Measuring top wealth shares in the UK

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Abstract

We examine how the measurement of *aggregate* wealth affects our understanding of wealth distribution. We explain why choices over wealth aggregates can affect the measured level and composition of wealth concentration. Applying this to the UK, we find estimates of the top 1% wealth share vary by 2.1pp – between 14.4% and 16.5% – in 2016-18, depending on the choices we make regarding aggregates and the source of distributional information. Alternative definitions for aggregates lead to a reranking of who is at the top, replacing 40% of individuals in the top 1%, and changing the share of women and older individuals. We discuss conceptual and measurement issues with the National Accounts as a source of wealth aggregates, and argue that in many cases they are poorly aligned in both regards with the measure of personal wealth one would like to target, and in practice are less comparable internationally than they initially seem. In the UK, where the wealth survey has reasonably good coverage across the distribution, we therefore prefer survey aggregates.

JEL codes: D31, E01, G51

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1 Introduction

Interest in the measurement of wealth inequality has grown in recent years, reflecting increasing public concern over the concentration of resources and inequality in living standards. Recent academic contributions have been motivated by a desire to understand the distribution of macroeconomic growth and make international comparisons (Atkinson and Piketty, 2007; Saez and Zucman, 2016; Piketty et al., 2018; Alvaredo et al., 2020), understand the drivers of wealth accumulation and intergenerational mobility (Artola Blanco et al., 2021; Fagereng et al., 2020; Martínez-Toledano, 2023), and to understand the potential for redistributon (Saez and Zucman, 2019; Advani et al., 2021b). Much of the recent debate has focused on the use of tax data combined with estimated rates of return on assets to capitalise income flows (Smith et al., 2023; Saez and Zucman, 2020, 2022). However, individual wealth estimates produced by this approach are usually still scaled up, separately by asset class, typically to the National Accounts (Alvaredo et al., 2020).

In this paper, we explore the impact of the choice of wealth aggregates for the wealth share and characteristics of the top 1%. We explain how and why different asset distributions affect the direction of changes in top shares that result from targeting different aggregates, and illustrate this using two of the commonly-used sources of distributional information: survey and income tax data. In doing so, we enable those who choose alternative sources of distributional information to better understand how aggregates play a role in explaining their results.

To examine the role of aggregates, we first show that top wealth shares can be decomposed into the share of each asset class held by the wealthiest, and the relative sizes of each asset class. In the UK, aggregate net wealth was £14.2 trillion in our survey data in 2016-18 – £4.3 trillion higher than the £9.9 trillion observed in the National Accounts. This difference is primarily driven by the treatment of pension and housing wealth, which are also relatively less concentrated than other asset classes.

The choice of aggregates matters quantitatively for estimates of wealth *concentration.* When there is heterogeneity in portfolio composition, scaling the value of a particular asset class in order to target a different aggregate produces a reranking of individuals, and a change in the aggregate value of wealth held at the top. Estimates of the share of wealth held by the top 1% vary by 2.1 percentage points – between 14.4% and 16.5% – in 2016-18, depending on the choices we make regarding aggregates and the source of distributional information.

The reranking of individuals as a result of switching from survey to National Accounts aggregates (NA aggregates) not only affects measured wealth concentration, but also the characteristics of those at the top. Using NA aggregates, 40% of individuals in the top 1% under the survey aggregates are no longer in the top 1%. The top 1% exhibits an older age profile and is less male-dominated relative to when survey aggregates are used.

National Accounts have become the de facto data source for measuring aggregate wealth, and methods to produce distributional statistics that are consistent with these aggregates have proliferated in recent years (Piketty et al., 2018; Saez and Zucman, 2016; Garbinti et al., 2021; Martínez-Toledano, 2023; Alvaredo et al., 2020; EG-LMM, 2020). As well as enabling us to understand the distribution of macroeconomic growth, the appeal of this approach lies partly in the fact that National Accounts are produced according to internationally standardised guidelines. Distributional statistics that are aligned with these aggregates are therefore considered to be internationally comparable (Chancel et al., 2022).

We argue that survey data should not be automatically dismissed in favour of National Accounts when it comes to measuring aggregate wealth for purposes of understanding wealth distribution. While National Accounts are appropriate for answering a certain set of research questions, they do not target the relevant definition of wealth for those interested in measuring inequality. These conceptual issues are not specific to the UK context: the fact that National Accounts are produced according to an internationally standardised framework implies that many of these issues apply elsewhere too. We also stress that, despite the common guidelines, there are significant differences in how National Accounts are constructed in practice, creating comparability issues across countries that are first order.

Recent research into wealth inequality has focused on the suitability of alternative sources of information on the distribution of assets, exploring the sensitivity of wealth concentration estimates to these choices (Kopczuk and Saez, 2004; Saez and Zucman, 2016; Alvaredo et al., 2018; Smith et al., 2023; Saez and Zucman, 2020). In this paper, we highlight the similar importance of how aggregate wealth itself is measured, showing that this also has important implications for estimates of the wealth distribution. Our work thus complements other studies which focus on different aspects of wealth measurement.

The remainder of the paper is organised as follows. Section 2 defines our target concept of wealth and describes the data sources. Section 3 sets out a conceptual framework for understanding the role of asset distributions and aggregates in explaining top wealth shares, and our approach to estimating these. Section 4 presents our results on aggregate wealth, and how and why it differs across the two data sources. Section 5 presents our results on top wealth shares and how these are affected by the choice of aggregates. Section 6 concludes.

2 Data and wealth definitions

Following Saez and Zucman (2016), we define wealth as:

"the current market value of all the assets owned by households net of all their debts. Following international standards codified in the System of National Accounts (United Nations 2009), assets include all the non-financial and financial assets over which ownership rights can be enforced and that provide economic benefits to their owners."

This includes housing, private businesses, equity, pension entitlements, deposits in financial institutions, and life and non-life insurance assets, net of mortgages and other financial debts.

As they are not included in the core National Accounts, we exclude unfunded DB pensions from our main National Accounts results (Sections 4-5). However, we argue that these types of pension scheme should be included based on the definition outlined above (Section 4.1). We therefore provide, in Appendix F.2, estimates of the wealth distribution based on including unfunded DB pension wealth as reported in the supplementary National Accounts, which we compare to using only the core accounts.

We exclude consumer durables such as household goods, collectibles and valuables, and cars and other vehicles. This is because they are not included within the National Accounts framework, making it difficult to consistently compare these aggregates with our household survey data (where these assets are measured).

Our population of interest includes all UK resident individuals. For these individuals, we include their worldwide assets rather than just those assets situated within the UK's national borders. We do not include UK-situated assets owned by foreign individuals or other institutional sectors, such as social housing that is owned by housing associations.

For the adult population control total we use Office for National Statistics (ONS) mid-year population estimates of the number of individuals aged 20 or older, following the standard adult population definition used in the WID (Alvaredo et al., 2020).

2.1 Income tax data

To estimate wealth using the income capitalisation approach, we use administrative income tax data from the UK tax authority (HMRC). These cover the universe of personal tax returns filed for tax years 2006 to 2018,[1] as well as a sample of tax records for individuals whose tax is withheld at source. The tax unit is the individual, and we use individuals as our unit of analysis throughout.

Taxpayers are required to file a tax return if their incomes are not subject to a withholding tax, or if their income exceeds a nominal threshold (currently £100,000). Around a third of UK taxpayers filed a tax return in recent years. All individuals with significant investment income (be it rental income, dividends, or interest) are required to file a tax return. We thus observe the majority of investment income received by individuals in our tax return data.[2]

Individuals who are not required to file a tax return may still receive some investment income (such as interest on bank accounts), below the tax-free allowance for these income sources. HMRC provide an imputed measure of the investment income received by these individuals in the Survey of Personal Incomes (SPI), a dataset which draws upon a sample of administrative tax records from tax returns and PAYE (employer filed automatic withholding through Pay-As-You-Earn). HMRC impute investment – interest and dividends – income to individuals using data from financial institutions and household surveys, to provide a comprehensive measure of all income assessable for income tax. We supplement our tax return data with records for non-filers from the SPI, using the imputed measures of investment income for these individuals. Imputed dividends account for 4% of dividends observed in our data for 2016-18, while imputed interest accounts for 59%.

As part of the SPI, HMRC provide sampling weights which enable us to scale up our PAYE-derived sample to the full population of those present in PAYE who do not file a tax return. We use these probability weights when calculating aggregate income and wealth among our SPI-PAYE sample.

Finally, as we use the WAS to impute non-income-yielding wealth, we must combine multiple years of tax data to replicate WAS 'rounds', each of which spans a two-year period. To replicate this in our tax data, we pool the two years of tax data for which there is greatest overlap with the WAS reference period.

[1] The UK tax year begins in April and ends in April the following year. Consistent with HMRC, we refer to tax years by the year end i.e. 2016-17 is referred to as 2017.

[2] For a more detailed treatment of what is reported, and how reported taxable income relates to national accounts income, see Advani et al. (2023).

2.2 National Accounts

The National Accounts record the aggregate net worth held by all UK resident 'sectors', including corporations, non-profit institutions, households, and different branches of government. The household sector covers all individuals residing in the UK. Following our target definition, we restrict our attention to the net worth of the household sector – known as 'personal net worth'. This is consistent with the definition of wealth used in the Distributional National Accounts framework adopted by Batty et al. (2019) and by the *World Inequality Database* (WID). Personal net worth encompasses financial and non-financial assets, less financial liabilities. It excludes consumer durables.

Wealth components are recorded in two separate tables in the UK National Accounts: the household sector table of the National Balance Sheet (Table 9.11 of the Blue Book); and the household sector Financial Balance Sheet (Table 6.2.11 of the Blue Book), which provides a more granular disaggregation of financial net worth than that presented in Table 9.11.

In principle, the National Accounts are constructed according to a common international framework: the System of National Accounts (SNA 2008), or the European System of Accounts (ESA 2010) which is largely consistent with the former. If the goal is to compare inequality statistics across countries, this standardisation offers an advantage over alternative measures of wealth based on tax or survey data, which tend to measure different things in different countries. However, in practice, the methods and concepts used to construct the National Accounts vary across countries, as does coverage of different asset classes. For example, the Spanish National Accounts omit non-financial assets such as housing and business assets (Artola Blanco et al., 2021). As a result, incorporating these asset classes requires drawing on external data sources, which may not be internationally standardised.

Wealth in the UK National Accounts is calculated on a calendar-year basis, and the latest 'Blue Book' publications provide consistent estimates of personal net worth dating back to 1995. To reconcile National Accounts estimates with the reference period used in the WAS, we adjust wealth totals in the National Accounts on a *pro rata* basis.[3]

[3] For example, for round 6 of the WAS which spans April 2016 to March 2018, we construct the equivalent 'round' in the National Accounts as $W_{r=6} = 0.5 \cdot (0.75 \cdot W_{2016} + W_{2017} + 0.25 \cdot W_{2018})$.

2.3 Wealth and Assets Survey

Our survey-based aggregates and distributions draw upon microdata from the Wealth and Assets Survey (WAS), a comprehensive survey of wealth held by UK resident households. The WAS is a longitudinal survey conducted by the Office for National Statistics. Data are collected in sequential 2-year waves (or "rounds"), beginning in 2006-08. We use the six rounds which overlap with the period for which we have income tax data, from 2006-08 to 2016-18.

The WAS captures a broad range of asset classes, including property, financial assets, businesses, and pensions. Asset values are self-reported, though individuals are encouraged to consult documentation (e.g. pension fund reports) where applicable. Appendix A provides details on how each individual asset class is measured. In Section 4, we draw attention to the key measurement differences between the WAS and the National Accounts.

Our population of interest is all adults (aged 20+) in the UK. See Appendix C for details on how we adjust the WAS, which samples individuals living in private residences in Great Britain, to be representative of the UK. Although the population is sampled at household level, each individual within the household responds to the survey, the majority of wealth components are measured at an individual level, and appropriate individual sample weights are provided. This enables us to use individuals as the unit of analysis, consistent with the units observed in our tax data.

3 Decomposing top wealth shares

3.1 Conceptual Framework

The full distribution of wealth can be characterised by the shares of wealth owned by different fractiles of the distribution. Starting at the top of the distribution – which is most common in the wealth inequality literature – we can write the share of wealth held by the top 1, 5, or 10 percent (for example) as

$$S_w(x) \equiv 1 - F_w(x) \tag{1}$$

for $x \in \{0.01, 0.05, 0.10\}$, where w is total wealth and $F_w(.)$ is the CDF of the wealth distribution.

This can in turn be decomposed as

$$S_w(x) = \sum_c S_c(x) \cdot \left[\frac{W^c}{W}\right] \tag{2}$$

where $W = \sum_c W^c$ denotes aggregate wealth and c represents different asset classes that make up total wealth. The wealth distribution therefore depends on how each asset class, c, is distributed across individuals ranked on total wealth, $S_c(x)$, and the relative aggregate size of these asset classes, $\frac{W^c}{W}$.

The main focus of recent debate has been around estimating the distributions of these asset classes, $\{S_c(x)\}^c$, with aggregates taken – in most cases – from the National Accounts (Saez and Zucman, 2016, 2020; Garbinti et al., 2021). In particular, the discussion has centered around the three data sources that can be used to obtain information on $S_c(x)$: income tax data, estates data, and survey data.

The Mixed Income Capitalization (MICs) approach draws on income tax data as the source of distributional information on assets which yield a taxable income flow, A, and survey data to estimate the distribution of non-income-yielding assets, N. (Alvaredo et al., 2020). Top shares under the MICs methodology can therefore be written as:

$$\begin{aligned} S_w(x) &= \sum_{a \in A} S_a(x) \cdot \left[\frac{W^a}{W}\right] + \sum_{n \in N} S_n(x) \cdot \left[\frac{W^n}{W}\right] \\ &= S_A(x) \cdot \left[\frac{W^A}{W}\right] + S_N(x) \cdot \left[\frac{W^N}{W}\right] \end{aligned} \tag{3}$$

where $S_a(x)$ are estimated using income tax data and rates of return from the National Accounts; $S_n(x)$ are taken (often but not always) from survey data; and $\frac{W^a}{W}$ and $\frac{W^n}{W}$ are taken from the National Accounts.

The importance of which aggregates are used has received little attention. Even where some aggregates are not taken from the National Accounts (e.g. business wealth in Smith et al., 2023), there has been little discussion of what difference this makes to the overall wealth distribution. However, since different asset classes are very differently distributed, changes to the relative importance of different asset classes is first order in terms of the effects on the wealth distribution.

3.2 Empirical Approach

In this paper, we present two alternative wealth distribution series which illustrate the importance of which aggregates are chosen. For both series, we use the same MICs methodology for estimating the distribution. The series differ only in which aggregates we use for capitalising investment income and imputing non-income-yielding wealth. Table 1 illustrates the data sources used to construct each component of Equation 3 under our two main approaches.

Table 1: **Data sources used to construct each series**

Series	$S_a(x)$	W^a	$S_n(x)$	W^n
Main approach				
Income capitalisation, NA aggregates	Income tax data	NA	Survey	NA
Income capitalisation, Survey aggregates	Income tax data	Survey	Survey	Survey
Alternative approach (Section 5.4)				
Survey distribution, NA aggregates	Survey	NA	Survey	NA
Survey distribution, Survey aggregates	Survey	Survey	Survey	Survey

Notes: Top shares in each series are produced by combining the listed data sources for the distribution and aggregate size of income yielding, and non-income yielding, wealth. Total wealth is constructed as the sum of total income-yielding wealth and total non-income-yielding for that series.

Under the 'Income capitalisation, NA aggregates' approach, we capitalise income tax data to estimate the distribution of income-yielding assets. We use survey data to impute the distribution of non-income-yielding assets following the MICs approach, again scaling these to match NA aggregates. All asset classes are scaled to match NA aggregates.[4] Our 'Income capitalisation, survey aggregates' approach replicates the above, but taking aggregates from survey data rather than the NA.

However, the effect of choosing different aggregates also depends on the relative distribution of different asset classes. We illustrate this in Section 5.4, where we show the effect of applying different aggregates to survey distributions of individual asset classes, rather than using the income capitalisation approach. Under the 'Survey distribution, NA aggregates' approach, we take the distribution of all asset classes as they are observed in household survey data, scaling these to match NA aggregates. Our 'Survey distribution, survey aggregates' takes the distribution and aggregate value of all assets from survey data.

In Appendix F.3 we provide results after including a Pareto adjustment to the survey distribution, to account for undercoverage of WAS at very high levels of wealth. The Pareto adjusted series is actually our preferred series for the UK, but for purposes of comparison to the literature we focus on the capitalised income distribution because this has become the standard in the literature, so that we can focus on the impact of denominator choice.

To produce each of our series, we must first reconcile the income flows observed in

[4] In Appendix F.1, we illustrate the effect of choosing broader asset categories for capitalisation, following the basic framework set out in the DINA guidelines (Alvaredo et al., 2020).

the income tax data with the stocks of wealth observed in the National Accounts and the WAS, to determine the categories of income and wealth to be used in our capitalisation procedure. The capitalisation categories we use are presented in Table 2.

In the DINA guidelines, it is recommended that as a first approximation, constant scaling factors should be used (Alvaredo et al., 2020). We adopt this approach, while acknowledging its limitations. There has been much debate on whether the assumption of a constant rate of return is empirically justified (Saez and Zucman, 2016; Smith et al., 2023; Saez and Zucman, 2020). However, our focus on this paper is on the impact of aggregates. The assumptions we make are common across both of our headline series; it is the use of different aggregates which drives variation in our results.

Though partnership trading income and the profits earned by sole proprietors include a return on capital assets such as machinery and equipment, which do not yield a direct income flow, they also include a return on labour. The share of income that derives from capital assets is likely to vary across businesses. Some, such as sole proprietors providing personal services, will own few if any assets, while others will derive a large portion of their income as a return on assets they own. We adopt the common assumption made in the DINA literature, that 30% of partnership trading income and profits earned by sole proprietors represents a return on capital (Alvaredo et al., 2020; Garbinti et al., 2021; Martínez-Toledano, 2023). For further details on our income capitalisation approach, see Appendix B.1.

Next, we must impute the value of non-income-yielding assets to individuals in our tax data using distributional information from our survey data. To do so, we first group individuals into vigintiles (20 groups) of income-yielding wealth. We then further subdivide individuals within each vigintile of income-yielding wealth as follows: within each of the bottom 15 vigintiles (bottom 75%), we assign individuals into vigintiles of non-income-yielding wealth;[5] within each of vigintintiles 16-19 of income-yielding wealth (75-90%), we assign individuals into 30 groups of non-income-yielding wealth; within each of the top two vigintiles (top 10%) we asssign individuals into 40 groups of non-income yielding wealth. This results in a total of 470 groups. As with all imputation procedures, there is a trade-off to be made between increased granularity (number of groups) and having a sufficient sample size in each imputation cell. The over-sampling of wealthier individuals in the WAS enables us to construct more granular imputation bins toward the top of the distribution, which helps us to better

[5]Non-income-yielding wealth here includes net housing, currency, life insurance assets, pensions, and consumer loans.

Table 2: **Capitalisation categories for each series**

Income component	Wealth component
Series: Income capitalisation, NA aggregates	
UK interest	UK deposits
Foreign interest	Foreign deposits
Gilt interest	Bonds and gilts
UK dividends + partnership income (30% of trading income)	UK equity
Foreign dividends + foreign property income	Foreign equity
Mutual fund dividends	Mutual fund shares
Profits of sole proprietorships (30%)	Business assets
Series: Income capitalisation, survey aggregates	
UK + foreign interest	Deposits
Gilt interest	Bonds and gilts
UK dividends + partnership income (30% of trading income)	UK equity
Foreign dividends	Foreign shares
Foreign property income	Foreign property
Mutual fund dividends	Mutual fund shares
Profits of sole proprietorships (30%)	Business assets

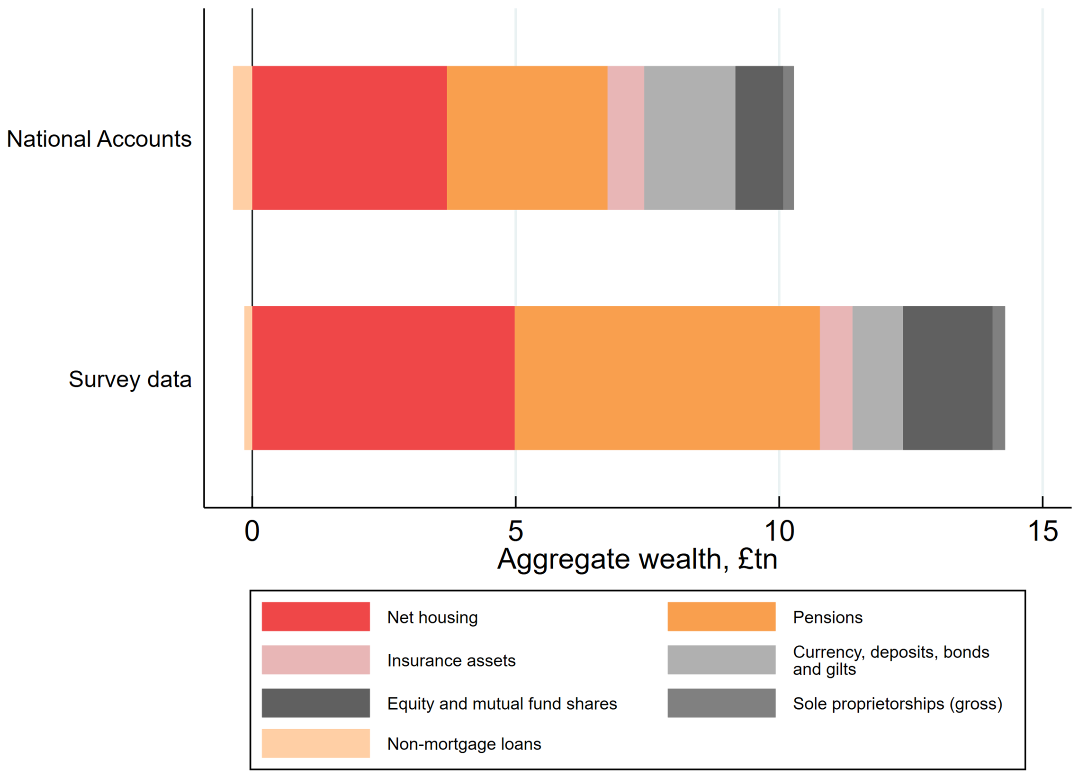
replicate the concentration of wealth at the top.

Within each imputation cell, we calculate the share of each non-income-yielding asset class held by each group to form our imputation matrix. In the tax data, we then allocate indviduals to vigintiles of income-yielding wealth (as above). We then randomly allocate individuals to one of 10/20/30 groups within each cell (depending on the vigintile of income-yielding wealth). These groups are generated to enable us to replicate variation in non-income-yielding wealth within each income-yielding wealth vigintile. We impute the share of each non-income-yielding asset held by these groups using our survey-based imputation matrix. Finally, we apply this share to the aggregate for each asset class – which varies according to which of our four approaches we are using – and take the average to estimate the non-income-yielding wealth held by each individual in the income tax data. In Appendix B.2 we show that, compared to a range of alternative approaches to defining imputation cells, our chosen method better replicates the distribution of wealth observed in the WAS.

4 Aggregate wealth by asset class

Discrepancies between aggregate wealth in the National Accounts and in survey data have been documented across a wide range of countries (Albers et al., forthcoming;

Figure 1: **Composition of aggregate wealth by data source, 2016-18 (£tn)**



Notes: Table shows the aggregate value of reconciled asset categories. For further details on how asset categories have been reconciled, see Appendix A.
Source: Authors' calculations based on the National Accounts and the Wealth and Assets Survey.

EG-LMM, 2020; Chatterjee et al., 2022; Batty et al., 2019). Both the magnitude and direction of the gap varies across asset classes, as does their explanation. Broadly, these can be attributed to two main factors: conceptual differences (differences in what the data source is trying to measure) and measurement differences (differences in the methods and data sources used to measure the concept of interest).

In this Section, we highlight both the conceptual and measurement issues that make the National Accounts problematic for studying the personal wealth held by individuals, and contrast these with what is measured in the WAS (see Appendix E for further details). Despite the limitations of the WAS – which we set out below – we argue there are compelling reasons for using it as the primary measure of personal wealth in the UK.

Aggregate differences In the UK, aggregate wealth is higher in the WAS than in the National Accounts, and this gap has increased over time. Aggregate wealth was £1.2tn (17%) higher in the WAS in 2006-08, rising to £4.3tn (43%) in 2016-18.[6] The largest gaps in absolute terms are in pensions and (net) housing, which are £2.7 trillion and £1.3 trillion higher in the WAS, respectively (Figure 1).

Relative differences by asset class If all asset classes were equally under-represented, the choice of aggregates would have no impact on the estimated wealth distribution. However, there is substantial variation across asset classes (Figure 2). Aggregate pension and equity wealth are twice as large in survey data as in the National Accounts, and housing wealth is 40% larger. By contrast, non-mortgage loans and currency are both much smaller in the survey, at around half the size measured in the National Accounts. In the next subsections we describe some of the reasons for these differences for the largest asset classes.

4.1 Aggregate pension wealth

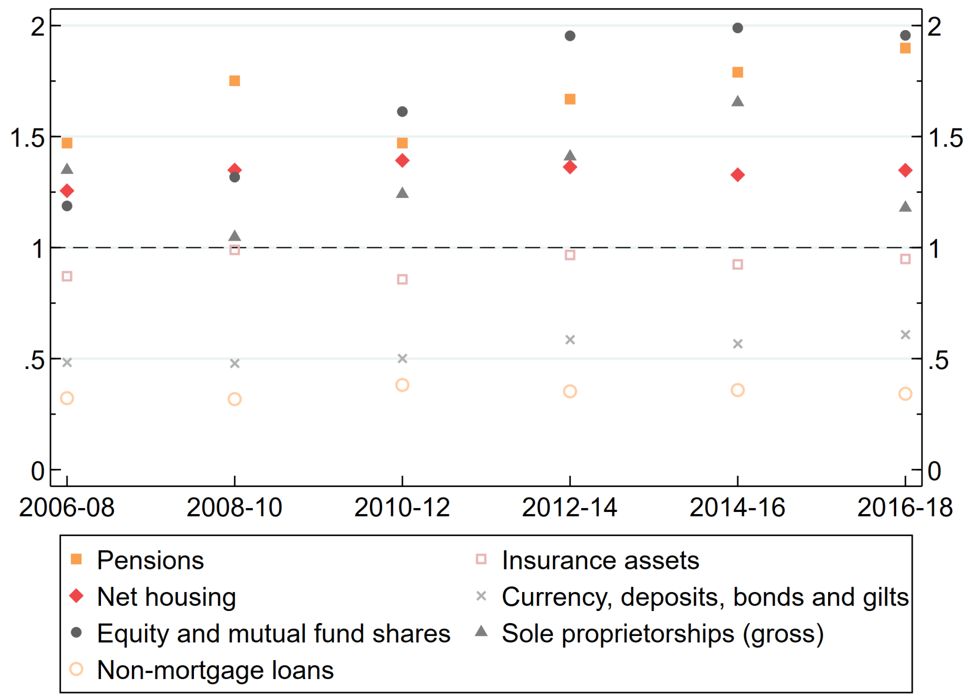
There are at least two factors that make the NA aggregate problematic as a measure of the pension wealth held by individuals. First, there are conceptual differences in what is being targeted: the National Accounts main tables target the liabilities of private sector schemes, rather than the market cost of individuals' repurchasing their current entitlements. The low conceptual comparability between the National Accounts measure of pension wealth, and survey data, is an issue that affects countries across Europe (EG-LMM, 2020). Second, international guidelines for the production of National Accounts impose differences in discount rates across pension types that affect the relative value of different schemes.

4.1.1 Conceptual differences

Types of pension Private pensions in the UK can be defined contribution (DC) or defined benefit (DB), and DB pensions may be 'funded' or 'unfunded'. DC pensions are comprised of savings made by the individual (and potentially their employers), and the returns on those savings. On retirement, that pot of cash is available to the individual, with some restrictions over speed of withdrawal.

[6] This excludes physical assets (consumer durables) from the WAS, for which there is no counterpart in the National Accounts.

Figure 2: **Ratio of aggregate asset value in survey data to aggregate asset value in the National Accounts**



Notes: Ratio is calculated by dividing aggregate wealth in the WAS by aggregate wealth in the National Accounts, for each asset class.
Source: Authors' calculations based on the National Accounts and the Wealth and Assets Survey.

A DB pension is instead an entitlement to a certain stream of income on retirement, with the annual income usually related to the individual's average or final salary, and tenure in the pension scheme. A funded DB scheme has a pot of assets within the scheme that can be used to discharge the liabilities, and this includes all private sector DB schemes. By contrast, in unfunded – or 'pay-as-you-go' – schemes, there are no underlying assets. These schemes include pensions paid to most public sector workers.

Target concept In determining the value of pension wealth to an individual, the appropriate benchmark is the (market) replacement value of the pension. For a DC pension, this is just the value of the fund. For a DB pension, it is the cash value needed to purchase an annuity with the same features as the original entitlement. Whether there is an underlying pension fund does not influence this value.

Social security We note that there is a clear distinction between DB schemes (funded and unfunded) and Social Security payments (the 'state pension' in the UK). Individuals have no contractual right to a future flow of social security payments, or any other form of government transfer. Social security payments are just one form of government transfer that an individual may receive, and they are continually subject to change. This is not true for DB pension entitlements provided to public sector employees. It is for this reason that social security payments were excluded from the tax base advocated by the UK Wealth Tax Commission (Advani et al., 2020). In contrast to Saez and Zucman (2016), we argue that this conceptual distinction provides a clear rationale for including unfunded DB schemes provided by government while excluding social security payments from our measure of personal wealth.

National Accounts In the UK, as elsewhere, the National Accounts includes both DC and funded DB pensions. The inclusion of *unfunded* DB pensions in the core National Accounts varies across countries. Whereas the overarching international framework (SNA 2008) recommends their inclusion in the core accounts, they are explicitly excluded in the framework used by European countries (ESA 2010).[7] In practice, countries have flexibility over whether to include unfunded DB schemes. The framework is designed to accommodate the diversity of pension schemes that exist across countries, but this flexibility complicates international comparisons based on the core National Accounts. All countries are, however, advised to include them in supplementary tables, to facilitate analysis and aid cross-country comparisons. In the UK unfunded DB schemes are excluded from the core accounts, but are available in supplementary tables.

Unfunded DB pensions are quantitatively important: adding them to the pension wealth recorded in the core National Accounts increases aggregate pension wealth by 21% in 2016-18. Ignoring unfunded DB pensions not only misses a significant share of aggregate wealth, it also distorts its distribution by under-valuing the pension wealth of public sector workers relative to their private sector counterparts. In Appendix F.2, we show that including unfunded DB pensions decreases the top 1% share of total wealth by 1pp (around 5-6%) in recent years, relative to using only the core National Accounts.

[7] As a general principle, the SNA 2008 guidelines exclude pension schemes and other forms of government transfer that operate on a pay-as-you-go basis, where there is no saving involved. Unfunded DB schemes are often excluded on the same basis, and are more likely to be excluded the "closer a government employer pension scheme is to the prevailing social security scheme" (SNA 2008, para 17.194). For further information, see paragraphs SNA 2008, paras 17.191–17.195 and ESA 2010, paras 17.127–17.128.

4.1.2 Measurement choices

Conditional on wanting to include DB pensions, both funded and unfunded, there is then a practical question of how to obtain a value.

National Accounts In the National Accounts, DB pensions are valued from the perspective of the provider and are based on actuarial assessments of pension providers' liabilities.[8] They ask the question: "how much would the fund need to be worth today to fund the future income stream we have promised, given the long-term return on our current asset portfolio?" Annuities – guaranteed income streams purchased by those who have already reached retirement, usually out of DC pension savings – are valued in a similar fashion. These liabilities are calculated as the present value of future payments to current scheme members and involve a number of modelling assumptions, including on the rate of return and life expectancy.

The discount rate adopted varies across different types of scheme. In particular, for private sector DB pensions, the NA aggregate assumes a nominal discount rate based on yields on 15-year fixed interest gilts, which was 1.6% in 2018 (Office for National Statistics, 2021d). For public sector DB pensions, a nominal discount rate of 4% is applied. This discrepancy is not based on any conceptual justification. Rather, the rate for public sector pensions is stipulated by Eurostat, while the discount rate used for private sector pensions is chosen by each country's statistical authority. Even if statistical authorities deem an alternative discount rate to be more appropriate, they do not have the flexibility to treat all types of pension scheme in the same way. As a result, estimates of the share of wealth held across different types of pension scheme becomes distorted. From the perspective of valuing individual wealth, it makes little sense to apply different discount rates depending on the sector in which the individual works. Doing so would imply different levels of wealth for individuals who are guaranteed the same income stream in retirement. The quantitative effects of choosing an alternative discount rate is non-trivial: a 1 percentage point reduction in the discount rate increases the value of public sector funded DB pensions by around 20% (Office for National Statistics, 2021d).

[8]The value of DB pensions and annuities is the value of scheme members' entitlements, regardless of whether the pension scheme is fully funded i.e. it is not equal to the value of assets held by pension providers. This means that for funded DB schemes, the National Accounts include value that will need to come from future contributions for under-funded schemes, as well as excluding some assets that exceed fund liabilities for schemes that are over-funded. It is difficult to understand the rationale for this treatment of private sector schemes alongside the exclusion from the main accounts of the liabilities of public sector schemes.

This difference in discount rate depending on whether the pension provider is general government or the private sector is not specific to the UK: other countries, such as Sweden and Portugal, also apply different discount rates in their core national accounts across private and general government pension schemes.[9] Both Portugal and Belgium additionally allow the discount rate to vary across individual private sector providers, meaning the value of an individual's pension entitlements can vary depending on who their provider is. This variation exists because it is the actuaries of individual pension providers who value pension entitlements, choosing whichever discount rate they see fit. The variation therefore bears no relation to the reliability of the counterparty to the future income stream, variation which could – in the absence of state guarantees – justify some pension promises being valued more highly than others even when the nominal promised income stream is the same.

WAS In the WAS, DB pensions and annuities are valued from the perspective of the individual: "how much in pension savings would the individual need in order to purchase the income stream they are guaranteed, if they were to purchase it today at current annuity prices?" The discount rate used to estimate the value of DB pensions in the WAS is similar to that used for public sector (funded) DB pensions, though as we note above this differs from the treatment of private sector pensions in the National Accounts.

In terms of explaining the discrepancy between the WAS and the National Accounts, including unfunded DB pensions – which are not distinguished from other pension schemes in the WAS – reduces the gap by 40% (see Appendix E.1 for details). The remainder of the gap could feasibly be explained by the choice of annuity and discount rates (see Appendix A.2).

4.2 Aggregate net housing

Two aspects of how property wealth is measured in the National Accounts make it difficult to obtain our target measure of net housing wealth – defined as all (UK and overseas) residential property held by UK households, net of mortgages. First, the National Accounts estimates of dwellings include foreign-owned property, and exclude the value of overseas property held by UK residents. Second, the value of land is reported separately from the value of residential property ('dwellings'), and

[9]For further details on the approach in other countries, see `https://ec.europa.eu/eurostat/web/pensions/information-member-states`

is combined with the value of land underlying non-residential structures. Moreover, there is some uncertainty over the accuracy of these aggregate estimates.

4.2.1 Conceptual differences

Target concept The target measure is the value of all housing wealth, net of any associated mortgage debts, owned by UK adults.

National Accounts The National Accounts concept of dwellings includes all dwellings situated within a country's national borders, regardless of ownership.[10] A balancing adjustment is then added to 'equities issued by the rest of the world', such that the National Balance Sheet only records, in aggregate, assets held by UK households rather than UK-sited assets owned by foreign individuals or institutions. 'Other equities' includes a liability representing UK property that is owned by foreign investors; and an asset representing overseas property held by UK residents. It is not possible to separately identify these items, hence we cannot construct a measure of property wealth in line with our target. This is a problem not just for our current exercise, but for anyone trying to construct DINA series using NA aggregates for property.[11]

4.2.2 Measurement choices

National Accounts From the perspective of measuring the market value of an individual's assets we care only about the combined value of land and property. Constructing this target measure from NA aggregates requires us to attribute land to dwellings and other structures, based on assumptions regarding the ratio of land values to the fixed assets that sit upon them. We split the value of land into land underlying dwellings and land underlying other buildings and structures using land-to-asset ratios derived from breakdowns of the value of land held in the economy as a whole (not just by private individuals). Further details can be found in Appendix D. There, we show that estimates of the value of UK residential property are reasonably robust to how one attributes land, though this may not be true in all contexts. In relative terms the choice makes a significant difference to the value of business assets, to which the value of non-residential property is assigned when one follows the classification set out in the DINA guidelines (Alvaredo et al., 2020).

[10] See ESA 2010, para 18.15 and para 7.76; also Office for National Statistics (2017)

[11] The lack of separation of between households and Non-Profit Institutions Serving Households (NPISH) under the ESA guidelines will also lead housing wealth in the National Accounts to over-estimate aggregate individual housing wealth in most countries (EG-LMM, 2020; European Central Bank, 2024).

Estimates of the combined value of dwellings and underlying land – which are constructed by the ONS in order to obtain the value of land via the residual method but are not reported in the core accounts – are often deemed to be superior in their accuracy owing to the fact that they are derived from objective measures of property values. However, a deeper investigation of the methodology casts doubt over the accuracy of these estimates in the UK. The approach draws on objective estimates of property values calculated for Council Tax purposes, which have not been updated since 1991. A 'quantity $\times$ price' method is used, which consists of three steps.[12] First, multiply the mid-point of each tax band (the 1991 price) in each region by the number of properties in the tax band.[13] Second, estimate the 'quantity $\times$ price' of houses in the highest and lowest bands (which have no mid-point) using a conversion factor. Third, uprate to current house prices using a flow-weighted, region-specific house price index.

This approach has three main deficiencies. First, it applies the same scaling to all properties in a given region and tax band, ignoring differences in property characteristics which may influence house price growth. Second, the approach to estimating the value of properties in the top tax band is unlikely to accurately capture the most valuable properties, which given the skewed distribution of property values could have a significant effect on the aggregate. Third, by using a flow-weighted house price index it will tend to over-state property wealth estimates, as more expensive properties are found to transact more frequently.[14] The ONS are in the process of developing a new methodology which addresses some of these deficiencies (Office for National Statistics, 2022a). However, for the time being, we believe these estimates should be treated with a degree of caution.

WAS The measurement of property wealth in the WAS also suffers from limitations. In particular, property values are based on the subjective beliefs of the home-owner. Subjective valuations are often found to differ from the true market value of the property, with individuals tending to be over-optimistic about the value of their home (Naidin et al., 2024; Hillyard et al., 2014; Henriques, 2013; DiPasquale and Somerville, 1995). Under-estimation of property wealth at the top is also a common cause for concern. Notwithstanding these issues, the WAS estimate is much better aligned conceptually with what it is we are trying to measure. It captures, directly, the

[12]For further details on the methodology, see Office for National Statistics (2022a).

[13]There are currently 8 Council Tax Bands in England and Scotland; 9 in Wales.

[14]This means that flow-weighted estimates tend to over-state house price growth relative to stock-weighted estimates. For further information see Office for National Statistics (2018).

property wealth held by UK residents both domestically and overseas.

In aggregate, gross UK housing wealth in the WAS is £1 trillion (21%) higher than in the National Accounts in 2016-18, after deducting the value of overseas property to make the comparison more consistent with the National Accounts. This WAS estimate excludes foreign-owned UK property, which it is not possible to exclude from the National Accounts. That survey-based measures of housing wealth exceed the National Accounts is not a phenomenon specific to the UK: Batty et al. (2019) find that housing wealth in the US was 29% higher in the Survey of Consumer Finances than in the National Accounts in 2016.

Verification exerise To get a sense for which aggregate seems most reasonable, we derive our own method for valuing the stock of properties in England and Wales using administrative data on transactions. This method can be summarised as follows. First, we extract the sale price of all residential transactions in England and Wales since 1995 using the 'Price Paid' dataset held by HM Land Registry (HM Land Registry, 2022a). Second, we identify unique properties based on the address string, so that for properties that transacted more than once we include only the transaction closest to April 2018 – our reference month for house prices.[15] Each sale price is uprated to April 2018 using the property type and local-area-specific House Price Index (HM Land Registry, 2022b). For each property type in each local area, we assign weights based on the total stock of such properties, taking the latter from Council Tax Statistics (Valuation Office Agency, 2018). Finally, we aggregate the 2018 prices for each property multiplied by their respective weights to estimate the aggregate gross value of all residential property situated in England and Wales. Further details on our methodology can be found in Appendix H.

Using the method described above, we estimate that residential property in England and Wales was worth £7.4 trillion in 2018. This is similar to UK property company Zoopla's estimates of roughly £7.2 trillion in 2016 and £8.3 trillion in 2020.[16] Our estimate is £1.3 trillion higher than our WAS aggregate for 2016-18, and £2.3 trillion higher than the NA. The WAS only captures property held directly by UK resident individuals. This excludes both foreign-owned property, corporate-owned property, and social housing, all of which are represented in our transaction-based estimates, suggesting we should expect our transaction-based estimates to be higher

[15] Specifically, we use the transaction closest to 5th April, which corresponds to the last day of the 2017-18 tax year.

[16] For comparability we deduct the value of property in Scotland from their aggregate estimate to get an estimate for England and Wales alone, since the Land Registry data does not cover Scotland.

than the WAS aggregate. If the combined value of these properties is large, it is possible that our WAS-based estimate is still too high, though it is reassuring that our transaction-based estimate is much higher than our WAS-based measure.

4.3 Aggregate business assets

Although 'business assets' represents a much smaller share of aggregate wealth than pensions and housing – accounting for 2% in the National Accounts and 4% in the WAS – its distribution is highly skewed. It is therefore an important asset class for understanding the distribution of personal wealth, and particularly for concentration measures of wealth inequality.

4.3.1 Conceptual differences

In the DINA literature, "business assets" refers collectively to all non-financial fixed assets belonging to households, other than dwellings (Alvaredo et al., 2020). These assets – which include cultivated biological resources (e.g. crops, livestock), machinery and equipment, computer software, Intellectual Property products, inventories, contracts, leases and licences, as well as non-residential buildings and structures and their underlying land – provide a measure of the business wealth held by households.

Conceptually, this aligns poorly with our target definition: what a business is worth if it were sold in its entirety at current market value. The summed value of these assets will often underestimate the amount for which a business could be sold, sometimes very substantially. Intangible assets such as good-will, which are not measured, will also be important factors in determining business value.

By contrast, business wealth in the WAS is much more conceptually aligned with our target. Individuals who are self-employed are asked "If you sold your business today, including any debts or liabilities, about how much would you get? Please include the value of financial assets, accounts receivable, inventories, land, property, machinery, equipment, customer lists and intangible assets." Though this business value is recorded net of debts, respondents are asked to separately report the value of any outstanding debts. We add these back to obtain the gross value of sole proprietorships, to be more consistent with the National Accounts.

4.3.2 Measurement choices

Private businesses are notoriously difficult to value, and the uncertainty around subjective valuations should be kept in mind when interpreting results based on these. Early rounds of the survey, particularly 2006-08 and 2008-10, appear to suffer from under-coverage of the number of sole proprietorships, likely resulting in some under-coverage in the aggregate. However, subsequent improvements to the structure of the survey have improved coverage in later rounds.[17]

Notwithstanding the uncertainty accompanying business wealth measurement in the WAS, it is not clear that the estimates of fixed assets reported in the National Accounts get us closer to what we are trying to measure.

Quantitatively, aggregate business assets are valued at 18% higher (£0.04tn) in the WAS than in the National Accounts in 2016-18, though both the sign and magnitude of the gap varies over time.

4.4 Aggregate equities and mutual fund shares

In principle the National Accounts target the (market) value of household shares in incorporated businesses and partnerships, the same conceptual definition of equity wealth as in WAS. However, measurement choices made in practice deviate considerably from this ideal.

4.4.1 Measurement choices

'Equities' in the National Accounts can be decomposed into listed and unlisted UK shares, other equity, equity issued by the rest of the world, and UK and overseas mutual fund shares.[18] However, while listed shares can be readily valued, valuing unlisted shares can be much more difficult. The ONS first estimate total issuance of unlisted shares using data from the ONS Financial Assets and Liabilities Survey (Office for National Statistics, 2019). They then attribute a portion of holdings in these shares to the household sector, though there is a much higher degree of uncertainty over this attribution than for listed shares.

The issuance value of shares is not suitable for measuring individual wealth as it does not align with the target concept. Issue value is effectively the acquisition cost

[17] Comparisons for 2016-18 suggest that the WAS captures 96% of the sole proprietorships recorded in the Business Population Estimates (Department for Business, Energy & Industrial Strategy, 2017).

[18] As discussed in Section 4.2, there is also a balancing adjustment for foreign-owned UK property as well as overseas property held by UK residents.

of the asset, not its current market value, which is often significantly higher (though is occasionally lower). When a company is first incorporated, shares are issued at a 'nominal' value, for example 1p or £1 per share. The total nominal value these shares reflects the total amount initially invested in the company. However, over time, the market value of these initially issued shares will depart from their nominal value, as the amount that a buyer would be willing to pay to acquire the existing shares changes. New shares may subsequently be issued at the prevailing market value of the existing shares: the amount by which their price on issuance exceeds the nominal share value is known as the share 'premium'. However, again, subsequent changes in the amount that buyers would be willing to pay for shares will mean that the issue value of these new shares (including any premium) will differ from their current market value.

This differs from the approach taken in the Financial Accounts of countries including the United States, France and Spain, where estimates of the current market value of corporate equity are constructed (Ogden et al., 2016; Banque de France, 2018; Banco de España, 2017). This discrepancy in the approach taken to valuing equity across countries illustrates why international comparisons of wealth and its distribution based on NA aggregates can be problematic.

Our WAS-based measure of equities reflects the current market value of the shares, companies, and partnerships owned by the individual, in line with the target concept. UK equities (excluding foreign equities and mutual fund shares) are £1tn (297%) higher in the WAS than the National Accounts. This is perhaps unsurprising; the current market value of shares is typically much higher than the issue value, assuming that the company is successful and so increases in value over time. As well as including the self-reported value of arms-length shares (including shares held in ISAs), our WAS-based measure includes the estimated sale value of companies of which the respondent is a director, and partnerships in which they are a partner. The question of how much these businesses are worth is framed in the same way as the question on the value of sole proprietorships (Section 4.3).

Aggregate foreign equity aligns closely across the two sources, which is unsurprising given that the National Accounts derives its aggregate estimate for this asset class from the WAS. Meanwhile, the aggregate value of mutual fund shares is twice as large in the National Accounts as in the survey data.

4.5 Aggregate deposits

Valuing deposits held in financial institutions or in national savings instruments is conceptually straightforward. The National Accounts estimate is based on objective information supplied by financial institutions.

4.5.1 Measurement choices

Deposits are the only quantitatively important asset class for which the NA aggregate is noticeably higher than the WAS – £0.6tn (61%) higher in 2016-18. Lower coverage for deposits in surveys is common across many countries (European Central Bank, 2024). One possible explanation is that deposits recorded under the household sector of the National Accounts includes the value of deposits owned through sole proprietorships. In contrast, business owners in the survey are asked to record deposits as part of the value of the business in the WAS. However, it is possible that some individuals whose business income is paid directly into their personal account record this under personal savings instead. Where individuals do report business deposits as part of their business wealth, this cannot be separated from the other business assets discussed in Section 4.3, meaning these deposits will be missing from the survey aggregate for deposits we estimate here. This could also partly explain why the value of business assets is higher in the WAS than in the National Accounts.

Under-reporting may also contribute to the discrepancy, though the extent of this appears to be limited. Comparing the aggregate value of cash ISAs – which account for 26% of deposits in the WAS – with administrative totals from the UK tax authority, supports the under-reporting hypothesis to a degree. Deposits held in cash ISAs in the WAS total £246 billion in 2016-18, compared to the £264 billion reported by the tax authority (HM Revenue and Customs, 2021).

Where survey data align conceptually with our target definition but estimates suffer from survey under-coverage, there is a clear argument for using other data sources to 'correct' for this under-coverage. This could be achieved by using NA aggregates in contexts where these are conceptually consistent with the survey data. In settings where administrative totals provide objective measures of both the aggregate and its distribution, such as with cash ISAs in the UK, a replacement method more similar to recent 'top income adjustment' methodologies may provide more accurate estimates.[19]

[19] For a review of the recent literature on top income adjustments, see Jenkins (2022).

5 Top wealth shares

5.1 Impact of aggregates choice

The choice of aggregates is quantitatively important for our estimates of top wealth shares (Figure 3). The top 1% share is 2.1 percentage points higher in 2016-18 – rising from 14.4% to 16.5% – when we switch from survey to NA aggregates. Over the sample period, back to 2006, the top 1% share has varied between 12% and 18% (2.1–3.3pp) higher when using NA aggregates than when using survey aggregates.

Two factors influence the impact of a switch from survey to NA aggregates. First, the aggregate value of a particular asset class may go up or down. This directly affects the wealth of individuals who are measured as holding those assets, moving them up or down the ranking of total wealth. Second, the relative importance of a particular asset class in aggregate wealth may go up or down as the aggregates for other asset classes also change. This affects the share of total wealth held by those holding that particular asset, by changing the denominator – aggregate wealth – in the top share calculation.

To better understand the underlying mechanisms at play here, let us consider the impact of changing the aggregate value of a single asset class, c, through the lens of our top share decomposition. Using Equation 3, we can write the share of total wealth held by the top x% as

$$S_w(x) = S_c(x) \cdot \left[\frac{W^c}{W^c + W^{\neg c}}\right] + S_{\neg c}(x) \cdot \left[\frac{W^{\neg c}}{W^c + W^{\neg c}}\right] \tag{4}$$

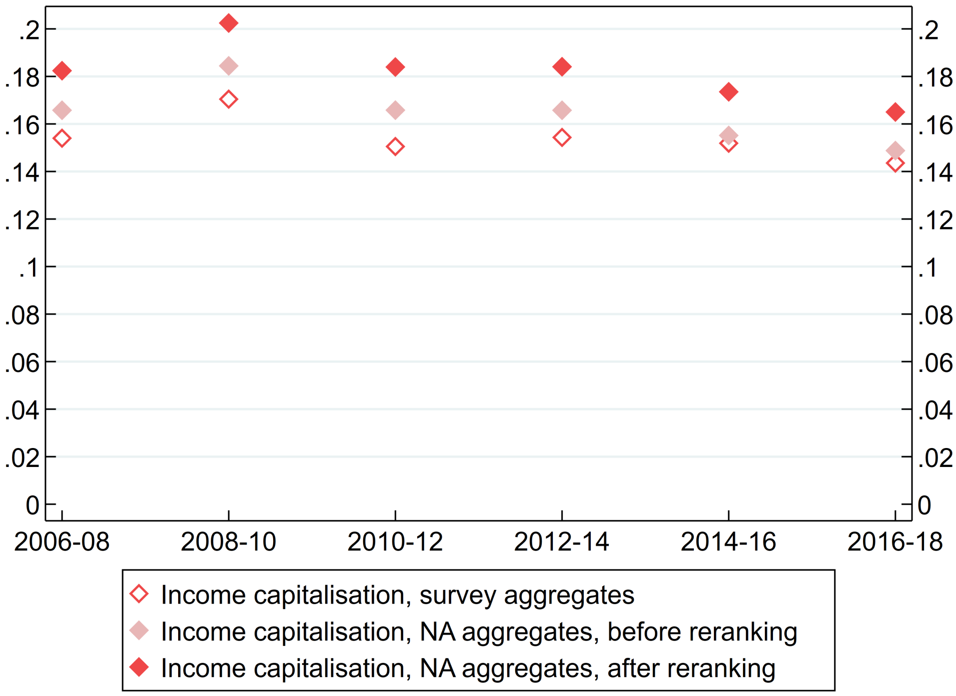
where $\neg c$ denotes all asset classes other than c. The effect of an increase in the aggregate value of asset c on the share of total wealth held by the *current* top x% – i.e. prior to reranking based on the new measure of total wealth – can be found by differentiating Equation 4. Note that if we scale the amount of asset c held by all individuals proportionally, then $\frac{\partial S_c(x)}{\partial W^c} = 0$. It follows that

$$\frac{\partial S_w(x)}{\partial W^c} = \big(S_c(x) - S_{\neg c}(x)\big) \cdot \left[\frac{W^{\neg c}}{(W^c + W^{\neg c})^2}\right] > 0 \tag{5}$$

$$\iff S_c(x) > S_{\neg c}(x) \tag{6}$$

Equation 5 tells us that an increase in the aggregate value of c leads to an increase in the share of total wealth held by those already in the top x% if and only if the

Figure 3: **Top 1% share of total wealth using National Accounts versus survey aggregates**



Notes: 'Income capitalisation, survey aggregates' shows the share of wealth held by the top 1%, where individuals are ranked on total wealth defined using the 'Income capitalisation, survey aggregates' method (see Section 3). 'Income capitalisation, NA aggregates, before reranking' shows the share of wealth when we switch to defining wealth using the 'Income capitalisation, NA aggregates' method, but still rank individuals based on total wealth defined using the 'Income capitalisation, survey aggregates' method. 'Income capitalisation, NA aggregates, after reranking' shows the share of wealth held by the top 1% after reranking individuals based on total wealth defined using the 'Income capitalisation, NA aggregates' method. We define top shares relative to the total number of individuals aged 20 or older in the population living in the UK.
Source: Authors' calculations based on HMRC administrative tax data, the National Accounts, and the Wealth and Assets Survey.

share of asset c held by this group exceeds their share of all assets other than c. It is also the case that the effect of a marginal change in the aggregate value of asset c will be smaller the larger the aggregate value of c is to begin with, relative to other assets. This is because the larger the value of the asset, the closer our original distribution of re ptotal wealth is to the distribution of asset c, and therefore scaling c proportionally makes little difference. In practice, we are scaling different asset classes by very different amounts, and it is the assets for which we increase/reduce the aggregate value the most that have the biggest impact on our overall top shares.

After scaling asset c to its new aggregate, reranking based on the updated measure of total wealth then leads to an increase in the top $x\%$ share. This is a mechanical effect that can only be positive, as reranking replaces individuals who were previously in the top $x\%$ with those who now have higher total wealth than those they replace.

Switching to NA aggregates increases the share of wealth held by those who were already in the top 1%, by 0.5 percentage points in 2016-18 (Figure 3). When we allow for changes in who is at the top, this increases by a further 1.6 percentage points. In earlier years, the effect of changing aggregates before reranking is often larger, but reranking always adds between 1.6 and 1.8pp.

5.2 Impact by asset class

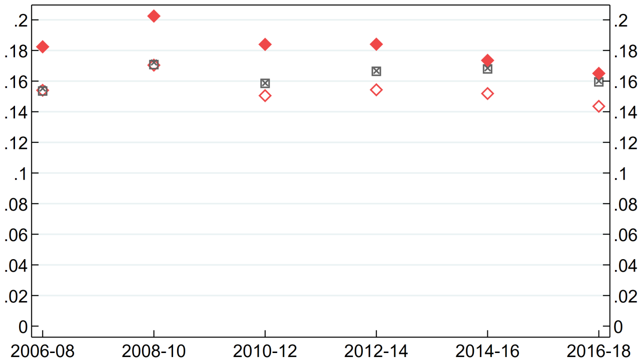
The effect of switching aggregates will depend very much on the distribution of the asset class we are scaling, as described by Equation 5. The net effect of switching *all* aggregates will depend on the extent to which the effects of scaling individual asset classes offset each other.

To show the role of individual asset classes in explaining the patterns observed in Figure 3, we document the effect of using survey aggregates for all assets except one: in turn DB pensions + annuities, net housing, and UK equity (Figure 4). These are the three asset classes for which the aggregate discrepancy between the WAS and the NA is largest (Figure 1), and which therefore make the biggest difference to the overall top share. For each of these assets, the survey aggregate is higher.

There are two points to note. First, a lower aggregate value for assets that make up a relatively smaller component of wealth for the top 1% – true for both pensions and housing – increases the measured top 1% share (Figure 4a and 4b). By switching from survey to the (lower) NA value for each of these asset classes, more weight in the top share calculation is put on other assets, which are more concentrated at the top. By contrast, lowering the aggregate value of UK equity, which is highly concentrated at the top, reduces the top 1% share.

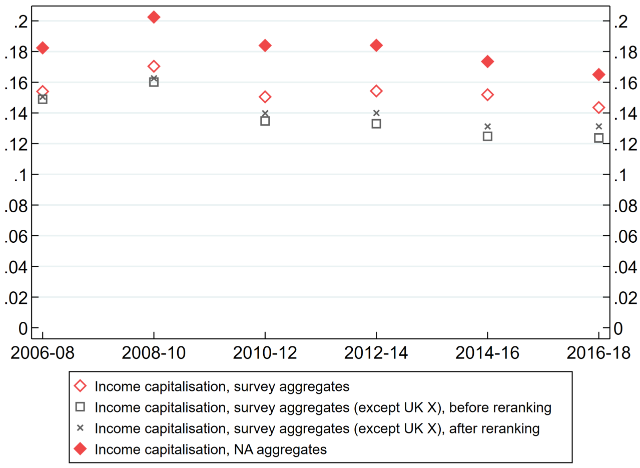
Figure 4: **Share of wealth held by the top 1% after scaling individual asset, with and without reranking**

(a) DB pensions and annuities



(b) Net housing

(c) UK equity



Notes: 'Income capitalisation, survey aggregates' shows the share of wealth held by the top 1%, with individuals ranked on total wealth defined using the 'Income capitalisation, survey aggregates' method (see Section 3). 'Income capitalisation, survey aggregates (except X)' shows the share of wealth held by the top 1%, with individuals ranked on total wealth defined using the 'Income capitalisation, survey aggregates' method except that asset class X is scaled to the National Accounts, rather than survey, aggregate. This is shown both with and without reranking individuals. 'Income capitalisation, NA aggregates' shows the share of wealth held by the top 1%, with individuals ranked on total wealth defined using the 'Income capitalisation, NA aggregates' method. We define top shares relative to the total number of individuals aged 20 or older in the population living in the UK.
Source: Authors' calculations based on HMRC administrative tax data, the National Accounts, and the Wealth and Assets Survey.

Second, reranking has little effect on the top 1% share of total wealth when scaling assets that are relatively equally distributed to begin with (pensions and housing). By contrast, it is somewhat more important in the context of UK equity, which is highly concentrated, resulting in a small but noticeable upward shift in the top 1% share. The more unequally distributed a particular asset class, the more likely it is that scaling that asset will result in moving people up and down the ranking.

5.3 Decomposing the top shares

The effect of aggregate choice on the top x% share can be decomposed, following Equation 3, into the effect of changing the aggregate for each individual asset class on the share of that asset held by the top x%, and the effect of changing all aggregates on the relative weights used in our top share decomposition. This can be seen in Table 3, which shows the decomposition of top shares by the components stemming from the distribution of income-yielding and non-income-yielding wealth.

When we switch all aggregates to their NA values, the relative weight on income-yielding wealth $\left(\frac{W^A}{W}\right)$ increases from 0.21 to 0.28, because the decline in (non-income-yielding) pensions and housing more than offsets the decline in UK equities. The top 1% share of both income-yielding and non-income-yielding wealth is unchanged across the two sets of aggregates. Consequently the difference in top share comes entirely from the difference in the relative weight put on income-yielding wealth.

It is not tautological that the top share by (non-)income-yielding wealth should be unchanged. Looking instead at the top 10% to illustrate this point, the share of income-yielding wealth using NA aggregates is 5pp lower than with survey aggregates. Under NA aggregates, UK equities are smaller and deposits and bonds larger; since the latter are more equally distributed, this reduces the top 10% share. Changes in shares and weights for the top 10% turn out to almost exactly offset, giving a top 10% share close to 52.4% under both measures.

5.4 Impact of alternative distributional information

Since the impact of changing aggregates depends crucially on the marginal and joint distributions of individual asset classes, it is perhaps unsurprising that the effect of changing aggregates varies depending on our source of distributional information. Survey data and tax data measure two different things: survey data aim to capture a direct measure of the stock, whereas the tax data measure the flow of income from which we can try to infer the stock. The distribution of assets obtained from survey

Table 3: **Decomposition of the top 1% share (2016-18)**

	$S_A(x)$	$\frac{W^A}{W}$	$S_N(x)$	$\frac{W^N}{W}$	$S_w(x)$
$x = 1\%$					
Income capitalisation, NA aggregates	0.37	0.28	0.08	0.72	0.165
Income capitalisation, Survey aggregates	0.37	0.21	0.08	0.79	0.144
Survey distribution, NA aggregates	0.27	0.28	0.11	0.72	0.159
Survey distribution, Survey aggregates	0.39	0.21	0.10	0.79	0.164
$x = 10\%$					
Income capitalisation, NA aggregates	0.68	0.28	0.46	0.72	0.524
Income capitalisation, Survey aggregates	0.73	0.21	0.46	0.79	0.525

Notes: $S_A(x)$ ($S_N(x)$) is the share of income-yielding (non-income-yielding) wealth held by the top $x\%$, ranked on total wealth. $\frac{W^A}{W}$ ($\frac{W^N}{W}$) is the share of income-yielding (non-income-yielding) wealth in aggregate wealth. $S_w(x)$ is the share of total wealth held by the top $x\%$, which can be decomposed as $S_w(x) = S_A(x) \cdot \left[\frac{W^A}{W}\right] + S_N(x) \cdot \left[\frac{W^N}{W}\right]$ as shown in Equation 3.

data differs from the distribution of income flows multiplied by the capitalisation rate.

Table 3 shows that whereas top shares increase when we switch from survey to NA aggregates using the income capitalisation approach, the same change in aggregates yields the opposite effect when we use survey distributions for all asset classes.

This happens because UK equity is much more concentrated at the very top in survey data than it is in the tax data. Ranked on total wealth, the top 1% share of UK equity (measured using survey aggregates) is 61% in the survey data and 37% in the tax data. As a result, the negative effect of scaling down UK equity on the top 1% share of total wealth is larger using the distributions implied by survey data, compared to Figure 4c. As Table 3 shows, this larger decline in the share of income-yielding wealth held at the top is enough to offset the positive effect of increasing the weight placed on income-yielding wealth. Overall, the survey distribution-based top share decreases when we switch from survey to NA aggregates.

This relationship between the choice of aggregates and the source of distributional information highlights the need to think carefully about the choice of both components, including the interaction between the two.

5.5 Characteristics of the top 1%

Since reranking is an important contributor to changes in top shares, the choice of aggregate also affects our understanding of *who* is at the top of the wealth distribution. Two in five (40% of) individuals in the top 1% under the survey aggregates are not in the top 1% under the NA aggregates. The new entrants to the top 1% are also different in terms of their characteristics.

Age We see that the age profile of the top 1% shifts to older age groups when we switch from survey to NA aggregates (Figure 5a). This is perhaps surprising given that we have scaled down pension wealth, which is concentrated among older adults. To understand this shift, recall from Section 5 that it is the scaling of more unequally distributed assets – and UK equity in particular – that results in reranking. Very few individuals moved in or out of the top 1% as a result of scaling pensions. Since among the top 1% equity makes up a larger share of wealth for younger adults than older ones, by scaling this asset class down we move younger individuals out of the top 1%, replacing them with older individuals.

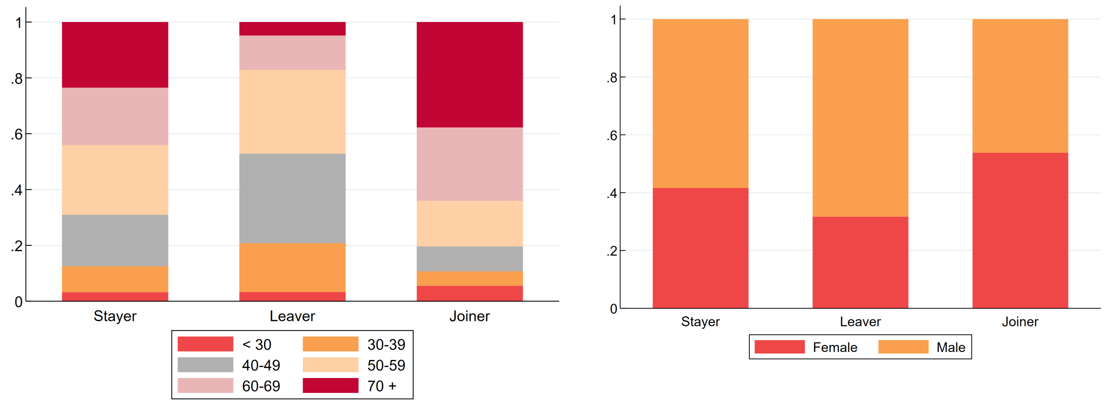
Sex Switching to NA aggregates reduces the share of males who make up the 1% (Figure 5b). 68% of those who leave the top 1% are male, compared to 46% of joiners. This is again driven by the lower aggregate value of UK equities, which men are more likely to hold.

In these results, as elsewhere in the paper, we have focused on the income capitalisation approach for distributional information.[20] The income capitalisation approach requires imputation of non-income-yielding wealth into the tax data. We note that a fuller treatment of wealth inequality by individual characteristics, if using the capitalisation approach should differentiate by these characteristics in imputation. As our primary objective in this paper is to accurately measure the wealth distribution, we opt for imputing based on cells of income-yielding wealth that are as granular as possible, sacrificing the use of other characteristics that may be informative of an individual's asset holdings. If the relationship between income-yielding and non-income-yielding wealth differs for men and women, or between age groups, this will not be reflected in our wealth imputation. Advani et al. (2021a) provide a deeper analysis of variation in wealth holdings by individual characteristics for the UK.

[20]See Appendix G for results using distributional information from the survey instead.

Figure 5: **Characteristics of stayers, leavers and joiners in the top 1% when aggregates are switched, 2016-18**

(a) Age (b) Sex



Notes: 'Joiners' are those who enter the top 1% when we switch from defining wealth using the 'Income capitalisation, survey aggregates' method to the 'Income capitalisation, NA aggregates' method, ranking individuals on total wealth. 'Leavers' are those who leave the top 1% when we switch definition. 'Stayers' are those who remain in the top 1% regardless of which definition we use. We define top shares relative to the total number of individuals aged 20 or older in the population living in the UK.
Source: Authors' calculations based on HMRC administrative tax data, the National Accounts, and the Wealth and Assets Survey.

6 Conclusion

Estimates of wealth inequality are known to be sensitive to the definition of wealth used (Saez and Zucman, 2016; Batty et al., 2019), assumptions about rates of return across the wealth distribution (Saez and Zucman, 2020, 2022; Smith et al., 2023), and the treatment of under-reporting (Alstadsaeter et al., 2019; Johannesen et al., 2020, 2024). In this paper we additionally highlight the importance of estimates of aggregate wealth.

We show that changes in the aggregate value of an asset class affect wealth inequality in two ways. First, they change the relative importance of that asset class in total wealth. An increase in the aggregate for one asset class makes overall wealth inequality more like the inequality of that asset class. Second, to the extent that the rank ordering of individuals varies across asset classes, changes in an aggregate will lead to a reranking of which individuals are at the top.

We find that overall concentration estimates in the UK depend somewhat on the choice of aggregate, with the top 1% share both lower – averaging 15.4% rather than 18.2% over the decade to 2018 – and more stable using survey aggregates relative to a more-usual National Accounts based alternative. We argue that in the UK the survey aggregates are preferable, because their definition of wealth aligns more closely with the target definition of personal wealth, and their measurement is more consistent with the measurement of wealth in the numerator of the top share.

Since the ratio between National Accounts and survey aggregates varies substantially by asset class, the choice of aggregates also has implications for *who* is measured as being at the top of the wealth distribution. Using National Accounts aggregates implies that more older people (aged > 60) and more women (although still a minority) are in the top 1%, relative to survey aggregates, with 40% of individuals in the top 1% being different across the two measures.

The main contribution of our work is methodological, demonstrating that the choice of aggregates affects both top shares and who is where in the wealth distribution. *Ex ante* it is not straightforward to know how these quantities are affected by the choice of aggregates: the direction of change depends on relative changes in different asset classes and how they are distributed across wealthy people. We provide estimates under some alternative assumptions for the numerator of the top share, but a fuller treatment should account for under-reporting, variation in returns to wealth, and the use of trusts, which allow people to benefit without legally owning wealth.

Looking beyond the UK, our findings have implications for the wider study of wealth inequality. Recent work has focused on estimating top wealth, taking as given the choice of aggregates for each wealth category. Our findings highlight that this choice is not innocuous. Though the relative merits of different potential data sources will vary by country, the choice of which to use should be made consciously and with an understanding of the implications for inequality measurement.

We also draw attention to measurement issues relevant to the construction of National Accounts generally. Differences in discount rates across defined benefit pension providers create comparability issues across countries, even after accounting for pension wealth reported in supplementary tables. In the UK, housing wealth continues to be estimated by region-tax band specific uprating of 1991 values; an approach which gives values below all external benchmarks. The UK choice to value unlisted shares based on value at issuance – in contrast with the United States, France and Spain, where estimates of the current market value of corporate equity are constructed – means equity wealth in the National Accounts is underestimated. For researchers we emphasise the need to understand how National Accounts data are constructed in practice, rather than taking them at face value or relying on the high-level guidelines on which they are based.

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Appendices

A Measuring wealth

In this section, we provide further details on what is measured in each data source (National accounts, NA and Wealth and Assets Survey, WAS) and why we define asset categories as we do. The formulae used to define each asset class using our two data sources are set out in Table A1. These are the reconciled definitions used to compare aggregate wealth across data sources in Section 4, with further detail on how the aggregates can be reconciled in Appendix E.

For the NA components in Table A1, we report the ESA 2010 asset classification codes. These can be found in the column headings of Table 9.11 “National Balance Sheet: households” or Table 6.2.11 “Households: Financial Balance Sheet” of the Blue Book (Office for National Statistics, 2021e). Some types of asset can be both an asset and a liability for the household sector, and where applicable we write ‘asset’ or ‘liability’ accordingly. Further details on each of the NA components can be found in Eurostat (2013).

Table A1: **Formulae for defining asset classes in the National Accounts and the WAS**

Asset	NA Formula	WAS Formula
Housing (gross)	Dwellings (AN.111) + land underlying dwellings (part of AN.211)	Main residence + UK second homes + buy-to-let property
Pensions	Pensions (AF.6M)	Occupational DC pensions + Occupational DB pensions + Additional Voluntary Contributions (DB/hybrid schemes) + Retained rights for draw-down + Occupational pensions in payment (annuities) + pensions expected from a former spouse
UK deposits	Deposits with UK MFIs (AF.22N1) + other deposits (AF.29)	Current account deposits + savings account deposits + cash ISAs + National Savings products
Foreign deposits	Deposits with the rest of the world MFIs (AF.22N9)	Not distinguished from UK deposits
Life insurance and (personal pension) annuities	Life insurance and annuity entitlements (AF.62)	Savings in endowment and regular premium policies + single premium policies + Friendly Society savings + insurance products providing guaranteed lump sum + endowment mortgage policies with life insurance element + personal pensions + pensions in payment arising from personal pensions

Business assets	Non-financial assets (AN) - dwellings (AN.111) - land underlying dwellings (part of AN.211)	Gross value of sole proprietorships + UK land + non-residential buildings
UK equities	Listed UK shares (AF.511N1) + Unlisted UK shares (AF.512N1) + other UK equity (AF.519N6) + UK shares and bonds issued by other UK resident sectors (AF.519N7)	UK shares (listed and unlisted) + net value of companies owned + net value of arms-length business investments + net value of partnerships + investment ISAs + fixed term investment bonds
Foreign equities	Equity issued by the rest of the world (AF.519N9)	Foreign shares + overseas property
Mutual fund shares	UK mutual fund shares (AF.52N1) + rest of the world mutual fund share (AF.52N9)	Unit and investment trusts
Currency	Currency (AF.21)	Informal savings
Non-life insurance	Non-life insurance technical reserves (AF.61)	Not measured in WAS
Bonds and gilts	Debt securities (AF.3)	UK bonds and gilts + foreign bonds and gilts
Financial derivatives and employee stock options	Financial derivatives and employee stock options (AF.7, asset)	Employee shares and share options

Non-mortgage loans	Short-term loans issued by UK and foreign MFIs (AF.41) + other long-term loans issued by UK resident sectors (AF.424N1) + financial derivatives owed to other sectors (AF.71, liability)	Formal loans including student loans + credit and store card balances + hire purchase balances + current account overdrafts + mail order balances + loans on buildings and land other than UK dwellings + outstanding business debts held by sole proprietors
Mortgages	Long-term loans secured on dwellings (AF.422)	Mortgages on main residence, second homes, buy-to-let property + equity release
Other financial assets	Other accounts payable (AF.8) - other accounts receivable (AF.8) + loans issued to other UK resident sectors (AF.424N1)	Not measured in WAS

A.1 Housing (gross)

We define housing wealth in the NA as the value of dwellings (AN.111) plus underlying land (part of AN.211). The value of land underlying dwellings is not disaggregated from land underlying other buildings and structures in the household sector balance sheet. However, the ONS have published a breakdown of land by the type of fixed asset situated upon it for the economy as a whole.[21] To estimate the value of land underlying dwellings for the household sector specifically, we compute the ratio of underlying land value to each type of fixed asset for the economy as a whole. We then apply this ratio to each category of fixed asset in the household sector account. This enables us to improve upon the proportional allocation approach advocated in the DINA guidelines for cases where breakdowns of underlying land are unavailable.[22]

Housing wealth in the NA includes all UK-situated property, regardless of whether the owner is a domestic or foreign resident. It excludes the value of overseas property held by UK residents. Instead, a balancing adjustment is made through the 'equities' (AF.519N9) component of the national balance sheet, so that foreign-owned UK property is recorded as a liability, and domestically owned-property as a financial asset in the household sector balance sheet. By contrast, the WAS records the value of all property held by UK residents only. To reconcile treatment of domestically-owned overseas property in the WAS with NA classifications, we assign this component to 'equity' in the WAS.

In Section 4.2, we explained how the components of housing wealth are estimated in both the NA and the WAS.

A.2 Pensions

Pension wealth in the NA includes the present value of future pension entitlements accrued by UK households, with the exception of certain public sector pensions, social security payments (state pension), and personal pensions (which are recorded separately). Though the NA and the WAS take a similar approach to valuing Defined Contribution (DC) pensions – a pot of savings where the amount available upon retirement is determined by contributions made over an individual's life time plus interest – their approaches to valuing Defined Benefit (DB) pensions and annuities differ.

[21] See `https://www.ons.gov.uk/economy/nationalaccounts/uksectoraccounts/adhocs/13941landunderlyingcultivationbuildingsandstructuresestimatesfrom1995to2020`

[22] For further details on our approach, see Appendix D.

Defined Benefit pensions promise a guaranteed income stream, with the annual income usually related to the individual's average or final salary. Annuities are similar to the decumulation phase of a DB pension, and are products offering a fixed income stream that can be bought by individuals out of their DC pension pot or savings upon reaching retirement. Only annuities arising from occupational pensions are included in the 'AF.6M Pensions' component of the NA; annuities arising from personal pension savings are classified under 'Life insurance and annuities (AF.62)'

Whereas the WAS comprehensively captures all types of pension, the NA excludes DB pension schemes offered to public sector workers for which there is no underlying fund (e.g. because they are funded out of general taxation).[23] The exclusion of unfunded pensions from our wealth definition is consistent with the DINA framework used by the World Inequality Database although, as we explain in Appendix 4.1, we do not think there is any reason why these types of pension should be excluded from our wealth definition in principle. Since 2017, many countries including the UK have produced supplementary tables on unfunded DB pension wealth in accordance with the ESA10 guidelines. Thus, it is possible to construct an alternative wealth series which includes all private pension wealth. We present estimates using this approach in Section F.2.

To reconcile treatment of personal pensions in the WAS with NA classifications, we reallocate personal pensions and annuities arising from these to 'life insurance and (personal pension) annuities' (see Section A.4).

A.3 Deposits

Deposits consist of funds held in monetary financial institutions (MFIs) and national savings instruments, both in the UK and overseas (AF.22 and AF.29). Estimates of deposits recorded in the household sector balance sheet of the NA are derived from three key sources:[24]

1. Deposits held with UK MFIs (AF.22N1): Bank of England surveys of MFIs
2. Deposits held with central government (AF.29): this largely includes national savings instruments, sourced from the National Savings Bank

[23] In particular, this includes the following groups: civil servants, NHS staff, teachers, Armed Forces, police officers, firefighters, members of the judiciary, members of security services, the UK Atomic Energy Authority, overseas staff at the Department for International Development, research councils, and Royal Mail employees.

[24] Further information can be found here: https://www.ons.gov.uk/economy/nationalaccounts/uksectoraccounts/methodologies/currencyanddepositstatisticsintheukflowoffundsaccountsmatrices

3. Deposits held with the rest of the world (foreign deposits) (AF.22N9): Bank for International Settlements

Reconciling deposits in the WAS with the NA is – in principle – straightforward, as respondents are asked to report the value of funds held in current accounts, savings or deposit accounts, and cash ISAs.

A.4 Life insurance and (personal pension) annuities

In the NA, 'Life and insurance and annuity entitlements (AF.62)' is defined as policy holders' claims against the technical reserves of corporations providing life insurance. The values recorded represent the reserves needed to meet all expected future claims for life insurance and annuity entitlements arising from personal pensions.

This is substantially different from the value of insurance policies in the WAS. Insurance policies (both life- and non-life) that have no value unless the insured event occurs during the term of the policy are not included in the definition of wealth. Insurance company reserves set aside to fund critical illness payments, death benefits etc., therefore have no counterpart in the WAS. However, life insurance products that have an individual fund associated with them, which act as a form of savings with an additional life insurance element, are included. This includes endowment policies, investment bonds with a life insurance element, Friendly Society Tax-Exempt Savings plans, and insurance policies that pay a lump sum on a specified date. The WAS records the current value of each of these policies.

To be consistent with the NA in excluding individual personal pensions from the definition of pension wealth, we add to the value of life insurance policies the value of personal pension pots and annuities arising from these, which are usually held by life insurance companies.

A.5 Non-life insurance

In the NA, 'Non-life insurance technical reserves (AF.61)' is defined as policy holders' claims against the reserves of non-life insurance companies. This includes premiums paid but not earned, and reserves set aside to meet outstanding claims. The latter represents the amount needed to meet all expected future claims against life insurance companies.

As discussed in Section A.4, the value of non-life insurance products is not estimated as part of wealth in the WAS.

A.6 Business assets

The NA capture the value of buildings, land, cultivated biological resources (e.g. crops, livestock), machinery and equipment, computer software, Intellectual Property products, inventories, contracts, leases and licences that are owned directly by households but are not acquired for final consumption by households. That is, in theory, items such as laptops that are used directly by households rather than as a production input are excluded, though in practice it is difficult to distinguish between the two. We take the sum of these as our measure of business assets, i.e. the sum of all non-financial assets (AN) less dwellings (AN.111) and land underlying dwellings, where the latter is estimated using the approach set out in Appendix D.

In the WAS, we calculate business assets as the self-reported sale value of businesses in which the individual is self-employed, as explained in Section 4.3. In principle, the value of business wealth in the WAS includes the value of fixed assets and land owned via a business. The value of other UK land and non-residential property owned by households is recorded as a separate component in the property wealth section of the questionnaire. To reconcile our WAS measure of business wealth with the NA classification, we reallocate these property assets to business assets.

The measurement of 'business wealth' in the WAS is somewhat imprecise, making a thorough reconciliation with the NA concepts of business assets difficult. First, individuals are asked about businesses from an employment perspective. Specifically, they are given the opportunity to record (separately) the value of businesses – net of debts – owned or partially owned that the individual is (a) a company director of; (b) a partner in a partnership or professional practice; or (c) self-employed in any other way. In valuing the business, individuals are asked "If you sold your business today, including any debts or liabilities, about how much would you get? Please include the value of financial assets, accounts receivable, inventories, land, property, machinery, equipment, customer lists and intangible assets." To reconcile net business wealth in the WAS with the gross value of assets captured in the NA, we add the value of business debts – which are reported separately – to the value of the business. Business loans are then imputed in our mixed income capitalisation method across those whose gross business wealth is positive.

A.7 UK equities

Formally, 'equities' measures the value of household shares in incorporated businesses. We exclude equity held through mutual funds as these form their own category (Section A.9). This excludes the value of assets held by households through pass-through businesses (Section A.6). UK equities in the National Balance sheet can be decomposed into listed and unlisted UK shares (AF.511N1 and AF.512N1); other UK equity (AF.519N6), and shares and bonds (AF.519N7).

In the WAS, we assign to UK equities the value of any business in which the individual serves as company director, or partnerships, as these companies would be classified as corporations in the NA (or quasi-corporations in the case of partnerships). We convert estimates of net business wealth to gross estimates by adding debts, as for sole proprietorships (Section A.6)

To this, we add the value of 'arms-length businesses'. These are captured in a catch-all question worded as "Apart from anything you've already told me about, do you own all or part of a business as an active or sleeping partner? About how much is your share of this business worth after deducting any outstanding debts?" Though it is not completely clear how these businesses would be classified in the NA, given that the individual is not actively working in the business it is likely that these fall in the category of corporation or quasi-corporation, in which case households' holdings of these businesses would be captured as part of 'equities' in the NA.

Finally, we include the value of UK listed and unlisted shares owned by the respondent, as well as the value of fixed term investment bonds and investment ISAs. These are categorised under 'financial wealth' in the WAS, which captures the value of arms-length investments.

A.8 Foreign equities

Foreign equities – the value of shares held by UK households in foreign companies – are included in 'equity issued by the rest of the world (AF.519N9)' in the NA. The value of foreign equities included in the NA is, in fact, based on data from the WAS (Office for National Statistics, 2019). As discussed in Section 4.4, this component also includes a financial claim representing ownership of overseas property by UK residents.

In the WAS, foreign equities is measured as the self-reported value of shares held in foreign companies. To reconcile the treatment of overseas property in the WAS with the NA, we add to our survey-based measure of 'foreign equities' the value of overseas property owned by the respondent.

A.9 Mutual fund shares

Mutual fund shares consist of a range of assets that are owned via trusts and collective investment funds. We match UK and foreign mutual fund shares in the NA (AF.52N1 and AF.53N9) to unit/investment trust funds in the WAS.

As with other forms of UK equity, mutual fund shares in the NA are valued based on issuance data (see Section 4.4). Their value is therefore likely to be lower than the current market value of the shares.

A.10 Other financial assets

'Other financial assets' consists of the net value of 'Other accounts receivable (AF.8)' less 'Other accounts payable (AF.8)', and lending to other sectors of the UK economy (AF.414N1). The former consist of trade credits and advances.

There is no corresponding category in the WAS.

A.11 Currency

In the NA, 'Currency (AF.21)' consists of banknotes and coins held by households. In the WAS, individuals are asked for the collective sum of 'money given to someone else to look after', 'money saved in cash', and 'money paid into a savings and loans club (informal)'.

Balance sheets in the NA are consolidated, meaning that loans between households net out in aggregate in the household sector account. Though loans to other private individuals are an asset at the individual-level, there is no corresponding aggregate for these in the NA. We do not include loans to other private individuals in our WAS-based measures.

A.12 Bonds and gilts

In the NA, bonds and gilts are comprised of debt securities (AF.3) issued by UK sectors and the rest of the world. We match this to bonds and gilts in the WAS, which consists of corporate bonds and gilts, corporate bonds issued by a foreign company, UK government or local authority, and government bonds issued by a foreign government. It is not possible to distinguish between corporate and government bonds in the WAS. We also add assets held in National Savings and Investment products to this category in the WAS, the most prevalent of which are premium bonds, income bonds, and guaranteed bonds.

A.13 Financial derivatives/employee stock options

In the NA, 'Financial derivatives and employee stock options (AF.7)' include financial assets such as options, forwards, and credit derivatives; and employee stock options (see Eurostat (2013), Annex 7.1, for details). In practice, the majority of the aggregate value of this component is accounted for by employee stock options (89% in 2018).

Financial derivatives are not captured in the WAS, however employee shares and share options are.

A.14 Non-mortgage loans

'Non-mortgage loans' consists of all formal loans other than those on dwellings. This can be broken down into short-term loans issued by UK and overseas monetary financial institutions (AF.41), other long-term loans (AF.424N1), and financial derivatives owed by UK households (AF.71). Other long-term loans includes student loans (issued by the UK government), credit and store cards, and car loans among others. The NA do not contain information on inter-household lending, as these consolidate out (the liability of the borrowing household is equal to the asset of the lending household). Loans in the NA may either be held as consumer loans, or as loans held by sole proprietors.[25]

In the WAS, we observe the value of outstanding formal loans from banks and building societies, student loans, credit and store card balances, hire purchases, current account overdrafts, mail order purchases, loans on buildings, and UK land and other property (excluding dwellings). We allocate each of these to non-mortgage loans. We also include the value of business debts held by sole proprietors, in line with the NA classification.

A.15 Mortgages

'Mortgages' is measured by 'long-term loans on dwellings (AF.422)' in the NA. In the WAS, we include in this category mortgages on the individual's main residence, second home, and buy-to-let property.

[25] For further information on loans in the NA, see `https://www.ons.gov.uk/aboutus/transparencyandgovernance/freedomofinformationfoi/whatconstitutesaloantothehouseholdsectorandwhattypesofloanentereachcategory`.

B Detailed Methodology

B.1 Capitalising income tax returns

Income-yielding assets are defined here as assets which generate a taxable income flow. These income flows, observed in our tax data, shed light on the distribution of the assets from which they are derived. In its simplest form, the income capitalisation method can be implemented by scaling the distribution of income flows derived from a particular asset by a constant scaling factor, using information on the aggregate stock of the asset. The value of an income-yielding asset a held by individual i can be calculated as:

$$w_i^a = y_i^a \cdot \frac{W^a}{\sum_j y_j^a} \tag{7}$$

where y_i^a is the income flow derived by individual i from asset w^a. The capitalisation factor $\frac{W^a}{\sum_j y_j^a}$ encapsulates two things: the rate of return on the asset, which is assumed here to be constant across individuals; and measurement or conceptual differences between the income flow observed in the tax data and the asset stock it is being scaled to. There has been much debate on whether the assumption of a constant rate of return is empirically justified (Saez and Zucman, 2016, 2020; Smith et al., 2023), as some evidence suggests that wealthier individuals receive higher rates of return on a given asset (Smith et al., 2023; Fagereng et al., 2020; Xavier, 2021). If so, then assuming a constant rate of return would lead to an over-estimation of wealth inequality. On the other hand, there may also be variation in the rate of return among individuals receiving a given amount of capital income. Applying a constant (average) rate of return would lead us to under-estimate wealth inequality, as we would not capture the variation in wealth held by these individuals.

If an asset class had a homogeneous rate of return and we knew the true value of this rate, we could divide the observed income yield by this rate of return to obtain the value of the asset. If these asset values did not sum to our external aggregate, this would tell us one of two things. Either the income yield we observe is not the full return received by the individual (e.g. due to evasion), or there are conceptual differences between the aggregate obtained from the tax data and the external aggregate (or both). As a reflection of this, there are various approaches to implementing the income capitalisation method in the literature. Saez and Zucman (2016) first scale capital incomes observed in the tax data up to aggregate capital income flows in the National Accounts, before dividing this by the rate of return, which they compute by dividing the flow in the National Accounts by the corresponding stock. Smith et al. (2023) instead apply external estimates for the rate of return, and subsequently scale the estimated asset values to match external aggregates from the National Accounts. If the rates of return and scaling factors used are constant across individuals, then the difference between these two approaches is merely presentational: the end result is as if Equation 7 were applied to the tax data directly. In implementing Equation 7, we are making an implicit assumption on how the conceptual and measurement differences are distributed.

In the DINA guidelines, it is recommended that as a first approximation, constant scaling factors should be used (Alvaredo et al., 2020). This assumes that conceptual and measurement differences that lead to discrepancies between tax data-implied aggregates (if the true rate of return were known) and external aggregates are distributed proportionally to the observed income yield. We adopt this approach, while acknowledging its limitations. Our focus here is on the implications of applying different aggregates in the estimation of this equation. At present, there is insufficient evidence on what drives differences in income-yielding wealth aggregates between the WAS and the National Accounts to suggest that we should scale differently under each approach.

To implement the capitalisation method, we carefully map income yields in the tax data to the different asset categories observed in our two datasets on aggregate wealth. Table 2 shows the different capitalisation categories used in our two capitalisation-based approaches.

Sole proprietorships are classified as part of the household sector of the National Accounts (Eurostat, 2013). The assets held by these businesses are recorded in the relevant columns of the household balance sheet. Though the profits earned by sole proprietors include a return on capital assets such as machinery and equipment, which do not yield a direct income flow, they also include a return on labour. The share of income that derives from capital assets is likely to vary across businesses. Some, such as sole proprietors providing personal services, will own few if any assets, while others will derive a large portion of their income as a return on assets they own. Since we do not have sufficient information to estimate the capital share of income at a micro-level, we adopt the common assumption made in the DINA literature, that 30% of profits earned by sole proprietors represents a return on capital (Alvaredo et al., 2020; Garbinti et al., 2021; Martínez-Toledano, 2023). This is likely to over-equalise the implied distribution of business assets, as it assigns some of the aggregate value to businesses whose income consists almost entirely of a return on labour.

Partnerships are classified as quasi-corporations in the UK National Accounts, and the value of households' holdings in partnerships is combined with their holdings of shares in corporations, classified under the heading of 'UK equity'.[26] Accordingly, we combine partnership income with dividends received by households, capitalising the combined value of this income flow up to the aggregate for UK equity. Partnership income consists of trading income, interest, dividends, and rental income. While interest, dividends and rental income all represent a return on capital, trading income is a combination of the return on labour, and the return on non-income-yielding assets such as machinery and equipment. As with profits earned by sole proprietors, we assume that 30% of partnership trading income represents a return on capital assets.

B.2 Imputing non-income-yielding wealth

We impute non-income-yielding assets to individuals in the income tax data using distributional information from our survey data. Our preferred methodology is outlined in Section 3. There are many ways in which one could go about this imputation. In this section, we test the performance of our imputation methodology and explain how and why this differs from the standard approach in the literature, originally developed by Garbinti et al. (2021) and used subsequently by Martínez-Toledano (2023).

B.2.1 Alternative imputation approaches

In this section we illustrate how our approach to imputing non-income yielding wealth compares with alternatives. We consider alternative approaches to defining imputation groups along four dimensions: age, sex, income-yielding wealth, and non-income yielding wealth. As with all imputation procedures, trade-offs must be made between the number of dimensions and the number of observations. To guard against making imputations based on small sample sizes, we require that each imputation cell must contain at least 30 observations, and at least 90% of imputation cells must contain in excess of 50 observations.

Table B1 illustrates how our alternative imputed wealth distributions compare against the actual distribution of total wealth. Though splitting individuals by age and sex enables us to better analyse the characteristics of individuals across the wealth distribution, this imputation approach comes at a high cost in terms of our ability to replicate the concentration of wealth than our preferred imputation method. This is evidenced by the imputed top share being much lower using the methods which

[26] Confirmed by the ONS in email correspondence, 15th August 2022.

stratify by age and sex, and the sum of absolute deviations from the actual CDF across the distribution being much higher.

B.2.2 Comparison with Garbinti et al. (2021)

Our preferred method differs from the imputation procedure set out in Garbinti et al. (2021), which can be summarised as follows. First, individuals in the survey data are allocated to groups defined by age, capital income, and labour and replacement income. Within each group, the extensive margin – the share of individuals holding each asset – is computed for each separate category of non-income-yielding wealth. For each group, and each asset category, individuals with positive holdings are ranked according to their asset value and grouped into quantiles. The intensive margin – the share of each asset held by each cell-quantile group – is then computed. In the tax data, individuals are allocated into groups defined using the same dimensions as in the survey data. Within each group, individuals are randomly assigned as holders of each particular asset, based on the extensive margin computed in the survey data for the respective group. Those who are assigned as asset holders are randomly allocated to a quantile group and assigned the share of each asset held by the respective cell-quantile in the survey data.

There are two key differences between the methods described above. First, we initially group individuals into cells defined by income-yielding wealth, rather than using information on capital and labour income. This difference arises partly due to data limitations. Income – particularly capital income – is poorly captured in the WAS. However, there is a more deliberate reason for using income-yielding wealth rather than income, which is that the primary goal of this exercise is to estimate the wealth distribution. This requires us to accurately estimate the joint distribution of income-yielding and non-income-yielding wealth, which is more likely to be achieved when income-yielding wealth is used to define the imputation matrix.

Second, the two approaches differ in how they account for the joint distribution of non-income-yielding assets. The imputation method developed by Garbinti et al. (2021) replicates the marginal distribution of each asset. However, within each age-income group, each of the non-income-yielding assets is imputed independently both at the extensive and intensive margin. For example, an individual assigned as having positive housing wealth is no more or less likely to be assigned as having positive pension wealth than someone who is assigned as having no housing wealth, which may not reflect reality. This is not necessarily a cause for concern, as it is not clear *a priori* whether holdings of different assets are correlated *conditional on* age,

Table B1: **Performance of alternative imputation methods for non-income-yielding wealth, 2016-18**

			Share of total wealth held by:			
Approach	Description	Sum of abs(deviations) from CDF of total wealth	Bottom 50%	50-90%	90-99%	Top 1%
Observed distribution		0.00	4%	43%	36%	16.4%
Preferred imputation method	Vigintiles (20 groups) of income-yielding (IG) wealth, then: within the bottom 15 vigintiles of IG wealth (bottom 75%), vigintiles of non-income-yielding (NIG) wealth; within vigintiles 16-18 of IG wealth (75-90%), 30 groups of NIG wealth; within vigintiles 19-20 of IG wealth (top 10%), 40 groups of NIG wealth.	0.12	4%	44%	36%	16.1%
Alternatives:						
Option 1	Percentiles of IG wealth, quartiles of NIG wealth	1.30	4%	46%	34%	15.0%
Option 2	Vigintiles (20 groups) of IG and NIG wealth, respectively	0.11	4%	44%	36%	16.0%
Option 3	40 groups of IG wealth, deciles of NIG wealth 10 groups	0.36	4%	45%	36%	15.5%
Option 4	Quintiles of IG wealth, 40 groups of NIG wealth	0.11	4%	44%	37%	16.2%
Option 5	Vigintiles of IG wealth, splitting the top two vigintiles further into 2 groups each (22 groups). Vigintiles of NIG wealth within each IG wealth cell.	0.37	4%	45%	36%	15.5%
Option 6	Vigintiles of IG wealth, splitting the top vigintile (top 5%) into 5 groups (percentiles) (24 groups), then: within the bottom 15 vigintiles (bottom 75%), vigintiles of NIG wealth; within vigintiles 16-19 of IG wealth (75-95%), 30 groups of NIG wealth; within the top five percentiles, deciles of NIG wealth.	0.14	4%	44%	36%	15.9%
Option 7	First split into 3 age bands, then within each: deciles of IG wealth, deciles of NIG wealth	0.22	4%	44%	37%	15.4%
Option 8	First split into 5 age bands, then within each: deciles of IG wealth, quintiles of NIG wealth	0.56	4%	45%	36%	14.9%
Option 9	First split into 5 age bands, then within each: quintiles of IG wealth, deciles of NIG wealth	0.59	4%	45%	36%	15.0%
Option 10	First split into 3 age bands, then split by sex, then within each age-sex cell: deciles of IG wealth, quintiles of NIG wealth	0.48	4%	45%	36%	15.2%
Option 11	First split into 3 age bands and by sex, then within each age-sex cell: quintiles of IG wealth, deciles of NIG wealth	0.22	4%	44%	37%	15.5%

Notes: Individuals in the WAS are allocated to imputation cells defined by the criteria listed in the 'Description' of each imputation method. The 'Sum of abs(deviations) from CDF of total wealth' is constructed by deducting the cumulative share of imputed wealth held by each percentile according to the stated imputation method, from the observed cumulative share of wealth held by each percentile.
Source: Authors' calculation based on the Wealth and Assets Survey (2016-18).

capital and labour income, which is what matters in this context. However, if there is indeed a correlation in non-income-yielding assets within each cell, the implication of ignoring their joint distribution is that the randomness introduced by the imputation procedure will have an equalising effect on the distribution of wealth. In the case of the United Kingdom, we find that ignoring the joint distribution of assets has a minor equalising effect on the distribution of non-income-yielding wealth (Figure B1). In the series 'Imputed wealth (ignoring joint distribution)', we take our groups defined by income-yielding wealth and, for each asset category, allocate individuals to quintiles of the marginal distribution for that asset, broadly following Garbinti et al. (2021).

Figure B1: **Cumulative distribution of non-income-yielding wealth using our imputation method, and when ignoring the joint distribution of assets, 2016-18 (%)**

Notes: 'Actual wealth' shows the actual distribution of non-income-yielding wealth according to the WAS; 'Imputed wealth (our method)' shows the distribution of non-income-yielding wealth imputed using our headline approach (see Section B.2; 'Imputed wealth (ignoring joint distribution)' shows the distribution of non-income-yielding wealth imputed by allocating individuals to quintiles of the marginal distribution of each non-income-yielding asset within cells defined by income-yielding wealth. The latter ignores the joint distribution of assets.)
Source: Authors' calculations based on the Wealth and Assets Survey (2016-18)

Though our method incorporates measures to account for the joint distribution of assets, it is worth noting that this is subsequently distorted by the scaling of asset distributions to match different aggregates. As we discuss in Section 3, the differential scaling of asset categories affects the ranking of individuals in the distribution of non-income-yielding wealth. As a result, the quantiles used to construct the imputation matrix will no longer be equivalent to quantiles of the final non-income-yielding wealth distribution. An alternative method would be to scale the categories of non-income-yielding wealth *pre*-imputation, and define the imputation groups using this adjusted measure of non-income-yielding wealth. This would require us to assume that the distribution of non-income-yielding wealth in the survey data was incorrect to begin with. Whichever method one chooses, the implication of scaling asset classes to different aggregates is that the distribution of non-income-yielding wealth must diverge from what is observed in the survey data.

B.3 Treatment of each asset class

Table B2 shows how each asset class is treated under our two headline approaches for estimating the distribution of wealth.

Table B2: **Treatment of each asset class under our two headline approaches for estimating the wealth distribution**

Asset	'Income capitalisation, NA aggregates'	'Income capitalisation, WAS aggregates'
UK deposits	Flows of interest derived from UK savings are capitalised to the NA aggregate for UK deposits.	Flows of interest derived from UK savings are combined with flows of foreign interest and capitalised to the survey aggregate for deposits (UK/foreign deposits cannot be distinguished in the survey).
Foreign deposits	Flows of interest derived from foreign savings are capitalised to the NA aggregate for foreign deposits.	See 'UK deposits'.
UK equities	Flows of dividends from UK companies are combined with partnership income (interest, dividends, rental income, and 30% of trading income) and capitalised to the NA aggregate for UK listed and unlisted shares (which includes partnerships) and other UK equity.	Same as for 'Income capitalisation, NA aggregates', except we capitalise the same flow to the survey aggregate for UK equity.
Foreign equities	Flows of dividends from foreign companies are combined with rental income from foreign property and capitalised to the NA aggregate for foreign equity (which includes overseas property as part of 'equity').	Flows of dividends from foreign companies are capitalised to the survey aggregate for foreign equity (which can be distinguished from overseas property).

Overseas property	See ‘Foreign equities’.	Flows of rental income from foreign property are capitalised to the WAS aggregate for overseas residential property.
Mutual fund shares	Flows of dividends from mutual fund shares are capitalised to the NA aggregate for mutual fund shares.	Flows of dividends from mutual fund shares are capitalised to the survey aggregate for mutual fund shares.
Business assets (sole proprietorships)	30% of the profits from self-employment are capitalised to the NA aggregate for business assets held by sole proprietors.	30% of the profits from self-employment are capitalised to the survey aggregate for business assets held by sole proprietors.
Bonds and gilts	Flows of interest from gilts are capitalised to the NA aggregate for bonds and gilts.	Flows of interest from gilts are capitalised to the survey aggregate for bonds and gilts.
Other financial assets	NA aggregate for other financial assets is allocated in proportion to the sum of all of the above assets held by each individual.	This category does not exist in the survey data.
Income-yielding wealth	Sum of above assets	Sum of above assets

Net housing	Imputed to individuals in the tax data based on the share of net housing held by quantiles of the income-yielding wealth distribution in the survey data. Individuals in the tax data are ranked based on income-yielding wealth defined using the 'Income capitalisation, NA aggregates' approach. Imputed distribution of net housing wealth scaled to NA aggregate for net housing.	Imputed to individuals in the tax data based on the share of net housing held by quantiles of the income-yielding wealth distribution in the survey data. Individuals in the tax data are ranked based on income-yielding wealth defined using the 'Income capitalisation, survey aggregates' approach. Imputed distribution of net housing wealth scaled to survey aggregate for net housing.
Defined Contribution pensions	Imputed to individuals in the tax data based on the share of DC pensions held by quantiles of the income-yielding wealth distribution in the survey data. Individuals in the tax data are ranked based on income-yielding wealth defined using the 'Income capitalisation, NA aggregates' approach. Imputed distribution of DC pension wealth scaled to survey aggregate for DC pensions (assumes difference between survey and NA aggregate for pensions is explained entirely by DB pensions and annuities).	Imputed to individuals in the tax data based on the share of DC pensions held by quantiles of the income-yielding wealth distribution in the survey data. Individuals in the tax data are ranked based on income-yielding wealth defined using the 'Income capitalisation, survey aggregates' approach. Imputed distribution of DC pensions scaled to survey aggregate for DC pensions.

Defined Benefit pensions and annuities from occupational pensions	Imputed to individuals in the tax data based on the share of DB pensions and annuities from occupational pensions held by quantiles of the income-yielding wealth distribution in the survey data. Individuals in the tax data are ranked based on income-yielding wealth defined using the 'Income capitalisation, NA aggregates' approach. Imputed distribution of DB pensions and annuities scaled to the difference between the survey aggregate for pensions and the NA aggregate for pensions.	Imputed to individuals in the tax data based on the share of DB pensions and annuities from occupational pensions held by quantiles of the income-yielding wealth distribution in the survey data. Individuals in the tax data are ranked based on income-yielding wealth defined using the 'Income capitalisation, survey aggregates' approach. Imputed distribution of DB pensions scaled to survey aggregate for DB pensions and annuities from occupational pensions.

Life insurance	Individuals in the tax data are ranked based on income-yielding wealth defined using the 'Income capitalisation, NA aggregates' approach. Life insurance investment policies are imputed to individuals in the tax data based on the share of life insurance assets held by quantiles of the income-yielding wealth distribution in the survey data. Imputed distribution of life insurance assets scaled to the survey aggregate for life insurance assets (assumes difference between survey and NA aggregate for life insurance is explained entirely by reserves set aside for term life policies, the value of which is not captured in the WAS). Term life insurance policies are imputed to individuals in the tax data based on the share of end-of-term payouts expected by quantiles of the income-yielding wealth distribution in the survey data. Life insurance assets are then defined as the sum of investment and term life policies.	Imputed to individuals in the tax data based on the share of life insurance assets held by quantiles of the income-yielding wealth distribution in the survey data. Individuals in the tax data are ranked based on income-yielding wealth defined using the 'Income capitalisation, survey aggregates' approach. Imputed distribution of life insurance assets scaled to survey aggregate for life insurance. Term life policies are not part of aggregate wealth in the WAS.
Non-life insurance	NA aggregate for non-life insurance assets is allocated in proportion to the sum of pensions and life insurance assets held by each individual, constructed using the methods detailed above.	This category does not exist in the survey data.

Currency	Imputed to individuals in the tax data based on the share of currency held by quantiles of the income-yielding wealth distribution in the survey data. Individuals in the tax data are ranked based on income-yielding wealth defined using the 'Income capitalisation, NA aggregates' approach. Imputed distribution of currency is scaled to the NA aggregate for currency.	Imputed to individuals in the tax data based on the share of currency held by quantiles of the income-yielding wealth distribution in the survey data. Individuals in the tax data are ranked based on income-yielding wealth defined using the 'Income capitalisation, survey aggregates' approach. Imputed distribution of currency is scaled to the survey aggregate for currency.
Non-mortgage loans	Imputed to individuals in the tax data based on the share of non-mortgage loans held by quantiles of the income-yielding wealth distribution in the survey data. Individuals in the tax data are ranked based on income-yielding wealth defined using the 'Income capitalisation, NA aggregates' approach. Imputed distribution of non-mortgage loans is scaled to the NA aggregate for non-mortgage loans.	Imputed to individuals in the tax data based on the share of non-mortgage loans held by quantiles of the income-yielding wealth distribution in the survey data. Individuals in the tax data are ranked based on income-yielding wealth defined using the 'Income capitalisation, survey aggregates' approach. Imputed distribution of non-mortgage loans is scaled to the survey aggregate for non-mortgage loans.
Non-income-yielding wealth	Sum of all above assets that are not part of income-yielding wealth	Sum of all above assets that are not part of income-yielding wealth
Total wealth	Income-yielding + non-income-yielding wealth	Income-yielding + non-income-yielding wealth

C Population coverage adjustment

The WAS samples private dwellings in Great Britain, excluding those in Northern Ireland and those living north of the Caledonian Canal (in Scotland). The sampling frame also omits individuals living in institutional settings such as student halls, care homes, and prisons. In all, this means that the WAS misses around 5% of the UK 20+ population. In this section, we set out our two-step approach to addressing the population under-coverage issue, creating a sample that is representative of the UK.

C.1 Imputing Northern Ireland

First, we make use of the Family Resources Survey, a cross-sectional survey of household incomes which *does* cover Northern Ireland, to implement a cell-based imputation of individual survey weights in the WAS. Effectively, we scale up the survey weights of groups of individuals who are 'similar' to those living in Northern Ireland in terms of income, age, tenure, and household composition, to add in the population of individuals in Northern Ireland who are represented in the FRS.[27] This does not account for the full population of Northern Ireland according to ONS population statistics, as the FRS also omits individuals living in institutional settings. However, this first step is designed to produce a weighted sample that is representative of the UK population less those in institutional settings.

In each dataset, we allocate individuals into cells according to:

1. Gross income (six groups: <£10,000; £10-20,000; £20-30,000; £30-40,000; £40-50,000; >£50,000)
2. Age (six groups: 20-30; 30-40; 40-50; 50-60; 60-80; 80+)
3. Tenure and household composition (three groups):
   (a) **Does not own a house:** The individual is *not* a main adult (head of household or their partner) and/or the house is not owner-occupied
   (b) **Sole owner of a house:** The individual is the head of household, with no partner, and property is owner-occupied
   (c) **Joint owner occupier:** The individual is the head of household or their partner, and partner exists, and property is owner-occupied

[27] It is not possible to account for the population north of the Caledonian Canal – which represents around 0.5% of the adult population – in the same way, as we lack sufficiently granular geographical information to identify these respondents in the FRS. This population is accounted for by our final age-sex scaling adjustment detailed below.

Overall this results in 108 distinct groups. Each of the categories (1)-(3) is a strong independent predictor of individual wealth, and in principle can be constructed in a similar fashion in both the WAS and FRS. In practice, there are some measurement differences between the two datasets. Though both measure income according to a similarly comprehensive definition, the FRS collects much more granular information, which is likely to lead to a much more accurate measure. Unfortunately, there are insufficient observations in the WAS to use higher income ranges in combination with the other categories. However, in testing our method for Scotland and Wales we show that using this combination of categories produces a closer replication of the wealth distribution than using a more granular categorisation of income alone.

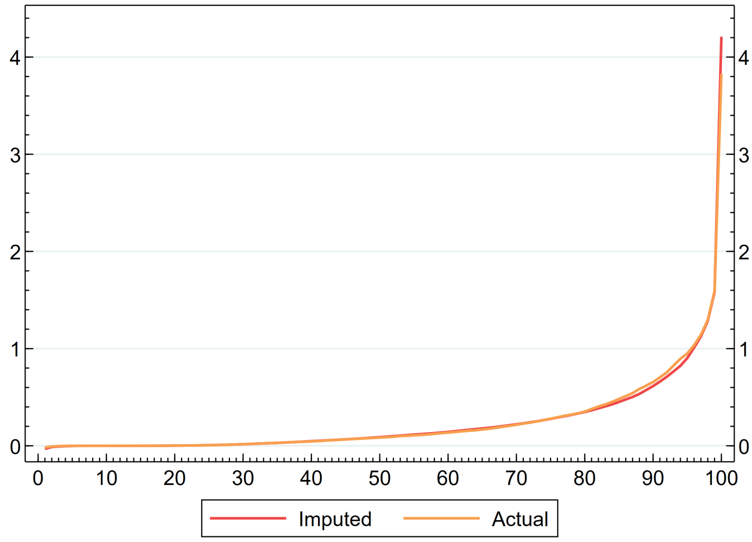
Having allocated individuals in both datasets to a particular cell, we compute cell population totals using the sample of individuals in the FRS who are resident in NI. We then scale up the individual weights of individuals in each cell of the WAS to match the original total plus the population total for the corresponding NI cell in the FRS. However, we do not scale up the population weights of *all* individuals in the WAS. In particular, we exclude individuals residing in London and the South East from our population adjustment (these individuals retain their original weight). This is because the distribution of wealth in these regions differs from the rest of Great Britain, with wealth generally being higher than elsewhere. Our tests for Scotland and Wales show that excluding these regions produces an imputed wealth distribution which is closer to the known distribution in those nations.

C.2 Testing our imputation method

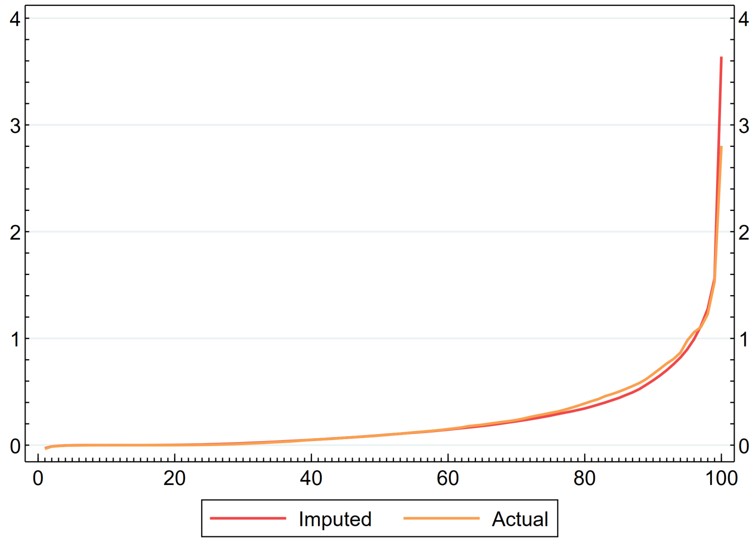
To test our population imputation method, we produce an imputed sample for Scotland by scaling the weights of individuals in England and Wales (excluding London and the South East), and do the same for Wales using the sample of individuals in England and Scotland. We compare the wealth distribution of individuals in our imputed sample for Scotland/Wales to the observed distribution of wealth in those nations. The imputed distribution closely replicates the actual wealth distribution in Scotland and Wales (Figure C1). Average wealth according to our imputed (actual) sample is £247,000 (£248,000) in Scotland and £241,000 (£244,000) in Wales; median wealth is £91,000 (£87,000) in Scotland and £95,000 (£93,000) in Wales. Note that while our method can closely replicate the shape of the wealth distribution, it cannot replicate the presence of outliers. This is illustrated in the case of Wales where one extremely wealthy individual skews average wealth. After exlcuding this individual, our imputed sample provides a good fit of the remaining distribution.

Figure C1: **Imputed and actual average wealth by percentile in (a) Scotland and (b) Wales, 2016-18 (£m)**

(a) **Scotland**



(b) **Wales**



Notes: 'Imputed' shows the average wealth by percentile using observations from (a) England and Wales excluding London and the South East, scaling their sampling weights to represent the population of Scotland; (b) England and Scotland excluding London and the South East, scaling their sampling weights to represent the population of Wales. 'Actual' shows actual average wealth in (a) Scotland; (b) Wales, according to the Wealth and Assets Survey. Actual average excludes an outlier at the very top of the distribution in Wales.
Source: Authors' calculations based on the Wealth and Assets Survey (2016-18) and the Family Resource Survey (2018).

Table C1: **Mean and median wealth using alternative imputation categories, 2016-18 (£)**

	Actual	Method 1 (income only)	Method 2 (income and age)	Method 3 (income, age, tenure and household composition)
Scotland				
Average	248,000	264,000	256,000	247,000
Median	87,000	96,000	98,000	91,000
Wales				
Average	244,000	231,000	235,000	241,000
Median	93,000	88,000	91,000	95,000

Notes: 'Method 1' shows statistics for imputed wealth in Scotland and Wales when 'similar' individuals in the WAS and FRS are defined with reference to income alone. 'Method 2' defines 'similar' individuals with reference to both income and age. 'Method 3' (preferred method) defines 'similar' individuals with reference to income, age, tenure and household composition. Individuals in London and the South East are excluded from the pool of 'similar' individuals.
Source: Authors' calculations based on the Wealth and Assets Survey (2016-18) and the Family Resource Survey (2018).

Table C1 illustrates how the imputed and actual wealth distributions compare when alternative imputation categories are used. Method 1 allocates individuals to groups according to gross income only, with additional income categories at the top end (going up to £100,000+). Method 2 uses the same income categories as in method 1, with individuals further subdivided into age categories as defined in our preferred method above. Method 3 is our preferred method as discussed above. Method 3 provides a closer fit of the mean and median for both Scotland and Wales.

Table C2 illustrates how the fit of the imputed distribution using our preferred method compares when the populations of London and the South East are scaled in the same way as the remainder of the population. It is evident that this results in a poorer match of the wealth distribution in Scotland and Wales, as the wealth distributions of London and the South East are not typical of the rest of Great Britain.

Table C2: **Mean and median imputed wealth - excluding vs. including London and the South East from the base population, 2016-18 (£)**

		Method 3 (income, age, tenure and household composition)	
	Actual	Excluding London and SE from base population (preferred)	Including London and SE in base population
Wales			
Average	244,000	241,000	266,000
Median	93,000	95,000	108,000
Scotland			
Average	248,000	247,000	269,000
Median	87,000	91,000	105,000

Notes: Table shows statistics for imputed wealth in Wales and Scotland when we define 'similar' individuals in the WAS and FRS using our preferred methodology: with reference to income, age, tenure and household composition. 'Excluding London and SE' excludes individuals in London and the South East from the pool of 'similar' individuals. 'Including London and SE' includes individuals in these areas as part of the pool of 'similar' individuals.
Source: Authors' calculations based on the Wealth and Assets Survey (2016-18) and the Family Resource Survey (2018).

C.3 Scaling to external population totals

In the second step of our population adjustment, we scale individuals in our adjusted WAS sample to match age-sex specific external population totals from the ONS mid-year estimates. Individuals are allocated to 5-year age bands and split by sex. For those below the age of 75, we adjust the weights of all individuals within each age-sex cell by the same scaling factor. This effectively means scaling up the youngest age category (20-24) to account for those living in student halls. Though the asset portfolio of students may differ somewhat from other individuals of the same age, on the whole the wealth held by this age group is fairly low, and so we do not expect this to have a significant effect on our analysis.

For individuals aged 75 and above, the gap in population coverage primarily reflects individuals living in care homes, who are likely to have different levels of wealth – and different asset portfolios – to their counterparts living in private accommodation. In particular, care home residents are likely to have less wealth as a result of drawing down savings to fund the cost of care, and are less likely to own a separate 'main residence'. Rather than scaling the weights of all adults aged 75+ proportionally, we create a 'care home sample' by duplicating the observations of those who self-report to be in 'poor health', and scale their weights accordingly. We expect this group to be more representative of the wealth holdings of those in care homes, as many of those in poor health will have had to fund the cost of care that they receive in their own homes.[28] We also reduce the ‘main residence’ wealth of our care home population to zero. Some care home residents will not sell their main residence when they move into care, particularly those with family members who continue to live in the property. However, these family members ought to be captured in the WAS sample, in which case the value of the property has already been assigned in full to those individuals. Assigning zero main residence wealth to our care home population avoids double-counting this wealth.[29]

[28]In a comparison exercise with data from the English Longitudinal Study of Ageing (ELSA), we find that the percentage difference in average property and financial wealth between those who report to be in poor health and those whose health is in better condition is similar to the percentage difference between those who have received care from a formal home care provider, and those who have not. The WAS does not capture information on receipt of care services.

[29]For those who do sell their main residence, it is possible that we should observe an increase in financial assets that would be drawn down over time to fund the care they receive. We do not model this, and so effectively assume that indiviuals use the funds received from the sale to pay for the cost of their care upfront. We will also undercount wealth for those who move into care but who retain their main residence as a vacant property, although we expect this group to very small.

D Allocating land

Where estimates of the value of land are not separated by fixed asset (e.g. land underlying dwellings is combined with land underlying all other buildings and structures), the DINA guidelines recommend allocating land in proportion to the value of the fixed asset (Alvaredo et al., 2020). In the UK National Accounts, there are four categories of fixed asset from which the value of underlying land is excluded. These are assigned either to housing wealth or business assets in our framework:

- AN.111 Dwellings (assigned to housing wealth)
- AN.1121 Buildings other than dwellings (assigned to business assets)
- AN.1122 Other structures (assigned to business assets)
- AN.115 Cultivated biological resources (assigned to business assets)

Though we do not have estimates of the breakdown of underlying land for the household sector specifically, the ONS have recently released statistics showing this breakdown for the economy as a whole.[30] This shows that allocating the value of land in proportion to fixed assets would grossly under-estimate housing wealth, and over-estimate business wealth (Figure D1).

This large discrepancy reflects two underlying facts. First, the ratio of land value to the fixed asset situated upon it differs across asset types. According to the whole economy estimates produced by the ONS, land underlying dwellings was worth 258% of the value of dwellings in 2018. Land underlying other buildings and structures was worth 59% of the fixed asset value, and land underlying cultivated biological resources was worth 2597% of the cultivated assets. Second, the composition of assets for the economy as whole is highly mixed. Dwellings accounted for 57% of fixed assets; other buildings and structures accounted for 43% and cultivated biological resources less than 1%. The proportional allocation approach assigns 43% of the value of all land to other buildings and structures, despite the fact that land underlying other buildings and structures is so much less valuable than the land underlying housing, relative to the value of the fixed asset.

However, for the household sector specifically, the proportional allocation approach will results in a much smaller margin of error than for the economy as a whole – at least in the UK. This is because dwellings account for over 98% of fixed assets

[30]See `https://www.ons.gov.uk/economy/nationalaccounts/uksectoraccounts/adhocs/13941landunderlyingcultivationbuildingsandstructuresestimatesfrom1995to2020`

throughout our sample period, with other buildings and structures accounting for almost all of the remainder.[31] The proportional approach therefore allocates 98% of the value of land to dwellings. The land to asset ratios for the economy as a whole suggest that the share of land value allocated to dwellings should be slightly higher than 98%, but at most we would under-estimate housing wealth by 2% of the value of land, or around 1% of the combined value of land and property.

In relative terms, the impact of the proportional approach on the over-estimation of business wealth will be much bigger. The misallocation of 1% of land to business assets rather than housing would inflate estimated business wealth by 16% in 2020. This would have a small effect on top shares, since business assets is small relative to aggregate wealth. It would, however, have a big effect on the composition and analysis of narrower definitions of wealth. It would also affect our comparison of aggregate business wealth between the WAS and the National Accounts.

To allocate land in a way that reflects the relative land to asset ratios, we calculate land underlying each fixed asset using the following steps:

1. Calculate the land to asset ratios for each fixed asset based on the whole economy breakdown published by the ONS.

2. Apply these land to asset ratios to each category of fixed asset in the household sector account, to obtain the implied land value.[32]

3. Compute the share of the implied total land value accounted for by land underlying each fixed asset.

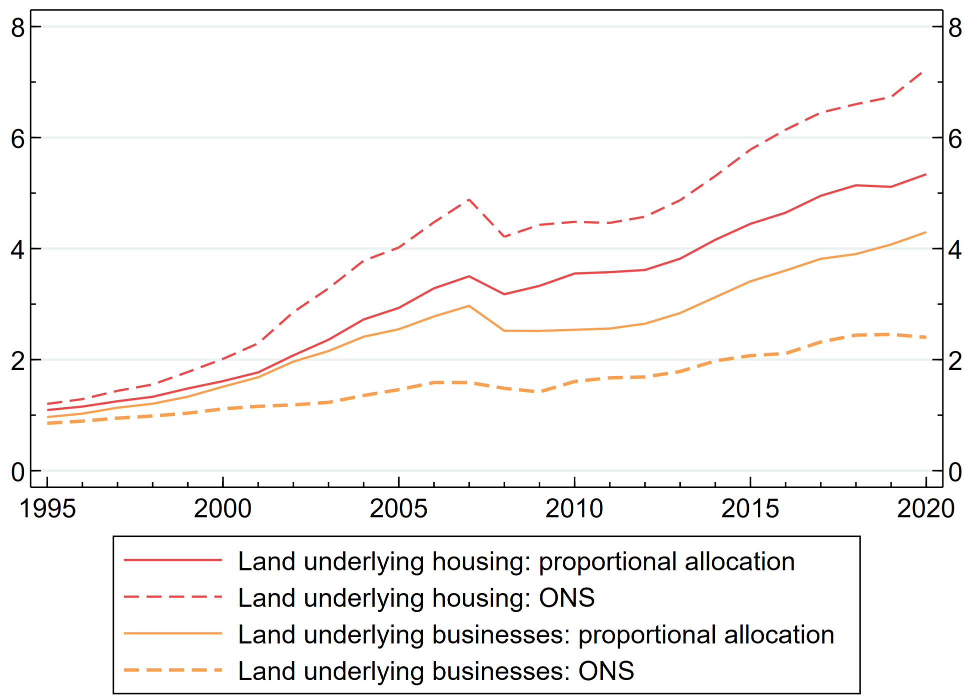
4. Apply the shares in step (3) to the actual value of land recorded in the household sector. This ensures that aggregate land value remains consistent with the household sector balance sheet.

The shares of land assigned to each type of fixed asset as a result of this process in 2018 are 99.5% to housing, 0.2% to other buildings and structures, and 0.3% to cultivated biological resources.

[31] Cultivated biological resources account for less than 0.05% of fixed assets in any year.

[32] Step (2) relies on the assumption that the land to asset ratios for the household sector are similar to the economy as a whole. The ratio of land to all fixed assets in the households sector was 260% in 2018. Since dwellings represent over 98% of fixed assets, this suggests that the land to asset ratio for dwellings must be similar in the household sector as for the economy as a whole. However, the implied total land value from step (2) is less than the actual value of land recorded in the household sector balance sheet, suggesting the land to asset ratio must be slightly higher overall for the household sector.

Figure D1: **Aggregate value of land allocated to housing and businesss wealth for the whole economy - two approaches (£tn)**

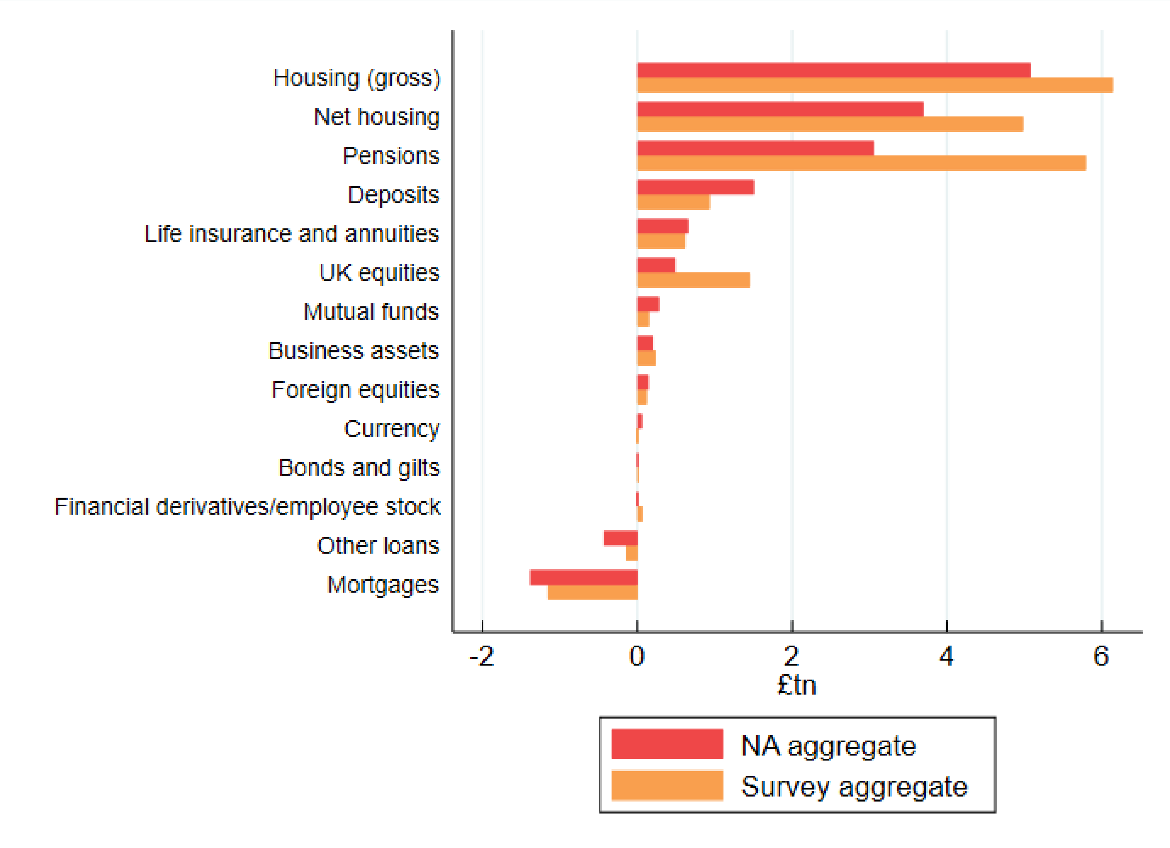


Notes: Figure shows the aggregate value of land underlying housing and businesses, splitting the combined value of this using two approaches. 'Proportional allocation' attributes land in proportion to the value of fixed assets sitting upon the land (dwellings versus non-dwellings). 'ONS' is the official breakdown provided by the compilers of the National Accounts as supplementary statistics. All estimates are for the economy as a whole, not just land owned by the household sector specifically.
Source: Authors' calculations based on the National Accounts, and Office for National Statistics (2021c) "Land underlying cultivation, building and structures estimates from 1995 to 2020".

E Explaining aggregate differences: further details

Figure E1 illustrates aggregate wealth by asset class in both the NA and the WAS, for 2016-18. Asset classes are defined as in Appendix A to be as comparable as possible across the two data sources. This enables us to pinpoint which gaps need to be explained. The key driving factors underlying these gaps are outlined in Section 4. In this section, we provide additional details and estimates of the magnitudes of each driver, where it is possible to do so. The aggregate values of each asset in the NA and the WAS for 2016-18 are provided in the section headings.

Figure E1: **Aggregate asset holdings by data source: 2016-18 (£tn)**



Notes: Each asset category is defined as set out in Appendix A.
Source: Authors' calculations based on the Wealth and Assets Survey (2016-18) and the National Accounts.

E.1 Aggregate pension wealth

There are two broad types of pension scheme: Defined Contribution (DC) and Defined Benefit (DB). A DC pension is simply a pot of savings, where the amount available at retirement is determined by the contributions made over an individual's lifetime, and interest earned on the pension fund. Both the NA and the WAS measure DC pensions on the same basis: the value is simply the value of the pension fund on the reference date. This information is provided by individual respondents in the WAS, and is sourced from pension providers in the NA.

Though we do not separately observe the value of DC pensions in the NA, the ONS have produced estimates of pension wealth broken down by scheme type separately for a number of years (Office for National Statistics, 2021a). Aggregate DC pension wealth is higher in the WAS (£578bn) than the NA supplement (£351bn) in 2016-18. However, in both data sources DC pensions account for just a small fraction of total pension wealth: 12% in the NA and 10% in the WAS. The gap in DC pension wealth therefore explains just 8% of the overall gap in aggregate pension wealth. Nevertheless, it is difficult to identify the cause of this discrepancy. It does not stem from a conceptual difference in the value assigned to DC pension pots.

The remainder of the gap appears to be driven by the exclusion of unfunded DB pensions from the NA and the role of annuity rates in valuing DB pensions and annuities (Section 4.1). According to the supplementary statistics produced by the ONS, unfunded DB pensions amounted to just under £1.2tn in 2018. Adding estimated unfunded DB pension wealth for 2016-18 to the pension wealth recorded in the core NA reduces the gap between the WAS and the NA by 40% (Figure E2). This is, however, sensitive to assumptions regarding the discount rate. As stipulated by Eurostat, the ONS apply a nominal discount rate of 4% in the valuation of unfunded DB pensions, considerably higher than the discount rate used for valuing private sector DB pensions. The use of a lower discount rate would imply a higher value for unfunded DB pensions, further reducing the gap between the WAS and the NA. As a general rule of thumb, a 1 percentage point reduction in the discount rate increases aggregate pension wealth by 20-25% (Office for National Statistics, 2021d).

WAS estimates of DB pensions and annuities depend heavily upon the current annuity rate. The formulae used in estimating the value of DB pension wealth (8) and annuities (9) are as follows:

$$W_i = \frac{A_R Y^p + L_i}{(1+r)^{R-a}} \tag{8}$$

$$W_i = A_a Y^p \tag{9}$$

where A_R is the current age-specific annuity factor at retirement age (inverse of the annuity rate) assuming average age-specific life expectancies; Y^p is the currently salary (if actively contributing) or expected annual income (if the individual has retained rights but is no longer contributing); L_i is the lump-sum the individual expects to receive at retirement; r is the real discount rate, set at 3% above CPI; $R - a$ is the difference between retirement age and the respondent's current age; and. A_a is the age-specific annuity factor based on the respondent's current age.

Annuity rates have fallen in recent years, particularly following the Financial Crisis. This has led to an increase in the estimated value of pension wealth using the WAS formulae. Figure E2 shows, for illustrative purposes, the effect on aggregate pension wealth in 2016-18 if we were to fix annuity rates at their 2006-08 levels. In doing so, aggregate pension wealth in the WAS falls by £2tn (34%), to slightly below aggregate pension wealth in the NA once unfunded DB pensions are accounted for.

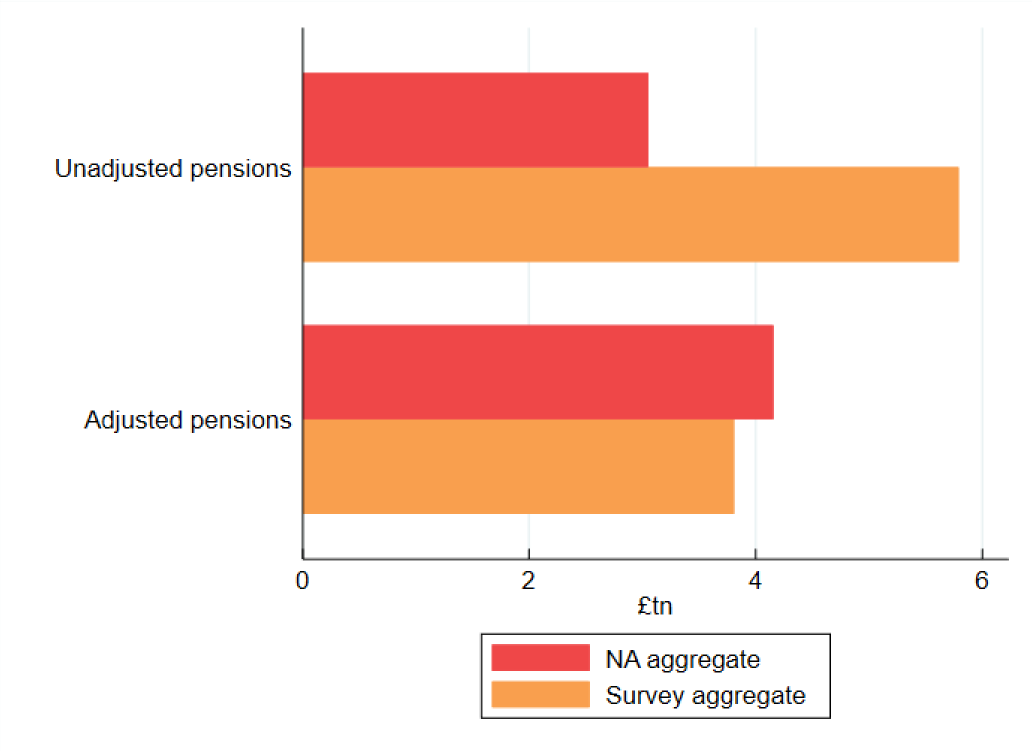
E.2 Aggregate net housing

The NA do not directly record the aggregate value of property held by UK resident households. Instead, the value of dwellings and other buildings (structures) is separated from the value of land underlying them. Structures are valued using the Perpetual Inventory Method, and are deducted from the combined value of land and structures in order to obtain the value of underlying land as a residual.[33] Though the value of dwellings (residential property) is separated from the value of other buildings and structures, the value of underlying land is reported as a single component. We allocate land to dwellings and other buildings and structures following the approach set out in Appendix A.1 (see Appendix D for further details).

A peculiarity with the NA is that rather than reporting the value of property held by UK residential households, the value of all *UK situated* land and property is reported instead. This is in accordance with SNA guidelines. It means that the value includes foreign-owned UK property and excludes overseas property held by UK residents. To account for this, a balancing adjustment is made by recording the value of overseas property as an equity in the financial assets section of the Households sector balance sheet, and the value of foreign-owned property as a financial liability.

[33] For further information, see `https://www.ons.gov.uk/economy/nationalaccounts/uksectoraccounts/methodologies/nonfinancialbalancesheetqmi`.

Figure E2: **Aggregate pension wealth before and after reconcilation adjustments, 2016-18 (£tn)**



Notes: 'Adjusted pensions' in the NA is constructed by adding ONS estimates for the aggregate value of unfunded DB pensions to aggregate pension wealth from the core accounts. To construct an estimate of unfunded DB pension wealth corresponding to the WAS 2016-18 round, aggregate unfunded DB pension wealth for calendar years 2009-15 and 2017-18 (inclusive) were taken from supplementary Table 29 (ONS). A value for 2016 was extrapolated by assuming a constant growth rate from 2015 to 2016 and 2016 to 2017. The values for 2016 to 2018 were then converted to WAS round 2016-18 on a *pro rata* basis, following the approach described in Section 2.2. 'Adjusted pensions' in the WAS shows the effect of applying 2006-08 annuity and discount rates to the 2016-18 round of survey responses. These estimates are based on ONS analysis (Office for National Statistics, 2020).
Source: Authors' calculations based on the Wealth and Assets Survey (2016-18), the National Accounts, Supplementary Table 29 (Office for National Statistics, 2021a) and Office for National Statistics (2020).

It is not possible to exclude the value of foreign-owned UK property from our NA aggregate, and therefore we cannot construct a NA measure of property wealth which covers all property held by UK resident households. This is not ideal given our target population, and is a problem that extends to other countries rather than just the UK. If we were able to deduct foreign-owned property, our NA aggregate would be even lower than our current estimate.

F Extensions

F.1 Using broader capitalisation categories

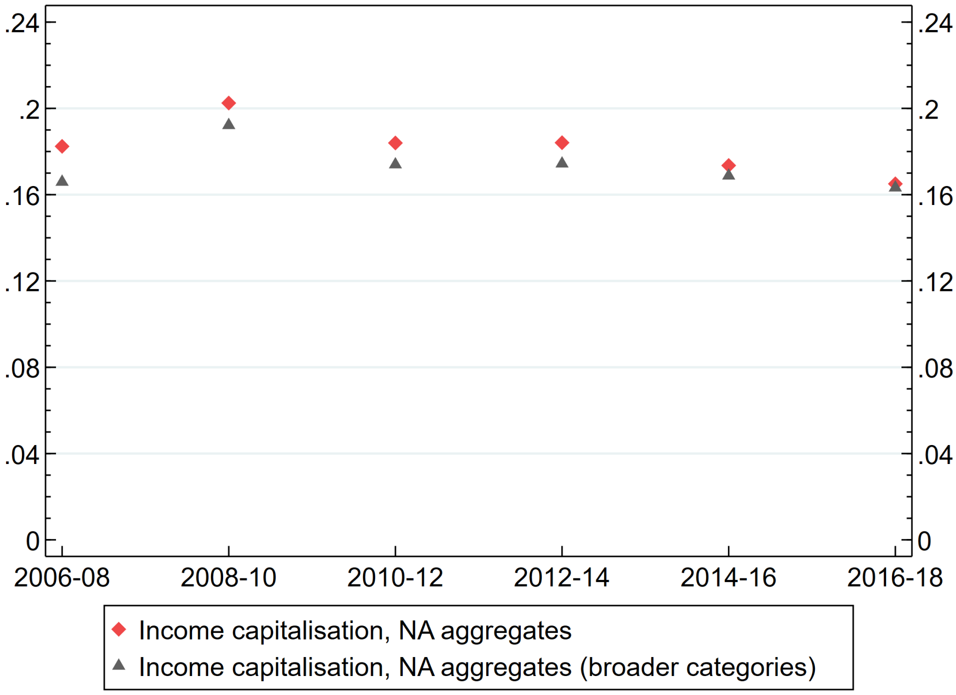
In this section, we illustrate the impact on top shares of using broader categories for capitalisation, following the high-level capitalisation categories set out in the DINA guidelines (Alvaredo et al., 2020). Using broader asset categories means applying a single capitalisation factor across a broader range of assets. As different asset classes produce different income yields, this means that the capitalisation factor is likely to be less accurate for each subcomponent, which could have an impact on top shares. For example, if the income yield were 1% on UK equities, but 3% on foreign equities, then capitalising these asset categories together would mean dividing the income flows derived from each of these assets by a rate between 0.01 and 0.03. This will results in the over-estimation of foreign equities and under-estimation of UK equities. Accordingly, those with foreign equities could be ranked higher up the distribution of total wealth than they should be, and those with UK equities too low down. The broader capitalisation categories we use are set out in Table F1.

Using broader capitalisation categories reduces top shares slightly, but only in the early years of our sample (Figure F1).

Table F1: **Broader capitalisation categories**

Income component	Wealth component
UK + foreign interest + gilts	Currency, deposits and debt securities (bonds and gilts)
UK dividends + partnership income (taking 30% of trading income) + mutual fund dividends + foreign dividends + foreign property income	Equity
Profits of sole proprietorships (30%)	Business assets

Figure F1: **Top 1% share using broader capitalisation categories**



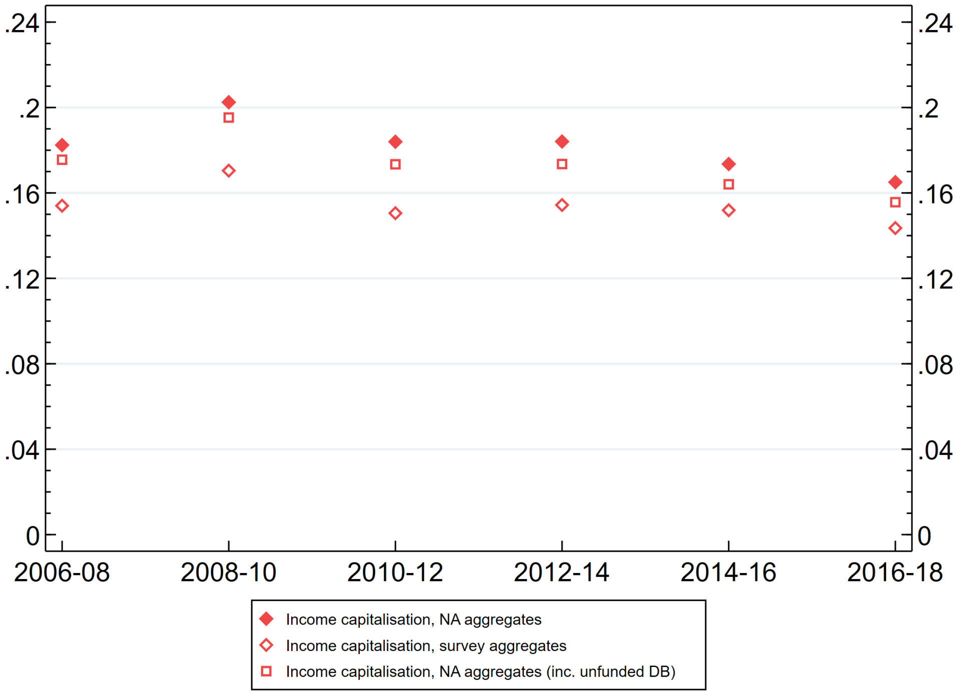
Notes: Top shares produced using NA aggregates and either our headline capitalisation categories as in Table 2 or broader capitalisation categories as set out in Table F1. Individuals are ranked on total wealth. We define top shares relative to the total number of individuals aged 20 or older in the population living in the UK.
Source: Authors' calculations based on HMRC administrative tax data, the National Accounts, and the Wealth and Assets Survey.

F.2 Including unfunded DB pensions

To illustrate the effect of including unfunded DB pensions in our National Accounts aggregate, we take information on the aggregate value of unfunded DB pension entitlements from supplementary tables produced by the Office for National Statistics (Office for National Statistics, 2021a). These tables provide estimates of the aggregate value of entitlements for 2009-15 and 2017-18 inclusive. We extrapolate these estimates to 2016 by assuming a fixed growth rate in the value of entitlements from 2015 to 2016 and 2016 to 2017. We extrapolate to 2006-08 based on the 5-year average growth rate between 2009 and 2014.

Including unfunded DB pensions increases aggregate NA wealth by 10-14% (£0.9-1.1 trillion) across our sample period. Pension wealth is more middle-weighted than

Figure F2: **Top 1% share including unfunded DB pensions**



Notes: Top shares produced using our two headline approaches ('Income capitalisation, NA aggregates' and 'Income capitalisation, survey aggregates', as in Figure G1), and with the addition of unfunded DB pensions to NA aggregates based on supplementary estimates provided by the ONS ('Income capitalisation, NA aggregates (inc. unfunded DB)'. Individuals are ranked on total wealth. We define top shares relative to the total number of individuals aged 20 or older in the population living in the UK.
Source: Authors' calculations based on HMRC administrative tax data, the National Accounts, and the Wealth and Assets Survey, and Office for National Statistics (2021a).

other asset classes. As a result, including unfunded DB pensions results in a reduction in our top share estimates (Figure F2).

F.3 Pareto adjustment

A common concern with relying on household survey data to measure the distribution of wealth is that surveys suffer from under-coverage, particularly at the top end of the distribution. Under-coverage may either be caused by under-reporting – where wealthy households omit or under-value certain assets they own – or differential non-response – whereby wealthier individuals may be less likely to respond to the survey.

Recent methodological approaches to adjust for under-coverage at the top of the distribution include combining survey data with information from rich list publications and/or exploiting the distributional properties of the top tail to implement a 'Pareto adjustment' (Vermeulen, 2018; Chakraborty et al., 2019; Advani et al., 2021a,b; Wildauer and Kapeller, 2022; Credit Suisse, 2021). In this Section, we combine information on the UK's richest households from the Sunday Times Rich List with the top tail of our WAS distribution, and subsequently fit a Pareto distribution to this top tail. We show the effect that each adjustment has on our aggreates and top shares. We set out the key features of our adjustment methodology below. For further details, see Advani et al. (2021a).

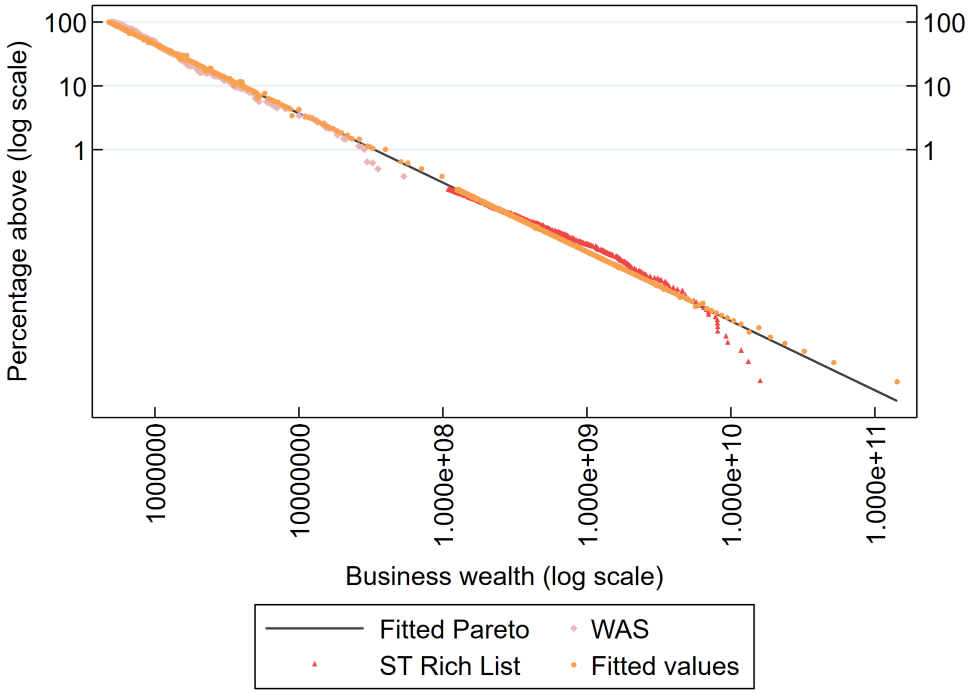
The Sunday Times Rich List (STRL) is an annual journalistic publication of the wealth of Britain's 1000 richest people or families. It is compiled on the basis of an individual's publicly observable assets, and primarily reflects the value of businesses owned by the individual. It does not capture private wealth such as funds held in bank accounts. Moreover, the compilers of the list take a cautious approach to valuing liabilities (Watts, 2020). The wealth recorded in the STRL therefore represents a plausible lower bound on assets held by those at the very top.

We do not have historical snapshots of the STRL for each year in our study period. For each round of the WAS, we combine the survey data with the edition of the STRL for which there is greatest overlap in the reference period, or the closest year where no overlapping dataset is available.[34]

A crucial assumption underlying the Pareto adjustment methodology is that both the STRL and the upper tail must be drawn from the same underlying distribution. We make two steps to ensure that this condition is met. First, we adjust the unit of analysis in the STRL to be consistent with the WAS. Members of the same family, such as husbands and wives, or siblings, can be named jointly in the STRL, with the compilers recording their joint wealth. To reconcile this with our use of individuals as the unit of analysis, we divide joint wealth equally among named members of the family. This reduces the minimum level of individual wealth observed in the STRL. However, we know that the compilers are not attempting to capture all solo individuals with wealth above this minimum level, and hence our observation of the Pareto tail is incomplete. As this would skew estimates of the Pareto distribution, we drop individuals with (equally split) wealth below that of the least wealthy solo-named entry in any year, which is £110 million. Second, we focus only on private

[34]Specifically, we combine 2016-18 of the WAS with the 2017 STRL; 2014-16 of the WAS with the 2015 STRL; 2012-14 of the WAS with the 2013 STRL; 2010-12 of the WAS with the 2010 STRL; and both 2008-10 and 2006-08 of the WAS with the 2009 STRL.

Figure F3: **Top tail of the business wealth distribution combining the WAS and STRL, 2016-18**



Notes: Pareto distribution fit to individuals in the WAS and STRL with wealth above £500,000. We exclude STRL individuals with wealth below £110 million in any year. Only business wealth and shares are included. See Section F.3 for details.
Source: Authors' calculations based on the Wealth and Assets Survey and the Sunday Times Rich List.

business wealth and shares held by individuals in the WAS when estimating our top tail. This is because this set of asset classes corresponds more closely with what is being measured in the STRL. Figure F3 supports the conclusion that the WAS and the STRL are drawn from the same underlying distribution of business wealth: the data points follow a straight line when plotted in log-log space.

The WAS is known to suffer from under-coverage of the top tail (Advani et al., 2021a). The WAS does capture some individuals with wealth above the lower threshold of the STRL, however it does not capture the variation in wealth at the top in granular detail. In estimating the Pareto distribution, we omit the handful of respondents in the WAS who overlap with the STRL – i.e. those with business wealth in excess of £110m – to avoid double counting this wealth.

We estimate our Pareto distribution using a lower threshold of £500,000 in busi-

Table F2: **Effect of Pareto adjustment on aggregate wealth**

Round	Pareto coefficient	Net addition to aggregate wealth £ billion	%
2006-08	1.14	373	4.7%
2008-10	1.12	276	3.2%
2010-12	1.15	439	4.9%
2012-14	1.13	404	3.8%
2014-16	1.10	404	3.2%
2016-18	1.08	648	4.6%

Notes: Pareto distribution fit to individuals in the WAS and STRL with wealth above £500,000. We exclude STRL individuals with wealth below £110 million in any year. Only business wealth and shares are included. See Section F.3 for details.
Source: Authors' calculations based on the Wealth and Assets Survey and the Sunday Times Rich List.

ness wealth. It is clear from Figure F3 that the number of people with wealth in excess of a given amount declines at a constant rate above this threshold. In practice, varying the threshold has minimal impact on the amount of wealth added by our adjustment.

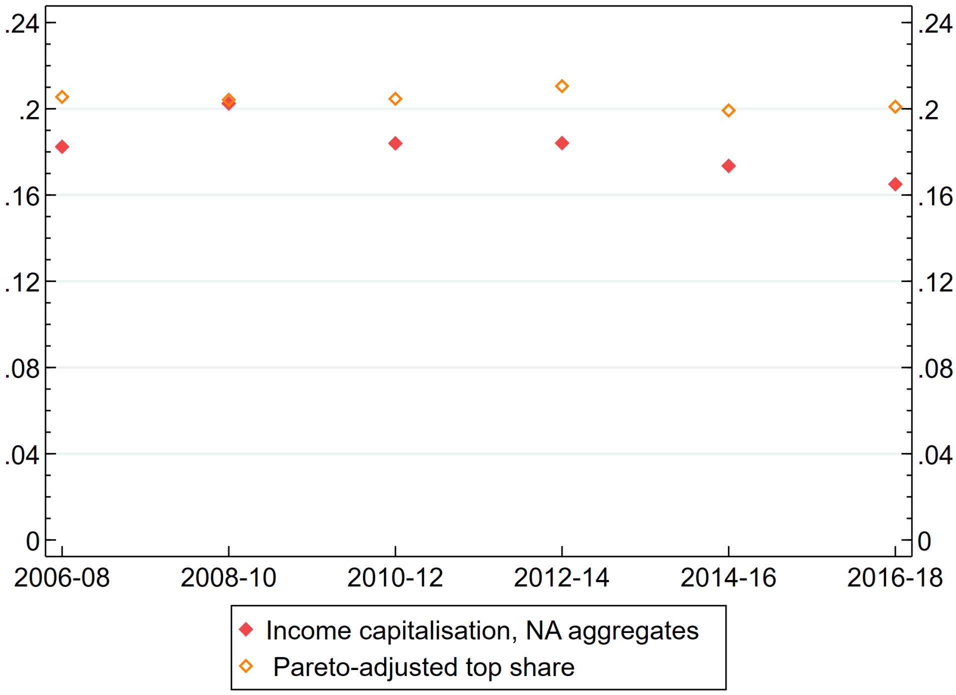
To estimate our Pareto coefficient, we run an OLS regression of the form specified in Equation A4 of Wildauer and Kapeller (2021). This takes into account survey weights both in the measure of each individual's rank, as in the methodology developed by Vermeulen (2018), as well as in the application of the Gabaix and Ibragimov (2011) method for bias correction. To estimate the aggregate wealth implied by our Pareto adjsutment and allocate this to observations in our microdata, we take the predicted value of each individual's wealth based on their (weighted) rank in the distribution. This is illustrated by the 'Fitted values' markers in Figure F3.

Combining the top tail of the WAS with the STRL, excluding overlapping individuals, increases aggregate wealth by £346 billion (2.4%) in 2016-18, from £14.2 trillion to £14.6 trillion. Implementing our Pareto adjustment increases this aggregate by a further £301 billion (2.1%), to £14.9 trillion. The effect in 2016-18 is greater than in earlier rounds, reflecting an increase in both aggregate wealth and the concentration of wealth at the very top (Table F2).

We construct Pareto-adjusted top shares in our survey data by assigning each individual with wealth above £500,000 the amount of wealth they would be expected to have according to our fitted Pareto distribution.

Our Pareto adjustment increases the share of wealth attributed to the top 1%

Figure F4: **Share of wealth held by the top 1% before and after Pareto adjustment, using income capitalisation and survey aggregates**



Notes: Pareto-adjusted shares are constructed using the method described in Section F.3. Individuals are ranked by total wealth. Top shares are defined relative to the total number of individuals aged 20 or older in the population living in the UK.
Source: Authors' calculations based on the Wealth and Assets Survey and the Sunday Times Rich List

from 16.4% to 20.1% in 2016-18 (Figure F4). Top shares exhibit a flatter trend over time after taking our adjustment into account. According to our adjusted series, the top 1% share fluctuated narrowly around an average of 20.4% over the past decade, compared to 18.1% in the unadjusted series.

G Characteristics of the top 1% using survey distributions

In this section we present evidence on the characteristics of those in the top 1%, and mobility into and out of this group, using survey data to obtain information on asset distributions rather than the income capitalisation approach. The two series we compare are 'Survey distribution, survey aggregates' – where distributions and aggregates are taken directly from the WAS – and 'Survey distribution, NA aggregates' – where survey distributions are scaled to NA aggregates.

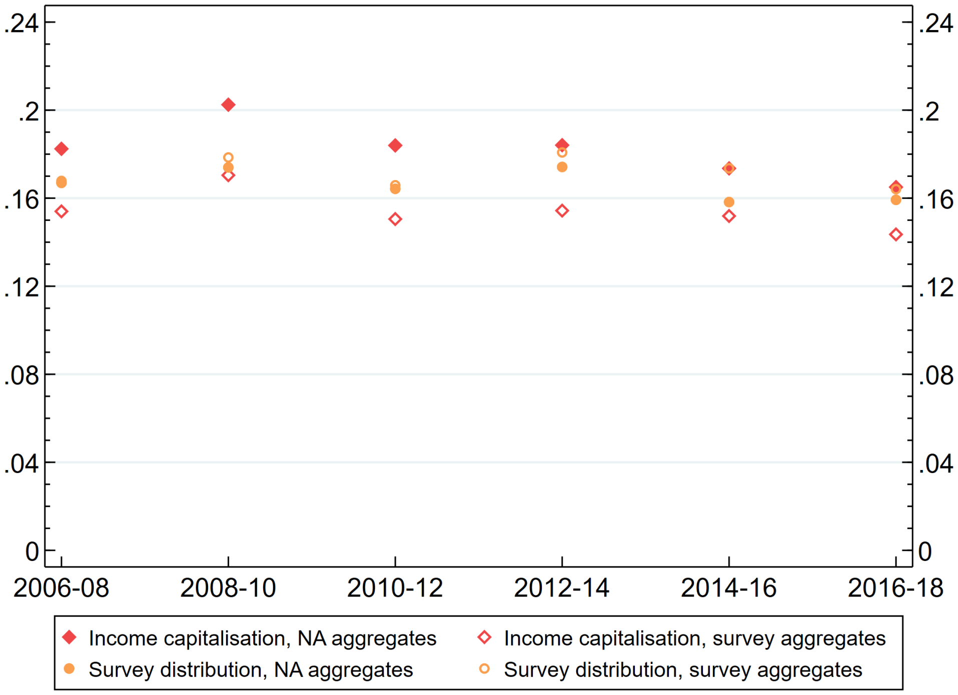
As we show in Section 5.4, the effect of switching aggregates on top shares is different using survey distributions than when we use the income capitalisation approach. Figure G1 provides a visual comparison of the different measures over time. Whereas top shares increase when we switch from survey to NA aggregates using the income capitalisation approach, the same change in aggregates yields the opposite effect when we use survey distributions for all asset classes.

We now provide results on the effect of switching aggregates on the *characteristics* of those at the top, which also differs from the results we present in Section 5.5.

Compared to the income capitalisation approach (Figure G2a), fewer people move out of the top 1% when we switch aggregates using survey distributions (Figure G2b). As a result, we see smaller changes in the characteristics of those at the top than we do using the income capitalisation approach

Joiners to the top 1% are also more similar to stayers than under the income capitalisation approach (Figure G3). The two effects – less change in the top 1%, and the replacements being less different to the stayers – together mean the changes in characteristics are more muted when the survey is used for the wealth distribution.

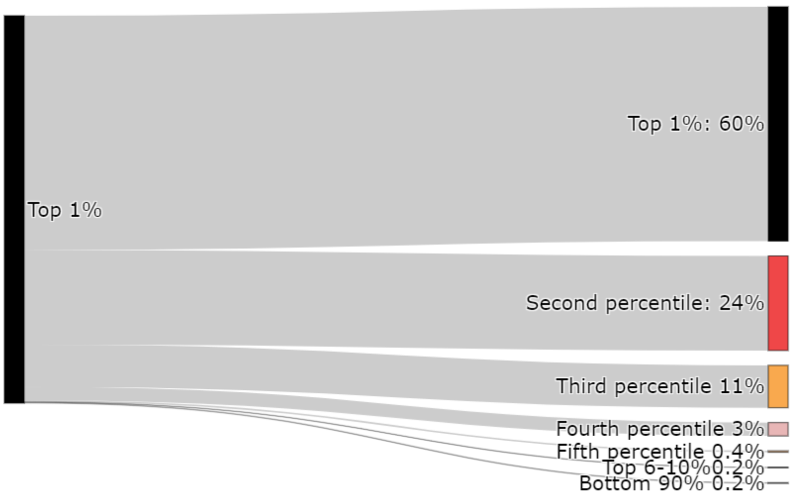
Figure G1: **Top 1% share of total wealth using different aggregates and different sources of distributional information**



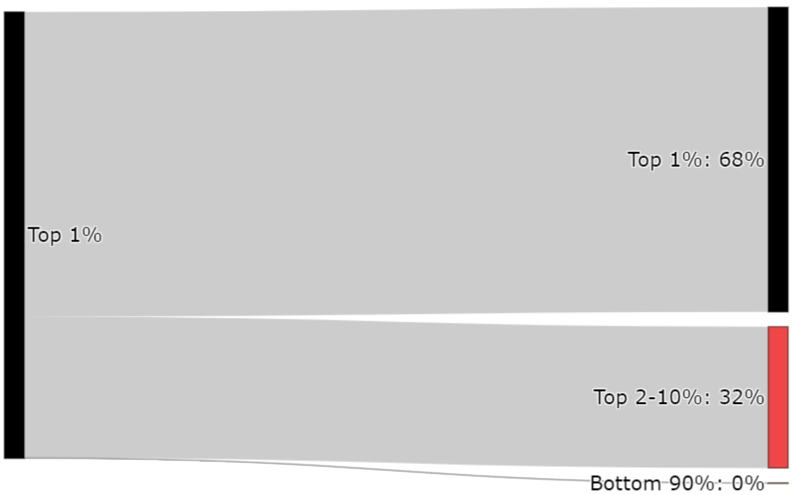
Notes: 'Income capitalisation, survey aggregates' shows the share of wealth held by the top 1%, where individuals are ranked on total wealth defined using the 'Income capitalisation, survey aggregates' method (see Section 3). 'Income capitalisation, NA aggregates' shows the share of wealth held by the top 1%, where individuals are ranked on total wealth defined using the 'Income capitalisation, NA aggregates' method. 'Survey distribution, NA aggregates' shows the share of wealth held by the top 1% when we scale survey distributions to match NA aggregates, ranking on total wealth. 'Survey distribution, survey aggregates', shows the share of wealth held by the top 1% when we use survey aggregates and distributions directly, ranking on total wealth. We define top shares relative to the total number of individuals aged 20 or older in the population living in the UK.
Source: Authors' calculations based on HMRC administrative tax data, the National Accounts, and the Wealth and Assets Survey.

Figure G2: **Reranking of the top 1% when switching from survey to NA aggregates, using survey distributions**

(a) Income capitalisation



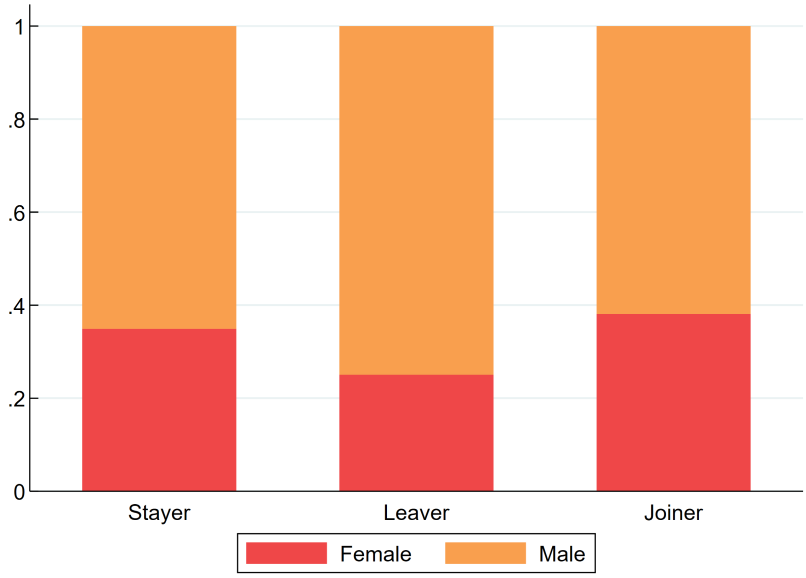
(b) Survey distribution



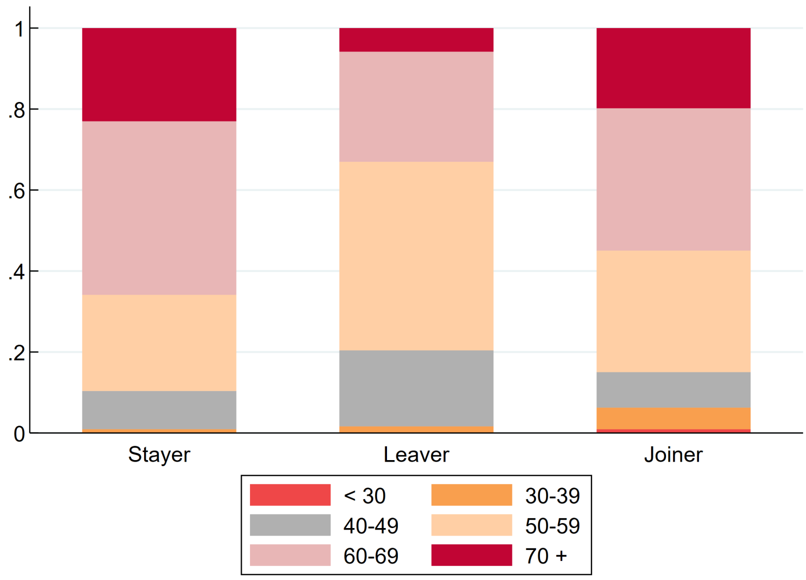
Notes: The left hand side represents the top 1% of the population ranked on total wealth defined using the (a) 'Income capitalisation, survey aggregates' method, and (b) 'Survey distribution, survey aggregates' method (see Section 3). The right hand side shows where in the distribution individuals in this group rank when ranking all individuals on total wealth defined using the (a) 'Income capitalisation, NA aggregates' method, and (b) 'Survey distribution, NA aggregates' method. We define top shares relative to the total number of individuals aged 20 or older in the population living in the UK.
Source: Authors' calculations based on the National Accounts and the Wealth and Assets Survey.

Figure G3: **Characteristics of the top 1% by series, 2016-18, using survey distributions**

(a) Sex

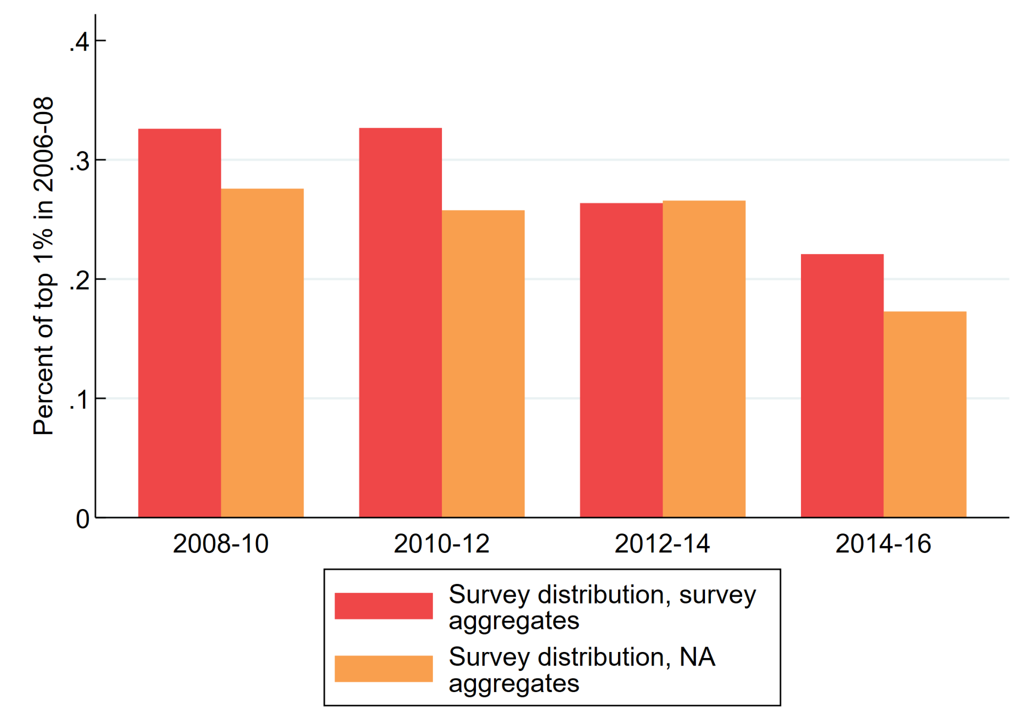


(b) Age



Notes: 'Joiners' are those who enter the top 1% when we switch from defining wealth using the 'Survey distribution, survey aggregates' method to the 'Survey distribution, NA aggregates' method, ranking individuals on total wealth. 'Leavers' are those who leave the top 1% when we switch definition. 'Stayers' are those who remain in the top 1% regardless of which definition we use. We define top shares relative to the total number of individuals aged 20 or older in the population living in the UK.
Source: Authors' calculations based on the National Accounts and the Wealth and Assets Survey.

Figure G4: **Likelihood of reappearing in the top 1% in subsequent years if in top 1% in 2006-08, using survey distributions**



Notes: Figure shows the share of individuals in the top 1% in 2006-08 who reappear in the top 1% in subsequent rounds, where the top 1% is defined using either the 'Survey distribution, NA aggregates' or 'Survey distribution, survey aggregates' method (see Section 3). We define top shares relative to the total number of individuals aged 20 or older in the population living in the UK.
Source: Authors' calculations based on the National Accounts and the Wealth and Assets Survey.

H Estimating aggregate house prices using transaction data

In Section 4.2, we provided an alternative estimate of the gross value of housing in England and Wales, derived using transaction date. To arrive at this estimate, we took the following methodological steps:

1. Extract the sale price of all residential property transactions in England and Wales between January 1995 and February 2022 from the 'Price Paid' dataset held by HM Land Registry (HM Land Registry, 2022a).

2. Assign each property a unique identifier, consisting of the 'Primary Addressable Object Name' (PAON), which is usually the building number or name; the 'Secondary Addressable Object Name' (SAON), which is usually the building number where an address is split into multiple properties e.g. Flat A (PAON), 1 (SAON) Baker Street; and the postcode. In the UK, postcodes are assigned in such a way that it is not possible for a building number or name to be repeated within the area covered by a given 7- or 8-digit postcode. This ensures that our identifier uniquely identifies properties in the transaction data.

3. For each unique property, retain only the transaction which took place closest to the 5th April 2018. We allow the closest transaction to have occurred after this date, as a transaction taking place in e.g. 2019 is likely to give a more accurate estimate of its value in 2018 than a transaction taking place in e.g. 2005.

4. Uprate sale prices to April 2018 house price values based on the property type (detached, semi-detached, terraced, or flat) and Local Authority District (LAD). We do this using the property type and LAD-specific House Price Index (HM Land Registry, 2022b).

5. For each property type in each Lower Super Output Area (LSOA),[35] assign weights based on the total stock of such properties, taking the latter from Council Tax Statistics (Valuation Office Agency, 2018). Stock data contain a separate estimate for bungalows, which are listed as either detached or semi-detached in the transaction data. To account for these in our weights, we

[35] An LSOA represents a smaller geographical area than a LAD. Though we have stocks data for this level of geography, we do not have an House Price Index broken down by LSOA and property type, hence the use of LADs for uprating house prices.

allocate bungalows in proportion to the share of detached and semi-detached properties in each LAD.

6. Aggregate the 2018 price for each property multiplied by each property's respective weights to estimate the aggregate gross value of all residential property situated in England and Wales.

We exclude properties of type 'other'. These consist of a mixed bag of property types that tend to depart from the common notion of residential property, including parking spaces and caravans. Moreover, as the definition of 'other' used for Council Tax purposes differs from the 'other' property types observed in transaction data, it is not clear how we should weight such properties.

We also exclude transfers of freehold titles for properties that also have a leasehold title. It is possible for freehold titles to be transferred separately without transferring the leasehold. The amount for which the freehold in isolation is sold does not correspond to the market value of the property, as owning the freehold but not the leasehold does not grant the freehold owner the right to live in the property. It is the amount for which the leasehold is sold, for the same property, which gives an indication of its market value.

H.1 Accounting for poorly represented property types

Complications arise where a particular property type is poorly represented in a given LSOA. This occurs when we observe zero or very few transactions of a particular type of property in an area where several of these properties exist. Social housing can generate this type of issue: properties that have only ever been owned by housing associations will not appear in our transaction data. Since these properties tend to be at the lower end of the distribution, excluding these properties would lead to an over-estimation of average house prices in an area, and over-estimation of the aggregate.

We implement a four-step method for accounting for poorly represented properties, which we define as cases where (a) the property type is completely unrepresented, i.e. zero transactions are observed in the price paid data even though the LSOA contains properties of that type; or (b) less than 10% of the stock of properties of that type are observed in the transaction data and the number observe amounts to fewer than 30. Of 34,759 LSOAs in England and Wales, the number with poorly represented properties is: 105 for detached properties, 47 for semi-detached properties, 5530 for flats, and 1932 for terraced properties.

In basic terms the method works by identifying a set of properties from a "similar" LSOA to act as proxy properties for an LSOA where that particular type of property is poorly represented. For all LSOAs with property types that meet the criteria above, the transactions that we do observe for this property type (if any) are dropped from the data, and replaced by the proxy observations.

For each property type we take the following steps (here using flats as an example):

1. Construct a "using" dataset consisting of all LSOAs with flats that are well-represented, i.e. LSOAs that have flats and do not meet the two criteria above. This serves as the pool of observations from which the proxy flats are selected.

2. For each LSOA with badly represented flats, identify the "most similar LSOA" in the using dataset using the following procedure:

    (a) Estimate a "composition similarity index" for each of the LSOA contenders in the using data. This is the sum of squared differences between the share of properties in an LSOA that are detached, semi-detached, flats, and terraced in our poorly represented LSOA (i) and the contender LSOA (j): $(TerracedShare_i - TerracedShare_j)^2 + (DetachedShare_i - DetachedShare_j)^2 + (SemiShare_i - SemiShare_j)^2 + (FlatsShare_i - FlatsShare_j)^2$. We then find the minimum value of the index across all LSOAs in the using data. This identifies the LSOA that is most similar to our badly represented one in terms of the composition of the housing stock.

    (b) Take the maximum value across all badly represented LSOAs of the composition similarity index that solved the above minimisation problem. This identifies the highest degree of similarity that is possible to achieve across all of our badly represented LSOAs.

    (c) Define the "most similar LSOA" as the LSOA from the using dataset with the closest average price when we exclude flats, conditional on its composition similarity index being lower than the maximum identified in step (b), i.e. the threshold of similarity that is possible to achieve for all LSOAs. Thus, our "most similar LSOA" is the one with the closest average property price conditional on being very similar in terms of housing mix.

3. Use the transactions of flats identified from the most similar LSOA to replace (if there are any) the transactions of flats in the poorly represented LSOA.

4. Calculate new weights for these flats, scaling the number of proxy flats to the stock in the poorly represented LSOA.

H.1.1 Testing the method

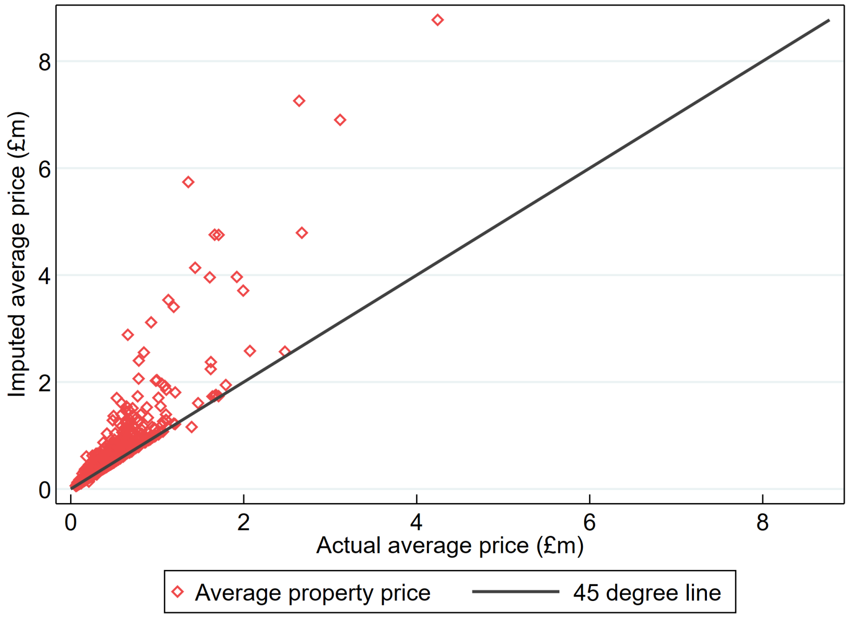
We have tested the method using a random sample of 2000 LSOAs from the set of those whose flats are actually well-represented, pretending their flats don't exist and using the remainder as the 'using' pool. Figure H1 compares the actual average property price across all types of property in the case where we ignore the "poorly represented" flats completely, and when we introduce proxy flats as described above.

Ignoring "poorly represented" flats leads to an over-estimation of average property prices, as flats tend to be worth less than other types of property. Using our correction approach, average property prices are located tightly around the 45 degree line, suggesting we do a good job of accounting for the missing transactions.

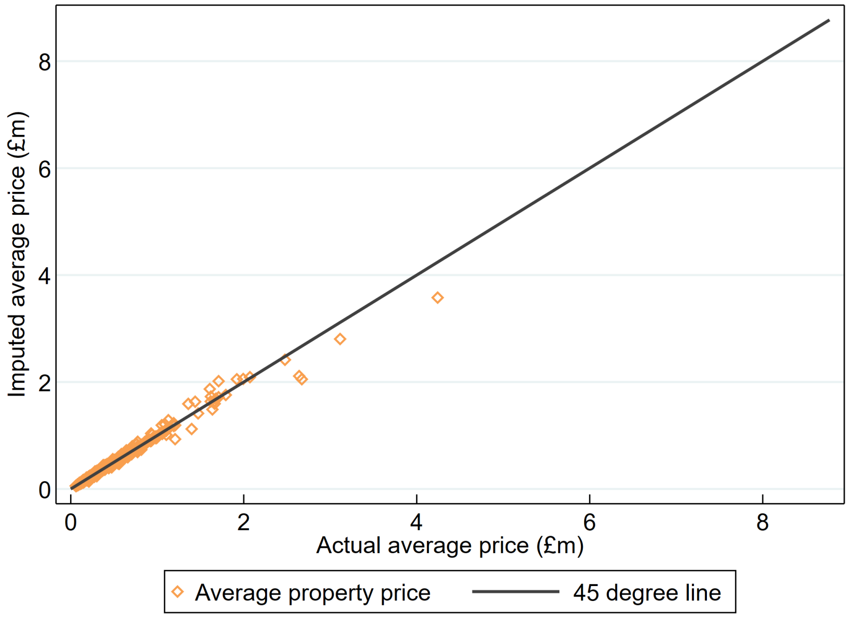
It remains possible that areas in which property types are actually poorly represented differ in important ways from the remainder of LSOAs used in our test analysis. For example, our approach may do a worse job at estimating average property prices if the value of properties missing from the transaction data – such as social housing – differs from the value of similar property types that are not part of the social housing stock.

Figure H1: **Imputed and actual average property prices by LSOA**

(a) **When flats are dropped from observed transactions**



(b) **When flats are replaced by proxy flats**



Notes: Graph shows the average price across all types of property in an LSOA when (a) flats are dropped from the set of observed transactions; (b) transactions of flats are replaced by a proxy set of observations from similar LSOAs in which flats are well-represented. This is based on a random sample of 2000 LSOAs in which flats are well-represented, using the definition set out in Section H.1.

Source: Authors' calculations using 'Price Paid' data (HM Land Registry, 2022a), the UK House Price Index (HM Land Registry, 2022b) and property stocks data (Valuation Office Agency, 2018).