is unclear. It is also difficult to combine a rank transformation (see below) with averaging wealth measurements for similar reasons.

Level of measurement and unit of analysis

Data on wealth is usually collected and measured at the household level (for an overview on data collection, see OECD 2013). Households are often composed of several individuals. The unit of analysis can be either the household or the individual, and should not be confused with the level at which wealth is measured. The choice of the unit of analysis is mainly driven by the research question—but the (in)capacity to measure wealth at the individual level may hinder addressing important research questions.

When the unit of analysis is the household, wealth is measured at the household level as the value of all assets held by household members. When the unit of analysis is the individual but wealth information is collected at the household level, it is necessary to adjust wealth estimates measured at the household level to reflect wealth at the individual level. The adjustment aims at correcting differences in household sizes and economies arising from sharing resources. The simplest way to proceed is to divide household wealth by the number of individuals composing the household (or number of adults in the household), which gives wealth per capita, and to impute this value to all individuals (or adults) in the household (e.g., Knight, Shi, and Haiyuan 2022). This per-capita method assumes that wealth ownership is equally distributed among household members, and generates no economies from sharing. Yet, households may generate economies from sharing wealth: for instance, they may be able to own more valuable assets, or receive larger returns to wealth due to larger portfolios. Wealth is often composed of assets, from which households derive flows of consumptions such as housing or cars. When considered under the lens of consumption, these goods tend to be public goods, as all individuals benefit equally from their consumption. In addition, it has been argued that wealth provides power and social status to all household members (Cowell and Van Kerm 2015). Considering wealth as a public good in the household means that the total value of wealth should be attributed to all household members, without any adjustment for household size and composition (Cowell and Van Kerm 2015). Considering unadjusted wealth would overstate the share of single households in the bottom of the wealth distribution (Sierminska and Smeeding 2005).

Per-capita wealth measures and unadjusted wealth measures are polar cases of the method of adjustment through equivalence scales. To consider potential economies from sharing but without assuming all components of wealth are public goods, an option is to proceed in a similar way as for income, and to use an equivalence scale (e.g., Fisher et al. 2022). There is no consensus on which equivalence scale should be used for wealth. Applied literature uses the same equivalence scales for wealth adjustment as for income (e.g. OECD modified scale, square root of the number of household members), for better comparability of the results. But potential economies from sharing wealth are expected to be different from potential economies from sharing income. Aittomäki et al. (2010) suggest economies of scale are larger for wealth than income, because important assets in a wealth portfolio, such as housing and cars, are also important public goods in the household.

Per-capita, unadjusted, and equivalized wealth are all based on the underlying assumption that wealth is evenly distributed within the household. But the wealth portfolio of a household is typically composed of assets held by different owners. Assets can be held by individuals as personal assets, or by a couple as joint assets[2]. In most surveys, wealth is measured at the household level and the distinction between personal assets and joint assets is not provided. Some surveys provide detailed information on ownership of assets, which enable the measure of wealth at the individual level. Attributing the same level of wealth to all household members leads to discard intrahousehold inequality and to underestimate the gender wealth gap, and wealth inequality in general (Schneebaum et al. 2018). Let us consider a population of two couples, both are observed with a wealth of 100k€. In this population, there is no wealth inequality between households. In the absence of information on wealth at the individual level, we would approximate wealth at the individual level by 100/2=50k€ in both couples. All individuals having the same level of wealth, there is no wealth inequality between individuals. Now let us assume that we obtain additional information unveiling wealth distribution within households. In the first household, the male partner owns 100k€ and the female partner owns zero wealth. In the second couple, the male partner owns 60k€ and the female partner owns 40k€. In this population, the gender wealth gap is 60k€ (the average wealth of men is 80k€ and the average wealth gap of women is 20k€). Wealth inequality between individuals, measured by the coefficient of variation, is 83%, while wealth inequality between households has not changed and remains zero.

When the data contains detailed information about each asset, they enable a measure of wealth at the individual level. Which assets are considered as personal assets or joint assets depends on the legal context. Most countries consider married individuals to hold joint assets, but with exceptions (assets held before marriage, inherited assets, etc.). The default division of assets can often be amended by a prenuptial contract (Frémeaux and Leturcq 2022). As a consequence, measuring wealth at the individual level requires detailed information on the owner of each asset, but also detailed information on the legal status of the couple (including prenuptial agreements and marital contracts), as well as information on the acquisition of the asset (inheritance, acquired before marriage, etc.). This information allows the identification of personal assets and joint assets. The value of joint assets may be divided equally between spouses or partners, unless we have exact share of ownership for joint assets. This method allows the analyst to measure wealth at the individual level in terms of ownership, but it does not consider potential economies from sharing. To our knowledge, no research has tried to combine wealth measurement at the individual level, taking into account economies from sharing.

The analyst needs to make an informed decision about whether individual or household wealth is appropriate for the research question, and whether the unit of analysis is the household or the individual. The choice of the unit of analysis has to be discussed jointly with the choice of the population covered by the analysis. As mentioned earlier, survey data usually cover the population living in ordinary households, which usually induce a deteriorated coverage of young adults and elderly, who are more likely to live in non-ordinary housing than other adults. A usual way of dealing with this issue is to restrict the analysis to a specific age-range. Following Modigliani's life-cycle hypothesis, individuals are expected to accumulate wealth up to retirement, then to consume. Some research on wealth accumulation uses this reasoning to restrict the analysis to the working population (e.g., Lersch and Dewilde 2018). Sample restrictions have to be discussed with the unit of analysis as sample restriction would be based on information on the unit of analysis. For instance, age restriction would be based on the age of the individual for an analysis at the individual level, but on the age of the older partner (or the richest partner) for an analysis at the household level. $

[2] We discard here assets held jointly by several individuals in different households (such as a family house held by adult children). In such cases, the individual share of a household member is considered as personal wealth.

Editing and Imputation

Price adjustment

When considering multiple years of wealth information, researchers are usually interested in real year-to-year wealth changes rather than nominal changes driven by general price inflation. Therefore, price-adjusting wealth to a reference year using an official consumer price index (from national statistical offices) is common practice. In international comparisons, wealth should be converted to a common currency and adjusted using purchasing power parity (OECD 2013, 174). Without well-justified exceptions, these adjustments should always be applied. For particular analysis, the consideration of domain-specific price indexes, e.g., for housing, may be advisable rather than using general price indices . Price, currency, and purchasing power parity adjustments are unnecessary if wealth is transformed using relative rank positions within observation years, but would not harm either (see below). We recommend that if using wealth from several years, use price adjustment if you do not rank transform wealth.

Winsorizing

Because the distribution of wealth is heavily skewed to the right—with many people having little and few people having immense wealth—and some extremely negative net wealth values (Figure 2 for the distribution in Germany, 2017), wealth can be winsorized to reduce the unduly influence of outliers. Winsorizing refers to top- and bottom-coding where values above (below) a threshold are replaced with the threshold at particular distribution percentiles to pull in outliers. In practice, the 0.01 and 99.9 percentiles are mostly chosen (e.g., Grabka, Marcus, and Sierminska 2015), but this is an arbitrary decision. If percentiles are chosen further away from the extremes, a larger mass of observations is created at these percentiles, which will likely have stronger implications for empirical results. In some cases, particularly when considering gross wealth, wealth is only top-coded. In some public data releases, e.g., in the U.S. Survey of Income and Program Participation, wealth is already winsorized to protect the privacy of respondents. Winsorizing should not be combined with a rank transformation.

Whether winsorizing is applied depends on the research interest. If distributional inequality in wealth is of interest, winsorizing the outcome may substantially reduce measured inequality (depending on how sensitive the measure of inequality is to the extremes of the distribution). Similarly, if simple group differences are of interest, winsorizing may substantially alter results if groups differ in their extreme positions in the wealth distribution. If used in the context of multivariable regression, winsorized wealth as an outcome excluding outliers may yield more robust estimates.

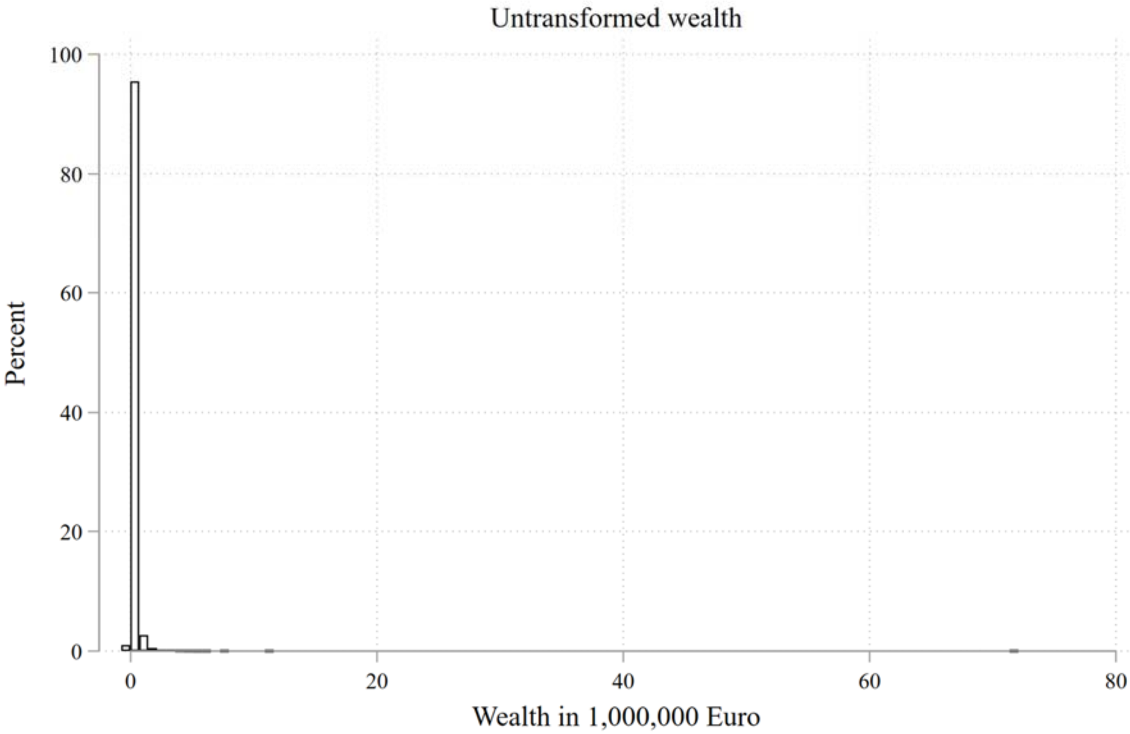

Figure 2: Household wealth distribution in Germany, 2017

Transformation

Because the distribution of wealth is heavily skewed (Figure 2), researchers often transform wealth in regression analysis to more easily meet statistical assumptions such as normality of residuals in OLS regression or to pull in outliers to reduce their influence on the estimation. There may also be good conceptual reasons to transform wealth. For instance, scholars may often assume that certain predictors have multiplicative rather than additive effects on wealth—in particular, because wealth attainment is cumulative. In our experience, the choice of transformation is consequential for results, and there is limited theoretical guidance on how to transform wealth appropriately.

Most social science scholars routinely turn to natural log transformations when confronted with skewed variables. As gross wealth distributions include large shares of zeros (although this may partly be a measurement issue because most people likely own small amounts of cash) and net wealth distributions additionally include negative values, however, simple log transformations, which are not defined for 0 and negative values, are inappropriate.

Several strategies are used by researchers to address this problem: categorization, natural log transformation with replacement of negative values and zeros, natural log transformation after adding a constant (started-log approach), inverse hyperbolic sine (IHS) transformation, and rank transformation. The last two options are increasingly popular in the literature (Killewald, Pfeffer, and Schachner 2017). However, there is little practical guidance on which transformation to use. No consensus on the optimal approach has yet been achieved. Different approaches may be appropriate for different applications. In addition, the underlying assumptions of these transformations are often not sufficiently discussed.

Categorization

A straightforward strategy is to categorize wealth. Then, wealth is treated as a categorical outcome ignoring all variance beyond the few categories. In the extreme, wealth may be collapsed into a binary indicator of ownership vs non-ownership of wealth or wealth components. We generally advise against using this approach because it is highly inefficient by wasting valuable information in the data. It is important to preserve as much variation as possible in wealth to better identify the relationship between wealth as an outcome and a limited number of characteristics as explanatory variables. However, there are cases in which ownership rather than value may be of theoretical interest. For example, there is a strand of literature on family transitions that argues that the symbolic value of wealth matters indicated by ownership rather than the value of assets (Schneider 2011).

Log-transformations

A common approach in dealing with right-skewed variables and allowing for multiplicative effects in linear regression is the natural log transformation (Wooldridge 2002, 183ff). The natural log is not defined for zero and negative values. Therefore, researchers use adjustments to transform wealth with the natural log.[3] A first approach is the log transformation with replacement (e.g., Bourdieu et al. 2019), where values are log-transformed after zeros, and negative values have been changed to some constant c (which is often 1 but may be any other positive number). This approach has several disadvantages. The replacement distorts the distribution and leads to a large mass at zero (or elsewhere in the distribution if c is not 1) in the transformed distribution (see Figure 3). Some subpopulations will be more affected by this distortion because they are more likely to have no or negative wealth (Friedline, Masa, and Chowa 2015). Finally, the choice of c is arbitrary (with no available theory to guide the choice) but may affect results, in particular with large shares of 0s in y (Mullahy and Norton 2022). This approach should not be used.

In the started-log approach, wealth is log-transformed after adding a constant k. In this approach, the distribution is shifted to the right so that the minimum is positive by adding a sufficiently large constant to all values. This approach is appealing because it preserves the variance in negative wealth values (Figure 3) and can be easily implemented. Again, the choice of k is arbitrary and may affect results.

Inverse hyperbolic sine transformation

The inverse hyperbolic sine (IHS) transformation is a third approach (Burbidge, Magee, and Robb 1988; Johnson 1949; MacKinnon and Magee 1990), which is increasingly recommended when studying wealth (Friedline, Masa, and Chowa 2015; Pence 2006) and applied by researchers (e.g., Grabka, Marcus, and Sierminska 2015; Schneebaum et al. 2018). This approach preserves the full variance in the wealth variable without shifting the distribution to the right. Often a tri-modal wealth distribution results with peaks in negative values, at 0, and at positive values (Figure 3). This transformation has the following form:

$$\square' = log(x + \sqrt{x^2 + 1}) = arcsinh(x)$$

[3] Another solution is to throw away all cases with 0 and negative values and use a log transformation without further adjustments. Because the data loss may be substantial with wealth data, we do not further consider this naïve log approach.

This function is defined for zeros and negative values, is linear at the origin, and is symmetric about zero. The addition of one in the square root term of the IHS transformation is as arbitrary as the addition of c and k above.

The IHS transformation, however, is not invariant to the unit of measurement (Aihounton and Henningsen 2021; Norton 2022). That is, the transformation of the variable depends on the magnitude of values, where no theoretical guidance exists on which scale to prefer (Mullahy and Norton 2022). With small values, the IHS transformation has only a small effect on the variable. With large values, the IHS transformation is close to the log-transformation shifted upwardly by log(2). When zeros are included, the unit of measurement also determines how "close" the transformed values are to 0 (Aihounton and Henningsen 2021; Mullahy and Norton 2022). For instance, Pence (2006) suggests including a scaling parameter θ (theta) to address this issue:

$$x'' = \frac{log\left(\theta x + \sqrt{\theta^2 x^2 + 1}\right)}{\theta} = \frac{arcsinh(\theta x)}{\theta}$$

Optimal values for θ with given data can be estimated using log-likelihood estimation (Pence 2006). A scaling parameter can also be selected based on model fit (Aihounton and Henningsen 2021). If θ=1, the IHS transformation is similar to a log transformation (symmetrically for both negative and positive values). As θ approaches zero, a larger area of the function around zero becomes linear. Choosing the unit of measurement (or θ) is non-trivial and can have considerable consequences for regression results and their interpretation (Aihounton and Henningsen 2021; Mullahy and Norton 2022). Only rarely do researchers examine different θ values (e.g., Bernardi, Boertien, and Geven 2019).

Rank transformation

Lastly, a rank transformation can be applied. For the rank transformation, observations are ordered by wealth and are assigned their percentile rank position in the distribution.[4] While the other transformations provide (log-transformed) absolute distances between observations, the rank transformation provides a relative ranking of observations where vastly different absolute distances can be translated into similar relative percentile distances. In other words, a percentile rank difference will indicate a huge absolute gap at the bottom of the distribution net wealth distribution, a small absolute gap in the middle of the distribution, and again a huge absolute gap at the top of the distribution.

Usually, the rank transformation is applied within each observation year (e.g., Boertien and Lersch 2021) because, when we refer to relative positions within distributions, we usually think about specific points in time (calendar years) rather than multiple years pooled. More generally, a crucial question to answer is which sample should be used to compute the rank positions. This sample does not need to be the complete analytical sample. For instance, Hansen and Toft (2021) compute ranks within birth cohorts. To compute ranks, adequate population weights should be applied. Another important question for the rank transformation is how to deal with ties, i.e., observations with equal wealth. This is particularly relevant for the usually large share of observations that have 0 wealth (Figure 2). There are two options: First, ties may be randomly assigned increasing ranks adding noise to the data (e.g., Black

[4] Alternatively, the cumulative density function can be used to compute the share of observations with less wealth which can then be used instead of the percentile rank. Both transformations yield very similar results with the cumulative density function providing more granular relative positions.

et al. 2020). Second, ties may get assigned the same rank creating a mass of observations at this point (Figure 3).

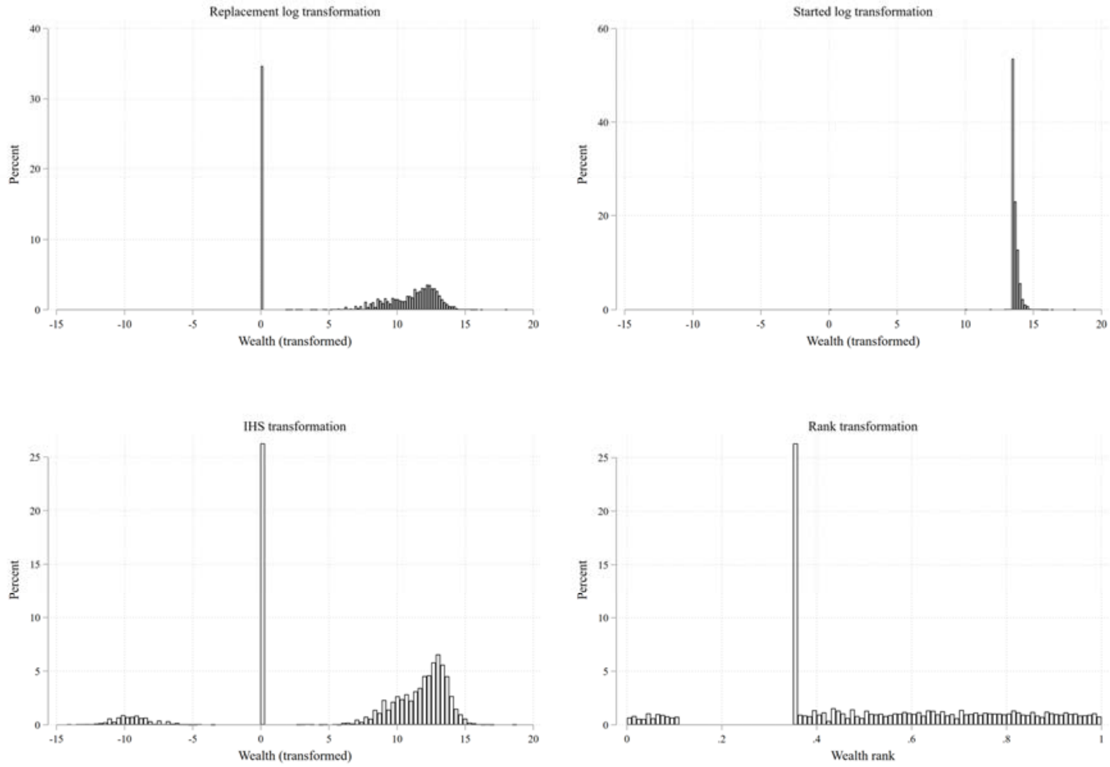

Figure 3: Various transformations of household wealth in Germany, 2017

Interpreting the results

For interpretation in a regression where log-transformed wealth is the outcome, non-transformed variables' coefficients *100 indicate the approximate percentage change in wealth for a unit change in the explanatory variable if coefficients are small. More accurately, the following formula can be used: 100*(exp(b)-1). For log-transformed explanatory variables, coefficients can be interpreted as elasticities, i.e. the percentage change in wealth when the log-transformed explanatory variable increases by 1 percent (Wooldridge 2002, 653ff). These interpretations also approximately extend to the IHS-transformed variables if wealth values are sufficiently large (Pence 2006). Bellemare and Wichman (2020) suggest that this is the case if the untransformed mean wealth is larger than 10 units (see their work for exact (semi-)elasticities; however, their simulation excludes 0s from y (Mullahy and Norton 2022)). See Norton (2022) for the computation of marginal effects after an IHS transformation, where extra care needs to be taken if large shares of 0s are present in y (Mullahy and Norton 2022).

When considering transformations, analysts will chiefly decide between the raw wealth measure, IHS and rank transformations. The choice of transformation should be dictated by the research interest and theoretical expectations. In general, using the natural scale implies that analysts expect constant additive effects. Using the IHS transformation implies that analysts expect multiplicative effects. Using the rank transformation implies that analysts care about the relative position of individuals in the wealth distribution—and population underlying the wealth distribution needs to be clearly defined. Once they decide for the IHS or rank transformation, they need to decide about the details of this transformation. In particular, when using the IHS transformation, the scale needs consideration.

An alternative approach is to use quantile regression to model the skewed wealth distribution. For instance, (Karagiannaki 2017) uses quantile regression to study the impact of inheritance on the raw changes in net wealth between two years in Britain. (Killewald and Bryan 2018) uses median regression to study wealth gaps by race in the US. However, the interpretation of quantile regression can be challenging to the uninitiated (Borgen, Haupt, and Wiborg 2023).

Imputation

Wealth is usually fraught with a larger share of missing information than other variables, because of the complexity and sensitivity of the information (Riphahn and Serfling 2005). For instance, in the SOEP about 49 percent of sample households (37 percent of sampled individuals) in 2017 have missing information on at least one wealth component. Traditionally, listwise deletion is applied where cases with missing information on wealth are ignored (Allison 2001). Listwise deletion provides accurate statistical inference. Under the assumption that the data is missing completely at random, i.e., the probability of missingness is the same for all observations, listwise deletion is a wasteful (because observations are not used) but unbiased strategy. It is also unbiased if missingness occurs only on the outcome variable. An alternative strategy is to use multiple imputation. In this approach, missing data is imputed, i.e., plausible replacement values are generated, multiple times with some noise added in each imputation. Under the assumption of missing at random, i.e., the probability of missingness does not depend on unobserved variables, multiple imputation is unbiased and uses all available observations. It is impossible to empirically evaluate the assumption of missing at random vs. completely missing at random. If data is not missing at random, listwise deletion and multiple imputation provide biased results (Allison 2001).

Multiple imputation is generally preferred over hot-deck or single imputation because it better reflects the uncertainty in the imputation process and can be more efficient as single imputation may produce outliers in data. Analysis results from multiple imputed data can later be pooled to produce a single set of quantities of interest and their statistical uncertainty (Allison 2001; McKnight et al. 2007). Different approaches can be used to multiply impute the data and an almost indefinite number of micro-decisions have to be made when analysts or data providers decide to impute data including the question of how many imputations should be generated. These decisions are beyond the scope of the present study.

An analyst can be confronted with three scenarios. First, the data provider distributes multiply imputed data. When the decision is to use the multiply imputed data or use listwise deletion, we would generally advice to use the imputed data because the data provider invested substantial resources in the imputation increasing its quality compared to individual solutions by the analyst (e.g., Grabka, Marcus, and Sierminska 2015; Lersch 2017). Using data imputed by the data provider also increases consistency across studies using the data. However, the analysts should be aware of potential issues. For instance, all analytical variables should be included in the imputation model which may not be the case if the data provider prepared the imputation.

Second, data providers may distribute only a single imputation. Here, the analysts faces a trade-off (e.g., Lersch and Baxter 2021). Single imputation will artificially reduce the uncertainty involved in the imputation process and will lead to the underestimation of standard errors. At the same time, the data providers may have done a better job in imputing than an individual analyst can do when implementing multiple imputation.

Third, data may be provided without imputation. We would generally recommend to multiply impute the wealth information in this case, because missing values are very likely not missing at random. However, multiple imputation needs many decisions, it is highly complex to implement, and can be computationally intensive. Not all analysts may have the necessary expertise and resources. Therefore, the sharing of imputation routines between analysts should become best practice. Optimally, analysts could refer to a library of imputation tools for their data.

Data providers have different practices. For instance, SOEP includes multiply imputed data, Household, Income and Labour Dynamics in Australia (HILDA) Survey includes a single imputation, and the British Household Panel Survey (BHPS) includes no imputation. As data providers have different practices, which necessitate different procedures by the analyst, we recommend to clearly document whether some data were imputed and if the imputation was provided by the data provider or done by the analyst in the data preparation. Furthermore, it is necessary that the data providers transparently document their imputation practice, and they should also clearly state whether any wealth data was edited.

Noteworthy, recommendations for multiple imputation of the outcome variable are different from explanatory variables. The outcome needs to be included in the imputation process, but then the question is whether the imputed outcome values should be included in subsequent analysis. In the multiple imputation, then delete (MID) approach, imputed wealth is not considered in the analysis. The alternative is multiple imputation then inclusion (MII). Because of the large number of missing values in wealth it is often impractical to use MID and there are also concerns about bias in MID in specific applications (Sullivan et al. 2015). The consequences of MID and MII for estimation results can be easily compared (Von Hippel 2007; Kontopantelis et al. 2017).

We want to close this section with some general advice regarding missing values in wealth. First, it is crucial to closely study the data documentation to clearly understand how missing values have been treated in the data. Second, based on this information, research goals, and individual expertise and resources, the analyst should decide which strategy of dealing with missing values to choose. Third, it is mandatory to transparently document the chosen strategy.

4. Example Application: A Multiverse Analysis of Wealth Returns to Education

Background

In the following section, we apply the methodological considerations discussed above to empirical data. To demonstrate the impact of decisions in wealth operationalization on study outcomes, we perform a multiverse analysis of the wealth returns to tertiary education.

Prior research shows that being a university graduate is substantially and significantly associated with one's level of wealth holdings (Cordova, Grabka, and Sierminska 2022; Sierminska, Piazzalunga, and Grabka 2018; Keister 2004; Emmons and Ricketts 2017), and the highest degree received can explain a quarter of the intergenerational association in wealth (Pfeffer and Killewald 2018). We expect wealth returns to education from a human capital perspective, where the labor market rewards higher skill levels in the form of a college wage premium (Ordemann and Pfeiffer 2022; Friedrich and Hirtz 2021 for Germany; Green and Henseke 2021 for Europe). A higher flow of income in turn enables individuals to accumulate higher wealth through savings. However, education is associated with wealth even net of income (e.g. Sierminska, Piazzalunga, and Grabka 2018). Although it is possible that education merely functions as a proxy for prior income flows not captured by measures of current income (Killewald, Pfeffer, and Schachner 2017), it may also be that more educated individuals accumulate higher wealth through more advantageous financial decision-making and portfolio choices. Education is strongly correlated with financial literacy (Lusardi and Mitchell 2014), which is associated with higher net wealth for a large part of the wealth distribution in Germany (Hou and Schuler 2022; Bannier and Schwarz 2018). Financial literacy is linked to stock market participation and the holding of risky financial assets that typically yield higher returns, as well as active retirement planning (Bannier and Neubert 2016; Bucher-Koenen and Lusardi 2011; Thomas and Spataro 2018). In line with these findings, research found the highly educated to profit more long term from intergenerational transfers (Benton and Keister 2017), and that prolonged schooling increases the returns on personal net wealth holdings (Fagareng et al. 2020). Still, higher income remains a central factor in the advantageous financial behavior of more educated households (Cooper and Zhu 2016). While there is little research directly connecting education and personal wealth, we increasingly see causal evidence from studies relying on statistical control or natural experiments (Hartog and Oosterbeek 1998; Bingley and Martinello 2017; Girshina 2019; Wang et al. 2022).

Analytical Approach

We aim to show the variability of effect size as a consequence of operationalization decisions for wealth as a dependent variable. To this end, we adopt the framework of multiverse analysis following Steegen et al. (2016), or multimodel analysis following Young and Holsteen (2017). Multiverse analysis aims at improving research practice and creating transparency around arbitrary methodological choices that can be consequential for the results of a study, addressing the "statistical crisis in science" (Gelman and Loken 2014, 460). It highlights the way in which data is actively constructed by the researcher through processing steps like the construction and editing of variables, sample restrictions and other data exclusions. Mutually exclusive choices create a multiverse of possible data sets and therefore statistical results. Instead of reporting the results of merely one or two alternative specifications in a robustness check, the multiverse perspective argues for exploring all possible outcomes. After listing the possible choices to be made, the data multiverse is constructed by considering all reasonable combinations of these choices. The analysis is then performed on every single data set. Because this can easily result in a very high number of data sets and corresponding model coefficients, communicating the results of a multiverse analysis and drawing conclusions poses a challenge.

We use the Socio-economic Panel (SOEP v37, doi: 10.5684/soep.core.v37eu), a nationally representative panel survey conducted annually by the German Institute for Economic Research (DIW Berlin) since 1984. Its most recent version contains data on about 20.000 households up to 2020. One of its merits is its detailed wealth module, first implemented in 2002 and collected in 5-year intervals since. It includes high-quality data on different asset and debt components at the household and individual level. To reduce measurement error from rounding and misreporting, wealth data is checked and edited for consistency and plausibility across household members. Further, complex multiple imputation procedures are used on missing data due to item non-response (for further information see Grabka and Westermeier 2015).

Based on the combination of methodological possibilities portrayed in Figure 4, we construct a multiverse containing a total of 1536 alternative versions of personal wealth. Variables containing a combination of winsorizing and rank transformation are excluded from the analysis.[5] An OLS regression on our independent variable, tertiary education, is then run for each of the 1536 variables. In the case of multiply imputed wealth variables, regression results are combined according to Rubin's rules (Barnard and Rubin 1999).[6] To facilitate comparison of wealth variables with different units, regression coefficients are normalized by dividing through the sample mean of the respective wealth variable prior to further analysis.[7] As a consequence, the estimates are expressed as proportion of the baseline, which is the sample mean of the dependent variable.

Tertiary education is defined on the individual level by the highest level of education being an academic tertiary degree. We do not differentiate between degrees from universities or universities of applied sciences, nor between academic levels. The regressions are controlled for a set of individual characteristics connected to wealth accumulation, namely age, gender, and German nativity.[8] To reduce bias produced by an influence of social origin on both education and wealth, parental socio-economic status at respondents' age 15 is included.[9] Regression is performed on individuals over the age of 30 which are likely to have completed their education. For the sake of maximum generalizability, no other sample restrictions are applied, leaving us with a sample of roughly 36.000 individuals with imputed information and 17.600 after listwise deletion of wealth data.

[5] For more detailed information on operationalization choices, see Table A1.

[6] Formulas for the combination of parameters can be found in Stata's Multiple-Imputation Reference Manual (2023) or, for example, Marshall et al. (2009).

[7] While comparability is typically achieved by standardization of coefficients, we avoid transforming coefficients using the variance of the dependent variable. The reason is that the different choices in wealth methodology, especially in transformations of the wealth variable, affect variance. Standardization by variance therefore obstructs an analysis of how these choices affect effect size. For a discussion of this problem, see Goldstein-Greenwood (2023).

[8] For an overview of central determinants of wealth, see Killewald et al. (2017).

[9] The SOEP provides biographical information on respondents' parents, including both parents' International Socio-Economic Index (ISEI) Scores at respondent's age 15. The ISEI was developed by Ganzeboom et al. (Ganzeboom, De Graaf, and Treiman 1992) based on information about income, education, and occupation (ISCO-88) and technically ranges between values of 16 and 90. Our variable takes the highest ISEI-Score of either parent.

Following Simonsohn et al. (2020), we employ the specification curve as a graphical solution for communicating multiverse analysis results. In an additional step, we perform an OLS regression of normalized outcomes (effect sizes) on the methodological choices producing the respective version of the wealth variable to better understand which choices are influential on the size of the coefficient.[10]

[10] Because weighting by standard errors, dependent on variance in the wealth variable, results in a problem similar to that of standardization of coefficients, we decided against performing a traditional, weighted meta-regression.

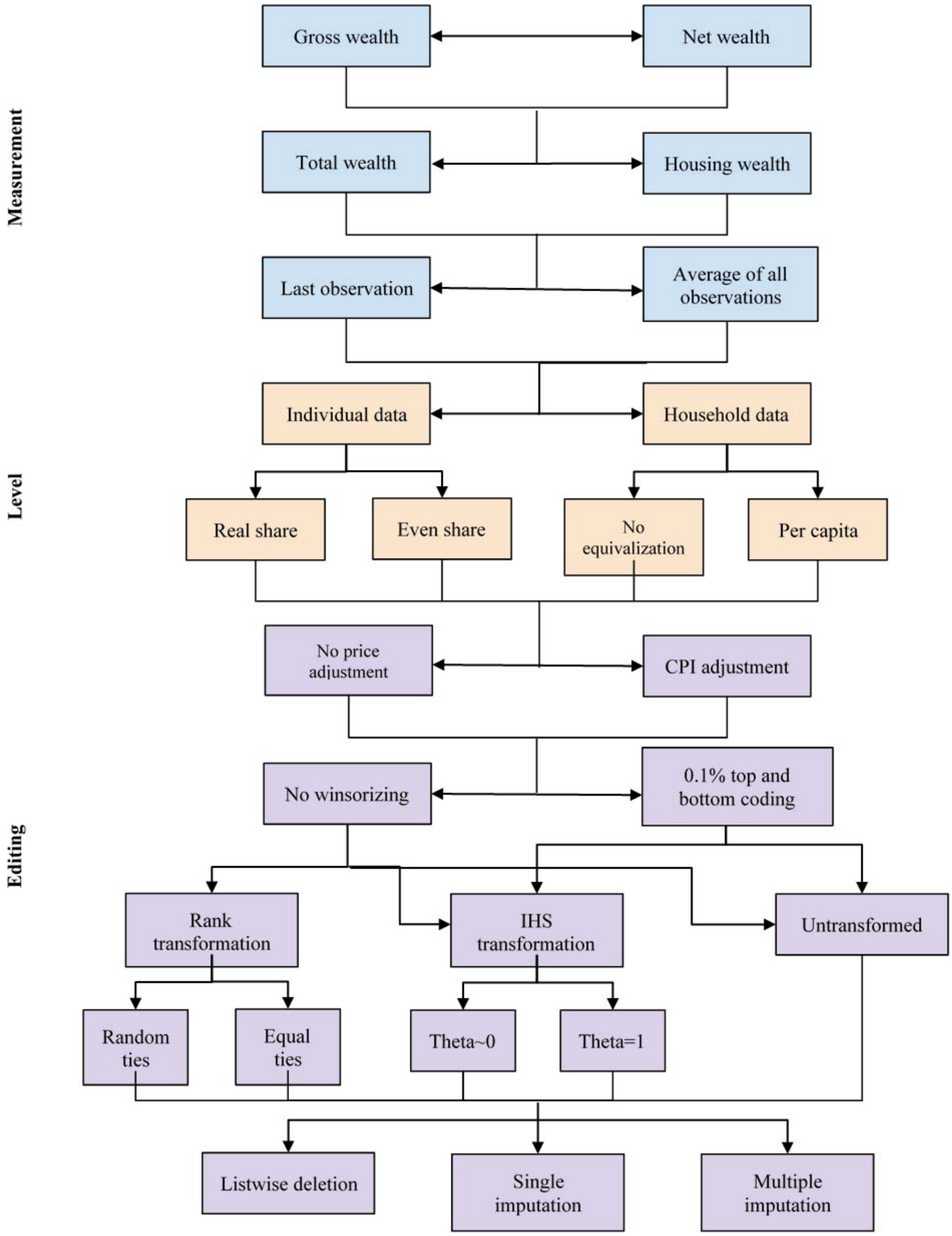

Figure 4: Methodological choices considered in the construction of the wealth data multiverse

Results

Table 2 displays exemplary regression results for two variants picked out of the total of 1536 wealth outcome variables. We draw on prior literature on education as a predictor of wealth in the choice of the example variables. To demonstrate the impact of our set of control variables on the education coefficient, a bivariate model as well as a model including individual demographic characteristics and parental socioeconomic status (SES) is presented.

Table 2: Example regression results (without normalization)

	Example 1		Example 2	
	Bivariate	Full model	Bivariate	Full model
Tertiary education	137256.546***	124170.298***	222285.417***	201831.591***
	(4286.778)	(4577.206)	(7189.584)	(7703.615)
Age		1607.375***		1911.806***
		(127.057)		(213.842)
Gender: female		-53251.758***		-22874.980***
		(3728.318)		(6274.903)
Not born in Germany		-74065.870***		-130493.826***
		(5371.842)		(9041.017)
Parental SES		877.940***		1667.029***
		(122.900)		(206.845)
Constant	117258.674***	37132.405***	226458.190***	90348.043***
	(2167.847)	(9569.556)	(3635.812)	(16105.932)
Observations	35814	35814	35814	35814

OLS-Regression of standardized variables * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Example 1, based on Girshina 2019: Gross total wealth, single observation, **individual data (real share)**, price adjusted, top and bottom coded, untransformed, single imputation.
Example 2: Gross total wealth, single observation, **household data (no equivalization)**, price adjusted, top and bottom coded, untransformed, single imputation. OLS-Regression of standardized variables.

The first example variable is based on the wealth operationalization in Girshina (2019), taking the last available observation of untransformed gross total wealth, top and bottom coded and price adjusted.[11] The second example is chosen to be similar but for one choice: while Girshina (2019) employ individual level (register) data, example two measures wealth at the household level, and as is most common, without adjusting for household size. The effect of education is positive and significant in both examples. While being reduced by adding covariates, the education effect is still very large in the full model. In example one, individuals with a tertiary education certificate are predicted to have wealth holdings of about 124.170,30€ higher than those without a degree, all else being equal. There is substantial difference between the two examples of wealth operationalizations, as using household level wealth data (example two) produces an education coefficient larger by more than 60% (about 77.600€).

The frequency distribution of normalized coefficient sizes in the multiverse analysis, rounded down to their first two decimals, is shown in Figure 5. Highlighted bars mark where coefficients produced with our equivalent of wealth variable operationalizations found in prior literature fall within the

[11]The example variable is chosen to be as similar as possible to the main analysis variable in Girshina (2019), based on the information provided in the publication. One deviation is that winsorizing is done at 0.5% of the wealth distribution in Girshina (2019), and at 0.1% in our data.

distribution.[12] The effect of education on wealth varies widely depending on exact operationalization, ranging from a coefficient size of about 0.05 to 1.00 with a mean of 0.37. Values of 0.26 are most prevalent. A gap is visible at effect size 0.39. A visual analysis of the distribution of the estimates keeping one factor fixed (Figure A1) shows that the lowest values are related to the use of housing wealth and all applied kinds of transformation, while the highest values are related to using an untransformed wealth measure.

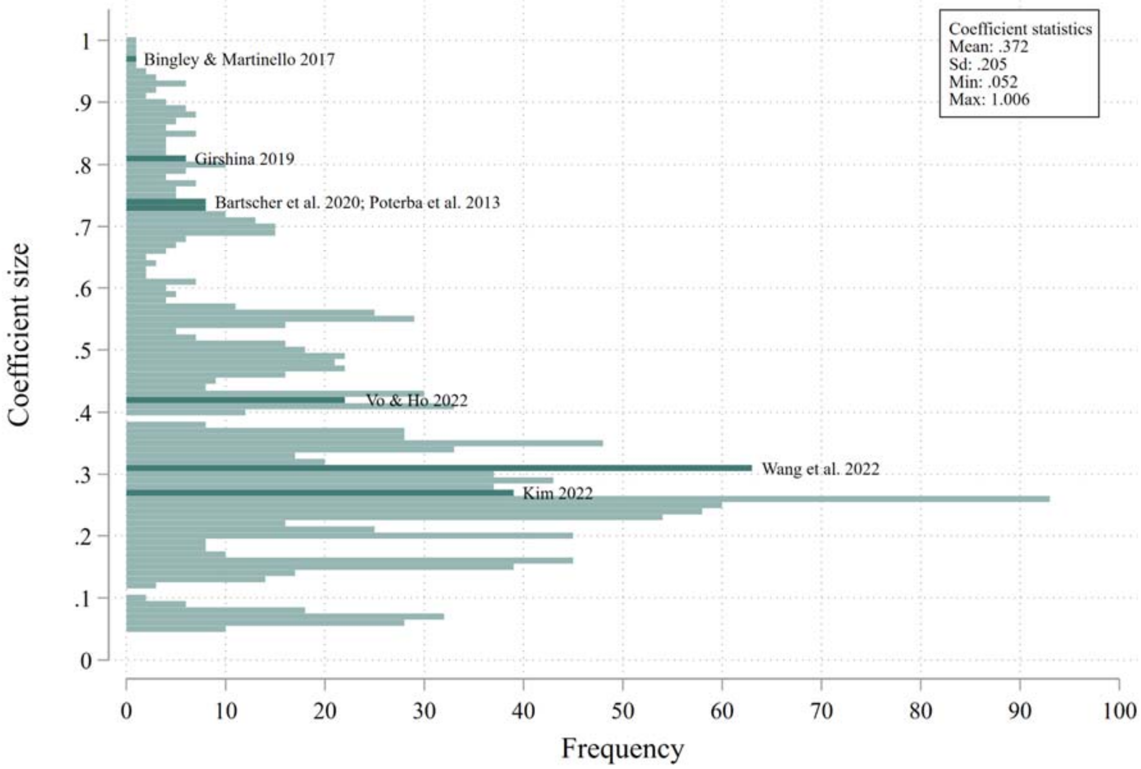

Figure 5: Model distribution of wealth return to education.

[12] Figure 5 does not display effect sizes from prior research, but the effect sizes produced with our data basis using the rules of operationalization found in other publications on wealth returns to education. We chose variables as close as possible to the original operationalizations, trying to be as accurate as possible with the information that was offered.

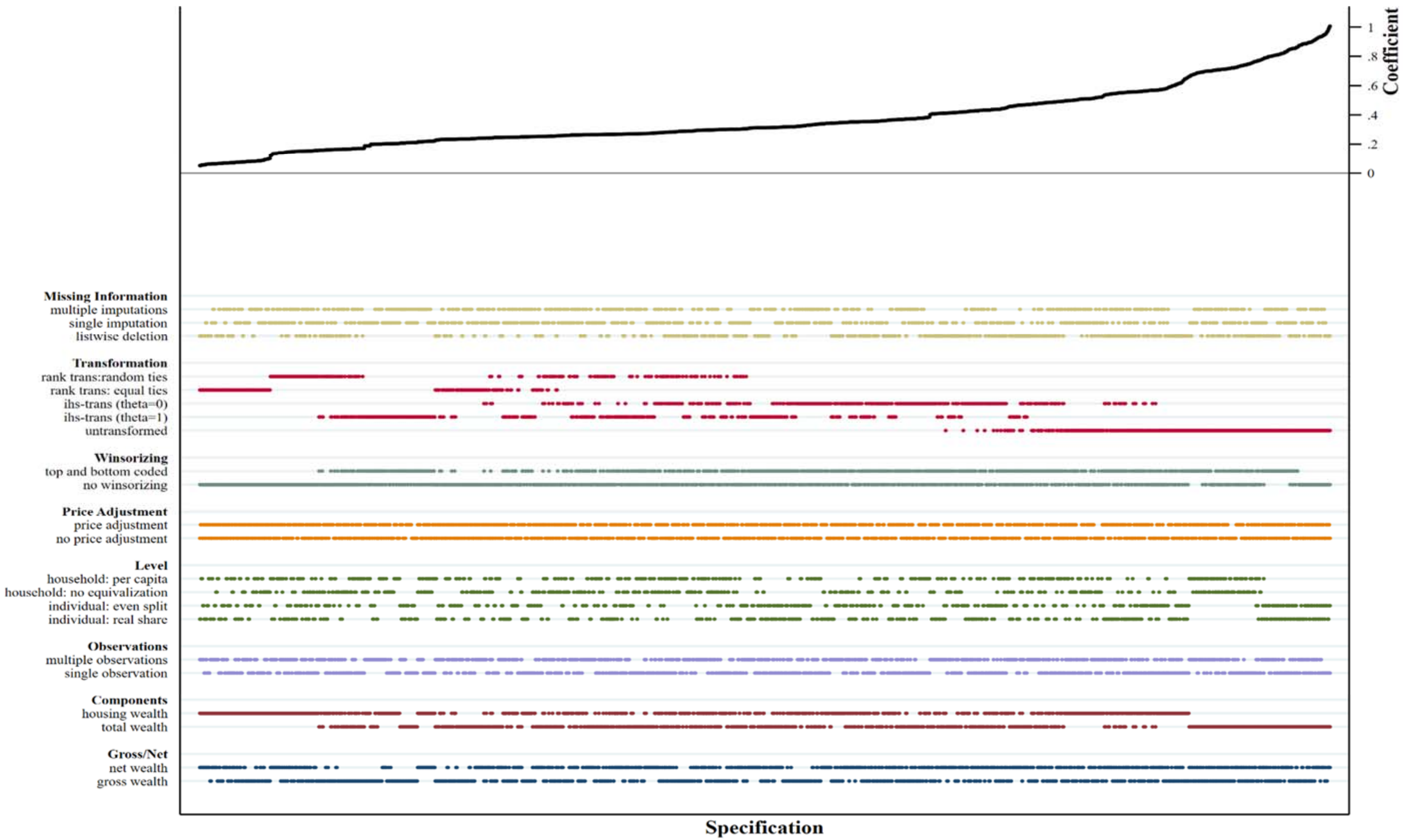

Figure 6: Specification curve to the multiverse analysis of the wealth return to education

We now turn to possible systematic connections between methodological choices and resulting effect sizes. The specification curve (Figure 5) is a detailed graphical representation of the multiverse analysis of wealth returns to education. It depicts outcomes for all 1536 wealth variables, with normalized regression coefficients ordered from left to right by size (black markers). Below, the colored markers connect each regression coefficient value to the combination of methodological choices underlying the construction of its outcome variable. To identify influential operationalization choices, we inspect the lines of markers connected to each one. While evenly distributed markers across the whole range of coefficients indicate no systematic connection to outcomes, the 'lumping' of markers on one side or in distinct patterns points to a choice's impact on effect sizes.

The most distinctive pattern emerges for wealth transformations. Untransformed variables clearly produce larger coefficients compared to transformed variables. The majority of coefficients lie above 0.5, and therefore well above the mean of the distribution. Rank transformation results in the smallest coefficients, especially when applying equal ties, but can also produce coefficients in the middle field of the distribution. Coefficients of IHS-transformed variables show the most variation in size, and are not represented on either tail end of the distribution. The IHS-transformation with a theta of (close to) zero shows a clear tendency to produce larger coefficients than that with a theta of 1, which is similar to a log-transformation. A pattern is also visible for wealth composition, with the smallest coefficients resulting from housing wealth, and the largest ones from total wealth. Winsorizing seems to influence regression outcomes, as the smallest coefficients below a size of 0.2 are produced solely by top and bottom coded data. Lastly, the largest coefficients result from individual level, as household level data coefficients are not represented above a value of 0.8. Individual level data can, however, also produce smaller coefficients than household data, as is the case in the example regression (Table 2). Both choices are represented along most part of the distribution. The same applies to wealth components.

Beyond this fact, the pattern produced by level of measurement choice stands out because coefficients are clustered in smaller lumps along the range of effect sizes, with fairly large gaps in between. To a smaller degree, this kind of 'dotty' pattern also applies to the choice in handling of missing information, as well as transformation choice. A likely conclusion is that their impact depends on other methodological choices made for a variable, pointing to possible interaction effects between factors. Price adjustment, the number of included observation points and the distinction between gross and net wealth on the other hand produce coefficients distributed more or less evenly across the graph. They seem to not be of much consequence for the magnitude of the education effect.

A meta-regression presents the average effect of single choices in variable construction on coefficient sizes, providing information beyond the graphical analysis of patterns (Table 3). Firstly, total gross wealth, as a single observation, based on individual data with the real share in joint assets, without price adjustment, winsorizing or transformation, employing listwise deletion, produces an education coefficient of 0.796 of the sample mean for the respective wealth variable (constant). All else being equal, using net instead of gross wealth increased the effect by 0.024 of the corresponding sample mean, and using an average of all observations instead of only the last one reduces it by 0.017. These effects are relatively small in size, corresponding to the absence of a distinct pattern in the specification curve, but they are statistically significant. Concerning the components included in the wealth measure, the specification curve and meta-regression unambiguously show that housing wealth coefficients are, on average, substantially smaller than total wealth coefficients, with a coefficient of 0.123 of the sample mean. Choice of wealth composition, however, is far from being arbitrary, and might have varying consequences for different explanatory variables.

For level of measurement, the specification curve showed individual level data to produce the largest coefficients. The meta-regression confirms this, as normalized coefficients from household level wealth data are on average 0.05 points smaller than those resulting from real share individual data, with no difference in coefficients produced by applying an equivalence scale on household wealth. Similarly, using an artificial even split between partners instead of their real share for individual data has no statistically significant effect.

Table 3: Meta-regression

Dependent variable: coefficient size		
Measurement		
Ref.: gross wealth		
net wealth	0.024^{***}	(0.003)
Ref.: total wealth		
housing wealth	-0.123^{***}	(0.003)
Ref.: single observation		
multiple observations	-0.017^{**}	(0.003)
Level of analysis		
Ref.: individual: real share		
individual: even split	0.005	(0.004)
household: no equivalization	-0.050^{***}	(0.004)
household: per capita	-0.050^{***}	(0.004)
Editing		
Ref.: no price adjustment		
price adjustment	-0.004	(0.003)
Ref.: no winsorizing		
top and bottom coded	-0.012^{**}	(0.004)
Ref.: untransformed		
ihs-trans (theta=1)	-0.391^{***}	(0.004)
ihs-trans (theta=0)	-0.294^{***}	(0.004)
rank trans: equal ties	-0.511^{***}	(0.006)
rank trans:random ties	-0.456^{***}	(0.006)
Ref.: listwise deletion		
single imputation	-0.069^{***}	(0.004)
multiple imputations	-0.063^{***}	(0.004)
Constant	0.796^{***}	(0.006)
Observations	1536	

Standard errors in parentheses
$^{*}\ p < 0.05$, $^{**}\ p < 0.01$, $^{***}\ p < 0.001$

In editing choices, all but price adjustment show a statistically significant impact on coefficient size. Top and bottom coding of the wealth measure reduces the normalized effect size by 0.01. Moreover, on average, every choice of transformation diminishes the effect size to varying degrees compared to untransformed variables. As reflected by the specification curve, the rank transformation with equal ties produces the largest average decrease upon the untransformed variants of 0.511 points, followed by random ties rank transformation with 0.456 points (statistically significant difference, p<0.001).[13] IHS-transformation with a theta close to zero and a theta of 1 reduce the coefficient by 0.294 and 0.391 points respectively (statistically significant difference, p<0.001). Overall, there are substantial differences in average normalized effect size between transformation choices. Lastly, imputed wealth data produces education coefficients that are between 0.63 and 0.69 points smaller than for listwise deletion on average, without a significant difference between single and multiple imputation.

5. Discussion and Conclusions

The literature on wealth is growing rapidly as many rich societies face high wealth inequality which is perceived as one of the defining social challenges of our times. The existing literature on wealth is still in its early stages, and research practices in analyzing wealth have not kept pace with the improved availability of data. Researchers often face numerous challenges in defining and measuring wealth and tend to make ad hoc choices without proper documentation. This lack of transparency violates scientific norms and hinders replication and further research. Unlike income research, which has clear recommendations for measurement, there are no established best practices for wealth research. Therefore, we argue that the progress in the field is hindered by the lack of justification for empirical decisions, research transparency, and result comparability. In this study, our objectives were to provide an overview of the empirical decisions involved in measuring wealth, discuss their underlying assumptions and implications, and demonstrate the significant variability in estimated associations resulting from different empirical decisions through a multiverse analysis using data from the German Socio-economic Panel Study.

The upshot of our multiverse analysis covering 1,536 different versions of the wealth variable is that empirical decisions matter and can have crucial implications for estimated relationships. While all estimated coefficients are statistically significantly positive in our application, the effect sizes vary widely suggesting very different conclusions about the strength of the relationship between education and wealth.

Why does the effect size vary? To understand better where variation comes from, recall that the estimated coefficient gives the mean wealth of individuals with a tertiary education diploma compared to individuals without a tertiary education diploma, after partialling out the effect of covariates.

Let consider the most influential choices determining the size of the estimates: the definition of wealth (housing vs. total wealth) and the transformation (IHS with different scaling parameters and rank with different treatment of ties vs. untransformed wealth). Housing wealth tends to vary less across social groups than total wealth. Less educated people’s most valuable asset is usually self-occupied housing. More educated people typically hold a more diversified wealth portfolio than less educated people, including business assets and financial assets. As a consequence, the wealth gap between these two groups is smaller when the measure of wealth is restricted to housing wealth.

The IHS transformation, as it is based on logarithms, tends to preserve more variation around zero and to minimize variation away from zero—and this is precisely why an IHS transformation is used, to reduce the influence of outliers. The distribution of wealth tends to be away from zero when wealth is unadjusted, it is closer to zero with IHS transformation when wealth is expressed in euros (theta = 1), and even closer to zero with IHS transformation when theta close to 0 (which means that wealth is

[13] Result from a wald test for difference in coefficients.

expressed in 10,000€). Therefore, the wealth gap between most educated and less educated individuals would be larger with unadjusted wealth than with the IHS transformation, even when the gap is expressed in sample means. Regarding rank transformation, the underlying logic is the same: the rank transformation gives the same weight to small variations in wealth in the bottom of the distribution than to large variations in the top of the distribution. As a consequence, a rank transformation leads to measuring a smaller wealth gap between highly and low-educated individuals.

Regarding the level of analysis, we find no difference when individual wealth is measured by real shares of joint assets as compared to equal-split measures. Similarly, we find no difference whether individuals are attributed all household wealth or per capita household wealth. But we find that measuring wealth at the household level leads to lower estimates of wealth return to higher education as compared with wealth measured at the individual level. Household-based measures only use inter-household variation, while individual-based measures also use intra-household variation. Using intra-household variation reinforces the positive correlation between education and wealth, as highly-educated spouses are richer than their low-educated spouses in heterogamous couples.

Regarding imputation results, the wealth gap between individuals who received a tertiary education and those who did not is lower when wealth is imputed for missing values. This indicates that listwise deletion does not delete individuals at random. Information on wealth is missing either for highly educated individuals who are poorer than other highly educated individuals, or for low-educated individuals who are richer than other low-educated individuals. In both cases, adding those individuals to the picture results in lowering the return of tertiary education on wealth.

The gap between highly and low educated individuals is smaller when net wealth, instead of gross wealth, is used, suggesting that highly-educated individuals hold more debts than low-educated individuals. This may reflect different access to the credit market between educational groups.

The empirical decisions related to the operationalization of wealth affect the bottom and the top of the distribution. The impact on the estimates might be particularly important depending on the research question. For instance, any research question related to the wealth structure of poor or rich households would be largely impacted by empirical decisions on how wealth is measured.

Based on our elaborations and findings, we have several recommendations for wealth researchers. Firstly, we strongly urge researchers to carefully consider their research questions, objectives, data specifics, and the context of wealth measurement when making analytical choices. It is crucial to take these factors into account to ensure accurate and meaningful results. Secondly, we advise researchers to test the sensitivity of their results to specific decisions they make during the analysis. Our multiverse analysis reveals that estimated relationships can vary significantly, and the direction of coefficient changes cannot be determined based solely on theory. Different choices by researchers can lead to unexpected changes in results. Therefore, it is essential to be aware of this potential and evaluate how alternative decisions may impact the outcomes. The main lesson from our article is that analysts' decisions play a significant role. The choices made throughout the research process can have a substantial effect on the results obtained. Researchers should recognize the importance of their decisions and exercise caution in making them. Lastly, we emphasize the need for transparent documentation of all empirical decisions as a minimum requirement to enhance research practices in the field. By documenting and sharing the details of the decisions made, researchers can promote openness and facilitate better understanding and evaluation of their work.

While our work provides valuable insights, it is important to acknowledge its limitations. Firstly, the multiverse analysis is constrained by focusing on a single country context, which may restrict the generalizability of our findings to other contexts with different socio-economic structures and wealth distributions. In comparative research, the choices outlined in the current study would be even more complex because issues of harmonization need to be addressed, so that differences across contexts reflect actual differences in the association between characteristics and personal wealth, and not variations in data preparation. Second, and more generally, by treating wealth solely as an outcome variable, we may overlook important decisions to be made for considering wealth as an explanatory factor in understanding other socio-economic phenomena. Third, our study did not incorporate a Monte Carlo simulation, which would have allowed us to assess the true relationship between variables by generating simulated data. Lastly, we acknowledge that our analysis may be incomplete as we did not fully consider the top end of the wealth distribution, which is not well covered in survey data and which consideration could provide valuable insights into wealth accumulation and inequality. These limitations highlight the need for future research to address these aspects and provide a more comprehensive understanding of wealth dynamics.

Notwithstanding these limitations, our conclusions are clear. We believe that a one-size-fits-all recommendation for measuring and operationalizing wealth is impossible, but research practice can still be greatly improved. Wealth researchers should carefully consider their research questions and data specifics, evaluate the sensitivity of results to different decisions, recognize the impact of their choices, and ensure transparent documentation of empirical decisions to improve research practices.

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Appendix

Table A1: Alternatives in wealth operationalization

<table>
<tr><td>Level</td><td colspan="7">Alternatives</td></tr>
<tr><td rowspan="2">Measurement</td><td colspan="3">Gross wealth</td><td colspan="4">Net wealth</td></tr>
<tr><td colspan="3">Total wealth
- at market value: primary residence, other real estate, financial assets, building loans and insurances, business assets, tangible assets
- Primary residence debt, other real estate debts, consumer debts</td><td colspan="4">Housing wealth
- primary residence
- primary residence debt</td></tr>
<tr><td rowspan="2">Unit</td><td colspan="3">Individual data with</td><td colspan="4">Household data with</td></tr>
<tr><td>Real share of joint assets
- primary residence share, other real estate share, financial assets share</td><td colspan="2">Even split
Of joint assets</td><td colspan="2">No equivalization</td><td colspan="2">Per capita</td></tr>
<tr><td rowspan="6">Editing</td><td colspan="3">No price adjustment</td><td colspan="4">Price adjustment
Consumer price index (2017=100, source: Statistisches Bundesamt)</td></tr>
<tr><td colspan="3">0.1% top and bottom coded</td><td colspan="4">No winsorizing</td></tr>
<tr><td colspan="2" rowspan="3">Untransformed</td><td colspan="2">IHS transformation with…</td><td colspan="3">Rank transformation with…</td></tr>
<tr><td rowspan="2">Theta=1
Theta=1.0</td><td rowspan="2">Theta~0
Theta = 0.0001</td><td colspan="2">Equal ties</td><td>Random ties</td></tr>
<tr><td colspan="3">weighted within observation years</td></tr>
<tr><td colspan="3">One observation (most recent)</td><td colspan="4">Multiple observations (averaged)</td></tr>
<tr><td></td><td colspan="2">Listwise deletion</td><td colspan="2">One imputation</td><td colspan="3">Multiple imputations
Five imputations; row-and-column imputation</td></tr>
</table>

Table A2: Descriptive Statistics

	Mean	SD	Min	Max
Untransformed: mean of	111361.61	296961.18	-355776.95	18400940
IHS-transformed (theta=1): mean of	7.4	5.94	-6.62	16.37
IHS-transformed (theta~0): mean of	17808.27	16551.22	-20139.91	71563.75
Rank-transformed (equal ties): mean of	0.58	0.21	o.17	1
Rank-transformed (random ties): mean of	0.51	0.29	0.00	1
Tertiary degree	.26	.44	0.00	1
Age	53.06	14.99	30.00	102
Gender: female	.54	.5	0.00	1
Foreign born	.14	.35	0.00	1
Parental SES	42.51	16.44	16.00	90

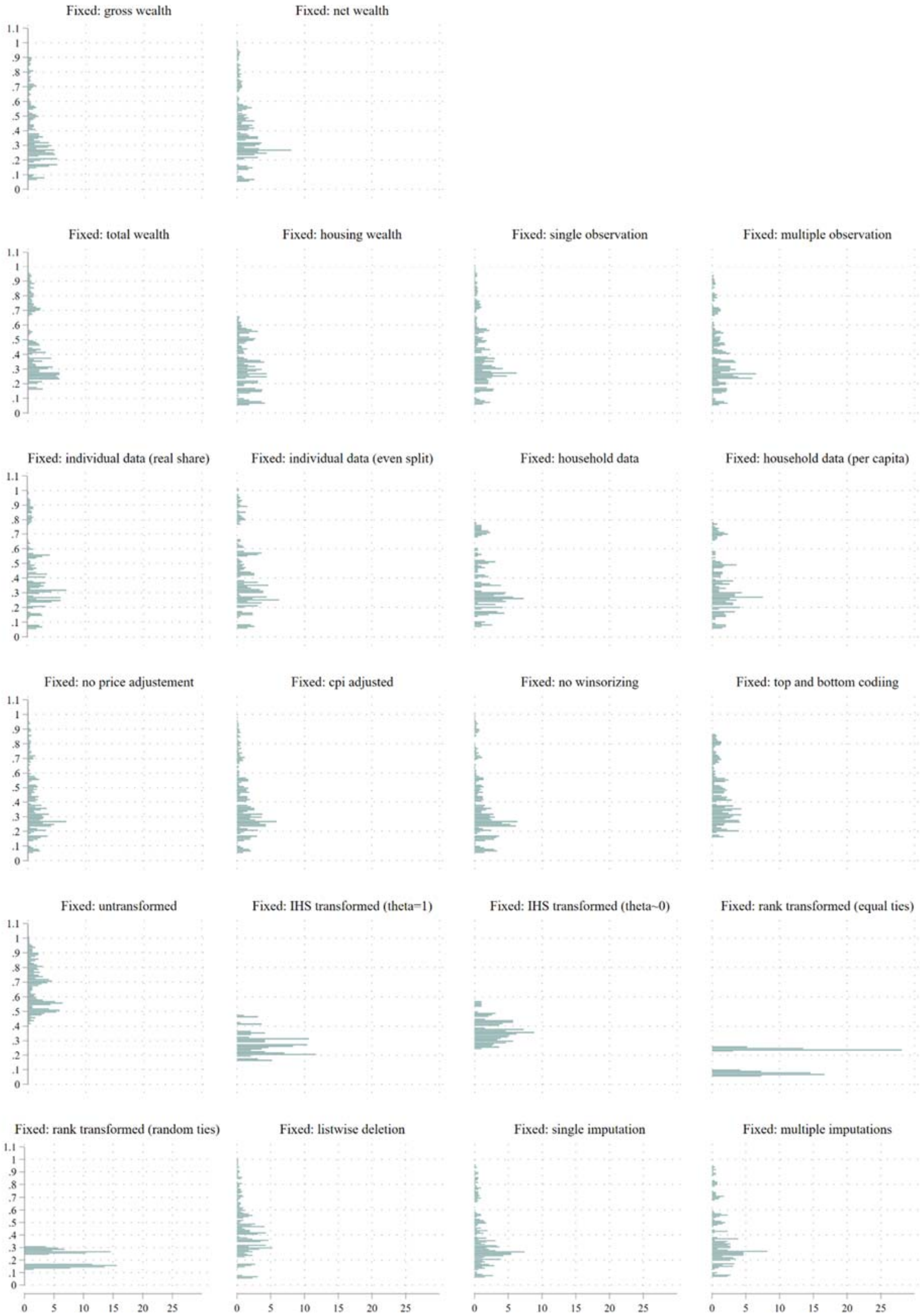

Figure A1: Distribution of effect sizes (in percent) with one option fixed

Source text	Ascribed Operationalization							
Bartscher et al. (2020)	net	Total wealth	Single observation	Household, no equivalizatio n	Price adjusted	No winsorizing	untransforme d	Multiple imputation
Bingley & Martinello (2017)	net	Total wealth	Single observation	Individual, real share	Price adjusted	No winsorizing	untransforme d	Listwise deletion *register data
Girshina (2019)	gross	Total wealth	Single observation	Individual, real share	Price adjusted	Top and bottom coding	untransforme d	Single imputation
Kim (2022)	net	Total wealth	Single observation	Household, no equivalizatio n	Price adjusted	No winsorizing	IHS-transformatio n (theta=1) *originally log	Multiple imputation
Poterba et al. (2013)	net	Total wealth	Single observation	Household, no equivalizatio n	Price adjusted	Top and bottom coding *originally 1%, I think	untransforme d	Single imputation
Vo & Ho (2022)	net	Total wealth	Single observation	Household, no equivalizatio n	No price adjustment	No winsorizing	IHS-transformatio n (theta=1) *originally log	Listwise deletion
Wang et al. (2022)	net	Housing wealth	Single observation	Household, no equivalizatio n	No price adjustment	No winsorizing	IHS-transformatio n (theta=1) *originally log	Listwise deletion