

Household financial fragility and asset poverty in OECD regions: New indicators and an experimental imputation method

By Josep Espasa-Reig, Ana I. Moreno-Monroy, Pedro Salas-Rojo and Piotr R. Paradowski

We provide new estimates on household financial fragility and asset poverty for regions in 11 OECD countries over 2010-2022. To extend coverage to countries lacking regional wealth data, we test several methods to impute financial fragility at the regional level. We find that the imputations of wealth on income datasets perform well using a hot-deck method. There is however a “regression to the mean” effect, whereby extreme values in the target indicator tend to be smoothed during imputation. We conclude by outlining directions for refining these methods in future research.

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1 Introduction

Disparities in financial fragility and asset poverty within countries are likely to be significant. Households under financial fragility may not have sufficient financial assets to shield themselves from economic shocks—many of which are geographically localised. Climate-related events such as heatwaves, water scarcity, droughts, and forest fires often impact specific regions disproportionately (OECD, 2024^[1]; OECD, 2021^[2]; OECD, 2022^[3]).¹ Asset poverty, which considers both liquid and non-liquid assets, may also vary substantially within countries, for instance because uneven increases in housing prices across cities and regions constrain wealth accumulation for lower- and middle-income households (OECD, 2024^[1]). Housing wealth has been increasingly concentrated among older households (Causa, Woloszko and Leite, 2019^[4]; Balestra, Caisl and Hermida, 2025^[5]) and residents of metropolitan areas (Economics Observatory, 2023^[6]; OECD, 2021^[2]), further exacerbating regional inequalities (Balestra, Jakub and Hermida, 2025^[7]).

It has been long recognised that wealth, together with income and consumption, is one of the key components of households' economic well-being. The OECD Framework for Statistics on the Distribution of Household Income, Consumption and Wealth (OECD, 2013^[8]; OECD, 2024^[9]) has so far been limited to the national level. Moreover, territorial indicators have so far focused on household income disparities (OECD, 2024^[1]) and have not yet explored territorial disparities in financial vulnerability mainly due to limitations in data availability.

To overcome this knowledge gap, this paper provides new regional financial fragility and asset poverty indicators at the regional level for 11 OECD countries with available data in the period 2010-2022. It also proposes an experimental approach to impute regional indicators by matching wealth and income datasets from the Luxembourg Income Study (LIS) and the Luxembourg Wealth Study (LWS). These datasets have been harmonised to enable consistent cross-country and cross-source comparisons, as well as to support robust longitudinal analyses over time. We propose imputation techniques that leverage the shared harmonisation processes across wealth and income microdata, ensuring comparable definitions for key demographic and socioeconomic variables.

We focus on two indicators at the regional level: 1) financial fragility (FF), defined as the share of individuals living in households without enough financial assets to cover three months of income equivalent to the national poverty line; and 2) asset poverty (AP), defined as the share of individuals living in households without enough net wealth to cover three months of income equivalent to the national poverty line. FF considers financial assets that can be liquidated easily in the event of an income shock. AP considers financial and non-financial assets such as housing, which offer a more comprehensive measure of household finances but are not immediately available to households in case of shocks.

After this introduction, the next section presents definitions and methods for the imputation and the validation setting. The third section presents results, and the final section concludes.

2 Definitions and methods

This section outlines the definition of financial fragility and asset poverty indicators and methods for the experimental imputation. The definitions presented here extend existing financial fragility and asset poverty indicators at the national level (Balestra and Tonkin, 2018^[10]; OECD, 2021^[11]; OECD, 2023^[12]) to the regional level. More information on the underlying variables can be found in Luxembourg Income Study (2025^[18]). The annex contains further description of the data and descriptive statistics.

Financial fragility and asset poverty in regions

To define regional indicators of financial fragility and asset poverty, we use a headcount financial poverty ratio approach. The national poverty line is defined as 50% of the median annual equivalised disposable income of households.² An individual j within a sample M and region r is considered financially poor if he/she belongs to a household with financial assets below 25% of the national income poverty line. Financial Fragility (FF) is defined as the share of individuals living in financially poor households in region r :

$$FF_r = \frac{\sum_{j=1}^{M_r} 1(\text{Household Equivalised Financial Assets}_r \leq 0.25 \text{ Income Poverty Line})}{M_r}$$

The underlying rationale is that individuals experiencing a temporary loss of income—such as from unemployment—may have to draw on their savings to maintain a minimum standard of living for a short period of time (i.e. at least three months), before they find a new job, relocate or receive the social benefits they are eligible to. See Annex A for more details.

The same approach can be used to derive a measure of asset poverty, which is based on household net wealth, i.e. the sum of financial and non-financial assets net of liabilities (see Annex A for more details). Asset Poverty (AP), for a population M of individuals based in region r is defined as:

$$AP_r = \frac{\sum_{j=1}^{M_r} 1(\text{Household Equivalised Net Wealth}_r \leq 0.25 * \text{Income Poverty Line})}{M_r}$$

Household net wealth offers a more comprehensive measure of household economic resources, better reflecting overall economic well-being and future economic prospects. However, including non-financial assets—such as primary residences or other real estate—may overstate the extent to which wealth can serve as a short-term self-insurance mechanism. For instance, an individual experiencing job loss is unlikely to sell their home in the short term; instead, it will likely rely first on its financial assets to absorb the income shock (Azpitarte, 2010^[13]).

Methods

Besides directly computing wealth indicators where data is available from LWS, we also explore an experimental cross-survey imputation approach, described below.

Matching across datasets

The objective is to impute regional information from wealth surveys (the “donor” dataset) into income surveys (“recipient” dataset).³ More precisely, the setting departs from two datasets:

- Dataset 1 acts as the donor dataset and includes N observations indexed by i . It includes an outcome y_i and a set x^{c1} of observed characteristics $\{x_i^1, \dots, x_i^{c1}\}$ like household disposable income quintile, age, and other sociodemographic factors of the household head. However, this dataset does not contain information on the region of residence.
- Dataset 2 acts as a recipient dataset and includes a set of M observations indexed by j . It includes a set x^{c2} of observed characteristics, including all variables in x^{c1} plus the region of residence, such that $x^{c1} \in x^{c2}$. Dataset 2 does not have information on the target outcome variable y_j .

The approach imputes the outcome of interest, $\hat{y}_j$ on the observations in the recipient dataset using the common observed sociodemographic factors x^{c1} to match observations across the recipient and the donor datasets, assuming that:

1. The Conditional Independence Assumption (CIA) is met (Balestra and Oehler, 2023^[14]);
2. Both datasets reflect the same objective population, with the surveying process being similar (or comparable), and the matching sociodemographic factors defined in the same manner (Luxembourg Income Study, 2025^[15]).
3. The imputed outcome $\hat{y}_j$ is reliable, i.e., close enough to y_i , for observations sharing the same socioeconomic characteristics in both datasets.

This last assumption highlights a well-known trade-off in imputation approaches (Brunori, Salas-Rajo and Verme, 2022^[16]). On the one hand, mean-based methods estimate the expected outcome conditional on a set of observed characteristics. When properly implemented, these methods are highly effective for prediction, as they aim to minimise a loss function—such as the root mean squared error (RMSE)—or to maximise measures of explanatory power, such as the coefficient of determination (R^2). However, despite their predictive accuracy, mean-based methods tend to perform poorly in the context of inequality analysis. This is because they often lead to a compression of the variance in the imputed distribution, thereby underestimating the true spread of outcomes across individuals or households.

On the other hand, matching methods -such as predictive means matching (Rubin, 1986^[17]) also rely on a set of common covariates shared across surveys, x^{c1} , but assign a real (random) outcome realisation taken from the donor rather than imputing the conditional mean. These methods perform well in terms of inequality measurement because they preserve the variance from the original distribution, but the individual accuracy of the prediction tends to be rather low because they assign a random realisation of the outcome.

Regional identifiers

Table 1 reports the number of TL2 regions available for each country-year in the LWS based on the region of residence (*region_c*) variable. See Table A.1 for more details. Regional identifiers remain constant across survey waves, and in some countries, these regions serve as stratification variables during household sampling (Luxembourg Income Study, 2025^[15]). LIS and LWS datasets provide reliable coverage of the national income and wealth distributions (Neugschwender, Munzi and Paradowski, 2023^[18]; Endeweld and Alkemade, 2014^[19]). However, small sample sizes may limit the precision of regional estimates in some cases.⁴

Table 1. Number of TL2 regions available by country-year in LWS

Country	ISO3	Year	Number of regions in LWS	Discrepancies from OECD TL regions
Australia	AUS	2020, 2018, 2016	8	None. Data provided at TL2
Australia	AUS	2014, 2010	7	Canberra region (ACT) and Northern Territory are merged into a single region
Austria	AUT	2021, 2017*	9	None. Data provided at TL2
Canada	CAN	2019, 2016, 2012	10	Missing Yukon, Northwest Territories and Nunavut
Denmark	DEN	2022, 2021, 2020, 2019, 2018, 2017, 2016, 2015	5	None. Data provided at municipal level, but recoded to TL2
Finland	FIN	2019, 2016, 2013	4	Missing Åland
France	FRA	2020, 2017, 2014	8	LWS has NUTS1 regions. TL2 regions correspond to NUTS2 regions
Germany	DEU	2017, 2012	16	None
Italy	ITA	2020, 2016, 2014, 2012	20	Province of Bolzano-Bozen and Province of Trento are merged into a single region
Japan	JPN	2021, 2017, 2014, 2010	8	Northern-Kanto, Koshin and Southern-Kanto are merged into a single region. Hokuriku and Toukai are merged into a single region
Slovak Republic	SVK	2021, 2017	8	None. Data provided at TL3
Slovenia	SVN	2021, 2017	2	None. Data provided at TL2

Note: Authors' elaboration based on Luxembourg Wealth Study (LWS) Database (2025_[23]), and European Central Bank (2025_[23]) Household Finance and Consumption Survey (HFCS) for AUS 2017, SVK 2017 and SVN 2017.

Validation setting

As we do not have an a-priori preferred method to accomplish the cross-survey matching imputation, we rely on a validation setting. As mentioned above, for some countries we have data in the LWS where we observe both the objective outcome y_i , and a set of sociodemographic factors x^{c2} (see Table A.1). We use these complete datasets to test the performance of five methods under two different approaches (see Annex B for more information):

1. Mean-based techniques:
 1. Group-wise mean imputation;
 2. Multiple parametric (Rubin and Thomas, 1996_[20]);
 3. Random forests (Hothorn, Hornik and Zeileis, 2006_[21]); and
 4. Extreme Gradient (EG) boosting (Chen and Guestrin, 2016_[22]).
2. Random hot-deck techniques:
 1. Random hot-deck (Rubin, 1986_[17]).⁵

We use these methods separately to match information across datasets and test their performance by comparing the poverty and inequality estimates in the original outcome and the imputed values. To decide the best method, we rely on the set of countries where information on the region is available in both datasets (LIS and LWS).

Then, we pool data across all available waves for each country and impute the outcome variable from the LWS (donor, original dataset) into the LIS (recipient dataset) using each of the five methods.⁶ Table C.1 and Table C.2 in Annex C show summary statistics for LWS and LIS variables used in the analysis. Upon imputation, we estimate a range of metrics that allow us to address their performance. We define the best-performing method as the one that minimises, on average, the difference between the real estimate and the estimate obtained from the imputed values. Finally, we use this best-performing method to impute the outcome in the remaining countries.

Common variables

The imputation and matching exercise relies on a set of covariates jointly available and harmonised across the LIS and LWS datasets, including: capital income (*hicapital*), homeownership status (*own*), number of household members (*nhhmem*), rural or urban residence (*rural*), age of household members (*age*), relationship to the household head (*relation*), educational attainment (*educ*), type of employment (*emp*), labour market status (*status1*), occupation (*occb1*), and labour force status (*lfs*). While these variables have been standardised to ensure comparability at the country-year level, we preserve specific national classifications where necessary to avoid misrepresenting survey-specific distinctions. See Annex A for more details.

The next section discusses the main results and this validation exercise, together with a discussion of its performance and its appropriateness to regional measurement.

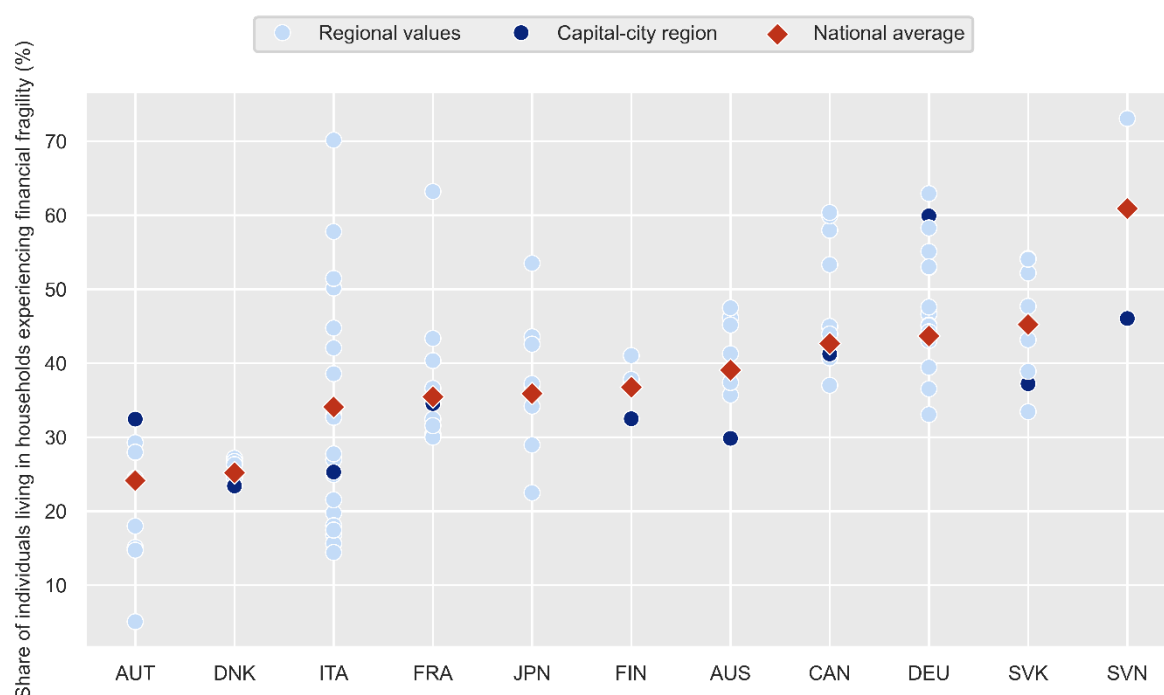
3 Results

The first part of this section presents the results for financial fragility and asset poverty indicators at the regional level using available data. The second part shows the results from the imputation experiment on financial fragility in regions.

Regional financial fragility based on available data

Figure 1 shows financial fragility (*FF*) across regions in the sample of OECD countries with available data, distinguishing national averages (red diamonds), regional values (light blue circles), and capital-city regions (dark blue circles).

Figure 1. Financial fragility by region, selected OECD countries



Note: Countries sorted by the national average in ascending order. Individuals are considered as financially fragile if they live in a household with financial assets below 25% of the national income poverty line. Financial assets are calculated as the market value of financial investments, deposit accounts, cash and other financial assets owned by household members. The poverty line is calculated using disposable income for all countries except AUT, SVK and SVN, where disposable income was not available and gross income was used instead. Disposable household income is calculated as current household income net of income taxes and social security contributions paid. Gross income is calculated as current household income before income taxes and social security contributions. All income and wealth measures are equivalised by dividing by the square root of the household size. The reference year is 2022 for DNK; 2021 for AUT, JPN, SVK, SVN; 2020 for AUS, FRA, ITA; 2019 for CAN, FIN; and 2017 for DEU. See Table A.2 for the territorial level used in each country.

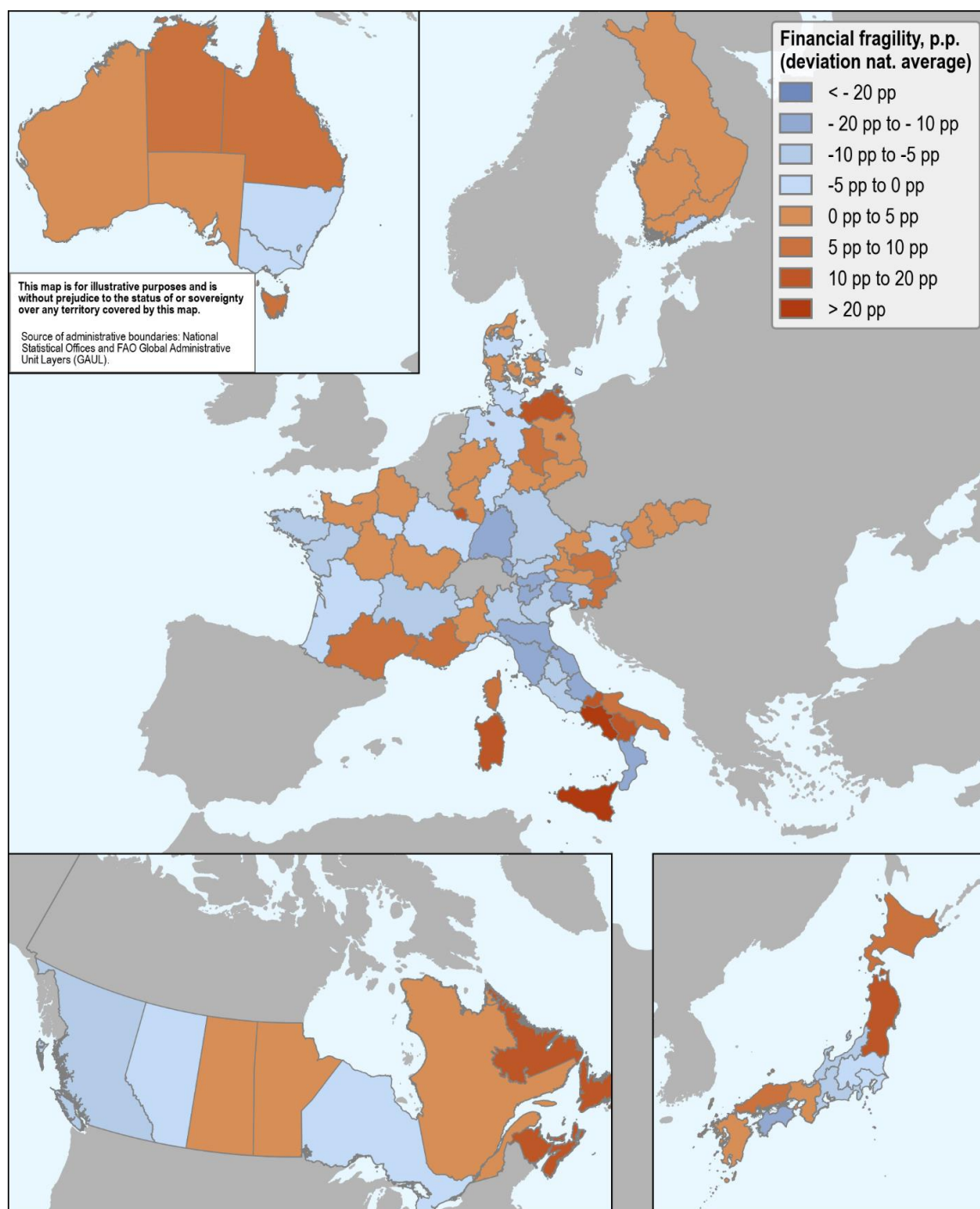
Source: Authors' calculations based on Luxembourg Wealth Study (LWS) Database (2025^[23]).

National averages of FF vary significantly across countries. Austria and Denmark show the lowest (below 30%) national poverty rates (below 30%), while Slovenia shows the largest (61%). Italy, France, Japan and Finland fall within a middle/low range (below 40%), while Canada and Germany show a relatively high national average (42-44%) despite their relatively high levels of GDP per capita.

The dispersion of FF within countries is substantial in most cases:

- Italy shows the largest intra-country variation of shares of financially fragile households with regions such as Abruzzo and Calabria showing relatively low shares (15-20%) and regions such as Campania and Sicily showing values 3 times as high (60%). Moreover, one third (7 out of 21) regions are below the national average, with 6 out of these 7 regions clustered in the South – reflecting the long-standing North-South divide in the country (Figure 2).
- Austria, Canada, Japan, and Germany also display wide regional variation, with some regions having financial fragility rates significantly below or above their respective national averages. In Germany, for instance, 4 out of 16 regions (Saarland, Berlin, Bremen and Mecklenburg-Vorpommern) are at least 10 percentage points below the national average in financial fragility (Figure 2).
- Nordic OECD countries such as Denmark or Finland exhibit much more compressed distributions, indicating relatively uniform levels of financial fragility across regions.
- Capital-city regions tend to have smaller FF rates compared to the national average in most countries, with the exception of Berlin (Germany) and Vienna (Austria), that have some of the highest rates of financial asset poverty in their countries (approximately 32% and 61%, respectively).

Figure 2. Deviations from the national average in financial fragility, OECD regions



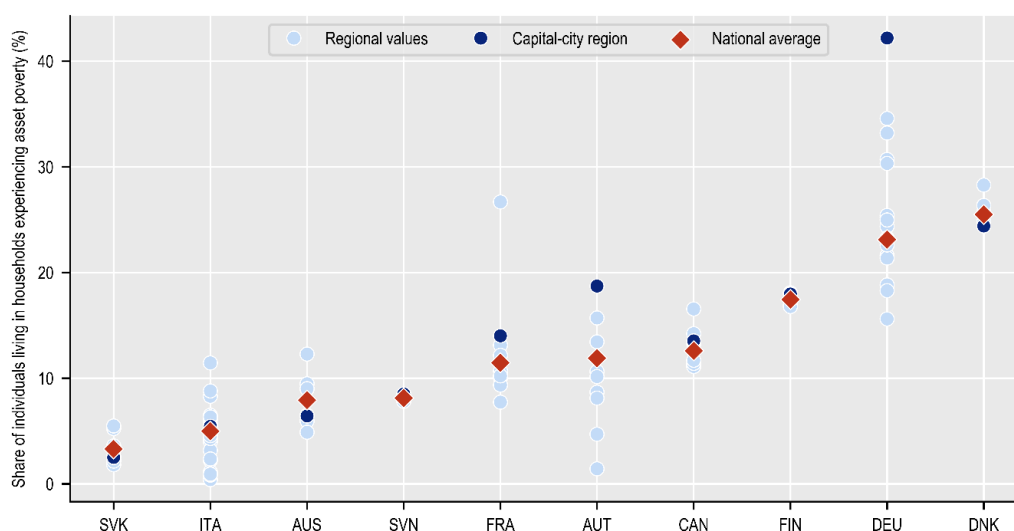
Note: Individuals are considered as financially fragile if they live in a household with financial assets below 25% of the national income poverty line. Financial assets are calculated as the market value of financial investments, deposit accounts, cash and other financial assets owned by household members. The poverty line is calculated using disposable income for all countries except AUT, SVK and SVN, where disposable income was not available and gross income was used instead. Disposable household income is calculated as current household income net of income taxes and social security contributions paid. Gross income is calculated as current household income before income taxes and social security contributions. All income and wealth measures are equivalised by dividing by the square root of the household size. The reference year is 2022 for DNK; 2021 for AUT, JPN, SVK, SVN; 2020 for AUS, FRA, ITA; 2019 for CAN, FIN; and 2017 for DEU. See Table A.2 for the territorial level used in each country.

Source: Authors' calculations based on Luxembourg Wealth Study (LWS) Database (2025^[23]).

Regional asset poverty based on available data

Figure 3 shows results for asset poverty (AP). The rank of national averages by AP is the opposite to the rank of countries by FF (Figure 1). This is expected, as net wealth encompasses a broader range of assets, including as housing or other real estates, which are not as liquid as financial assets.

Figure 3. Asset poverty by region, selected OECD countries



Note: Countries are sorted by the national average in ascending order. Individuals are considered as asset poor if they live in a household with net asset wealth below 25% of the national income poverty line. Net asset wealth is calculated as the sum of financial and non-financial assets minus liabilities. The poverty line is calculated using disposable income for all countries except AUT, SVK and SVN, where disposable income was not available and gross income was used instead. Disposable household income is calculated as current household income net of income taxes and social security contributions paid. Gross income is calculated as current household income before income taxes and social security contributions. All income and wealth measures are equivalised by dividing by the square root of the household size. The reference year is 2022 for DNK; 2021 for AUT, SVK, SVN; 2020 for AUS, FRA, ITA; 2019 for CAN, FIN; and 2017 for DEU. See Table A.2 for the territorial level used in each country.

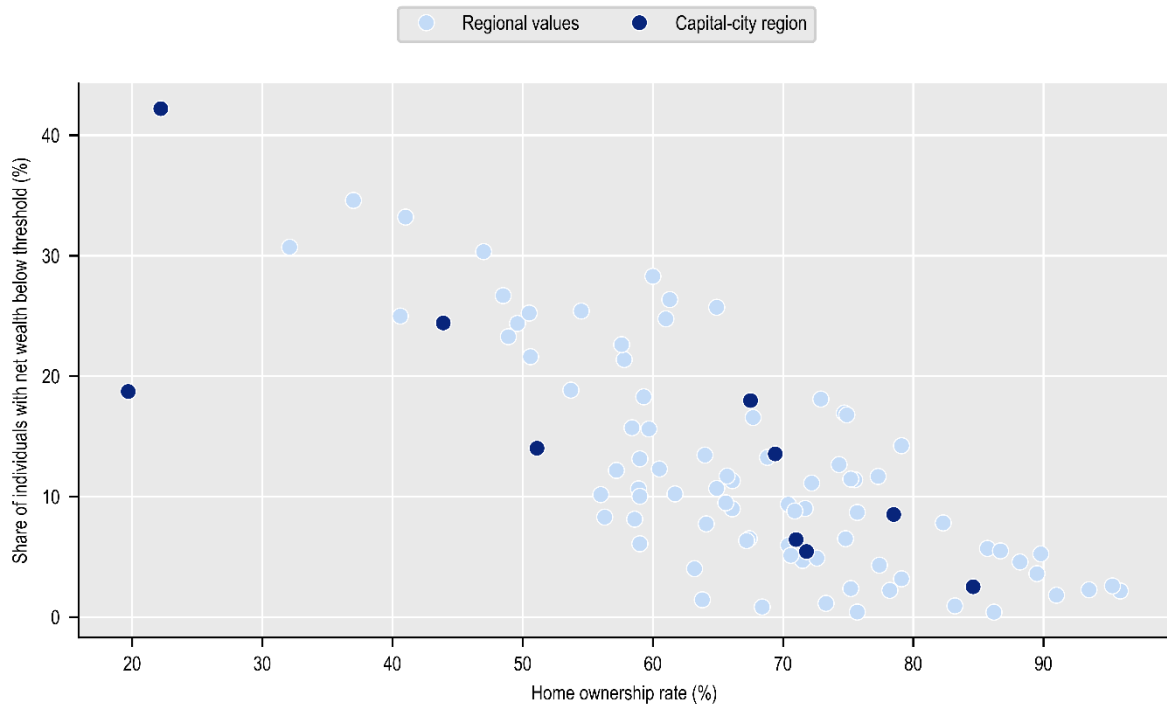
Source: Authors' calculations based on Luxembourg Wealth Study (LWS) Database (2025^[23]).

Regarding intra-country variation, Italy, Canada, Germany and to some extent Australia exhibit the largest regional variation in AP rates, with the remaining countries being rather homogeneous and clustered around the national average. Italian regions such as Molise or Abruzzo lie at the bottom of the distribution, with AP rates ranging 0.4% and 2%, while Liguria stands at the top (over 10%). Two other regions stand out: Départements d'Outre-Mer, in France, with a much higher (27%) rate than the national average, and Berlin, with almost twice the national rate (42% vs 23%).

Variations in homeownership rates across countries may explain the fact that some countries with high AP rank low in FF. For instance, Denmark which shows the lowest FF and the highest AP rates, has one of the lowest home-ownership rates across the considered countries.⁷ In contrast, countries with higher homeownership rates, including Slovakia, Slovenia or Italy have relatively low AP but relatively high FF.

Figure 4 shows the relationship between home ownership and AP rates in regions. The correlation coefficient between these variables is -0.77, indicating a strong negative relationship, with regions with higher ownership rates showing lower AP rates and vice-versa.⁸ Disparities in home ownership appear to contribute significantly to the nominal wealth gap between homeowners and non-homeowners. One notable exception is Vienna, which has both the lowest home ownership rate at 20% and an AP below 20%.

Figure 4. Asset poverty vs home ownership rates in regions



Note: The figure includes data regions in AUS, AUT, CAN, DEU, DNK, FIN, FRA, ITA, JPN, SVK AND SVN. Individuals are considered as asset poor if they live in a household with net asset wealth below 25% of the national income poverty line. Net asset wealth is calculated as the sum of financial and non-financial assets minus liabilities. The poverty line is calculated using disposable income for all countries except AUT, SVK and SVN, where disposable income was not available and gross income was used instead. Disposable household income is calculated as current household income net of income taxes and social security contributions paid. Gross income is calculated as current household income before income taxes and social security contributions. Home ownership includes households that own their main residence dwelling either outright or paying a mortgage. The reference year is 2022 for DNK; 2021 for AUT, JPN, SVK, SVN; 2020 for AUS, FRA, ITA; 2019 for CAN, FIN; and 2017 for DEU See Table A.2 for the territorial level used in each country.

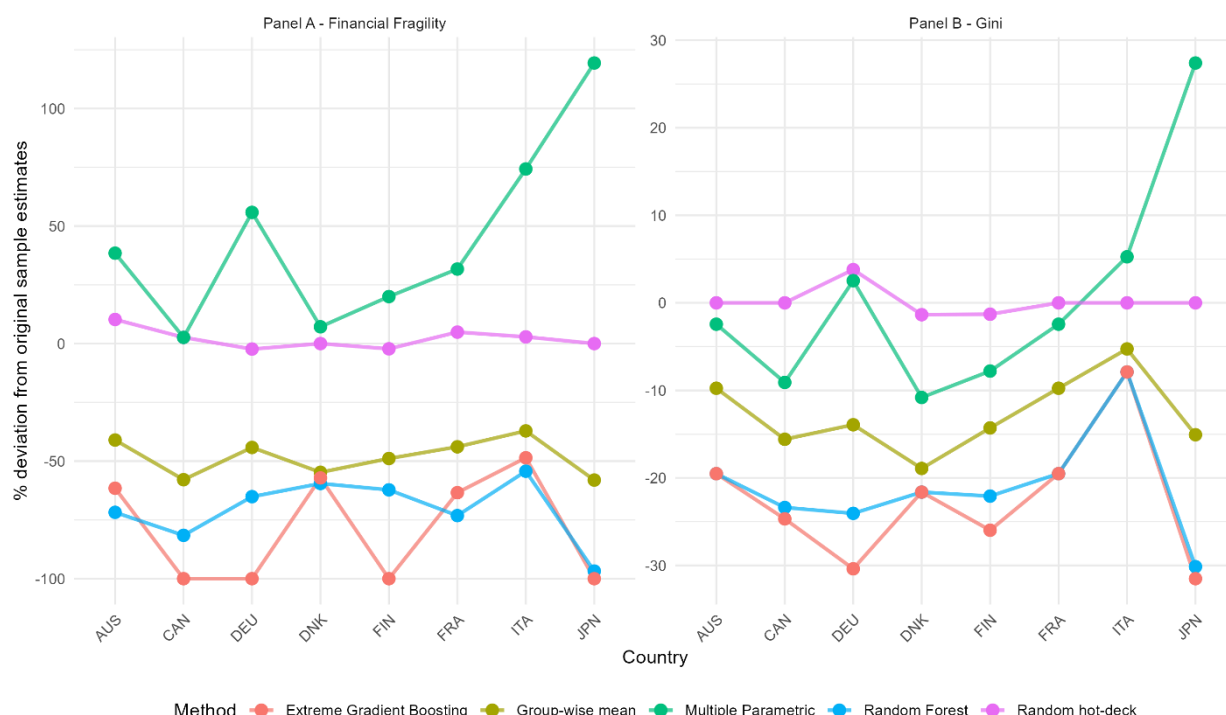
Source: Authors' calculations based on Luxembourg Wealth Study (LWS) Database (2025^[23]).

Imputation results

As explained in Section 2, we test the performance of five matching techniques that have been widely used in the literature. Table C.3 in Annex C shows the full set of results.

Figure 5 benchmarks the results of the simulation exercise based on country estimates. For each country, represented on the x-axis, we show the percentage deviation of the LIS-imputed results with respect to the original (LWS) estimate. Even though we have estimated other moments of the wealth distribution⁹, we focus on financial fragility (FF) and inequality (measured with the Gini coefficient). Positive values can be understood as overestimations, that is, the imputed values are higher than the original values, while negative values are underestimations.

Figure 5. Benchmark of imputation/matching methods



Note: The figure shows the deviations from the actual Gini and financial fragility rate computed from the sample. The sample is composed of all pooled waves for a given country. Individuals are considered as financially fragile if they live in a household with financial assets below 25% of the national income poverty line. Financial assets are calculated as the market value of financial investments, deposit accounts, cash and other financial assets owned by household members. The poverty line is calculated using disposable income for all countries. Disposable household income is calculated as current household income net of income taxes and social security contributions paid. Gross income is calculated as current household income before income taxes and social security contributions. All income and wealth measures are equivalised by dividing by the square root of the household size.

Source: Authors' calculations based on Luxembourg Wealth Study (LWS) Database (2025^[26]).

The imputation procedure, when performed at the country level, yields a close approximation to the financial fragility rates from the actual LWS sample. For FF, the estimations show small biases in most cases, though with notable differences in performance across models (Figure 5, Panel A). The random hot-deck method seems to outperform the rest. Specifically, for Denmark and Japan, the estimates match the original data exactly. Australia and France show a moderate overestimation of approximately 10% and 5%, respectively. Italy and Canada exhibit a slight overestimation of less than 3%, whereas Finland and Germany display a minor underestimation of around -2.3%.

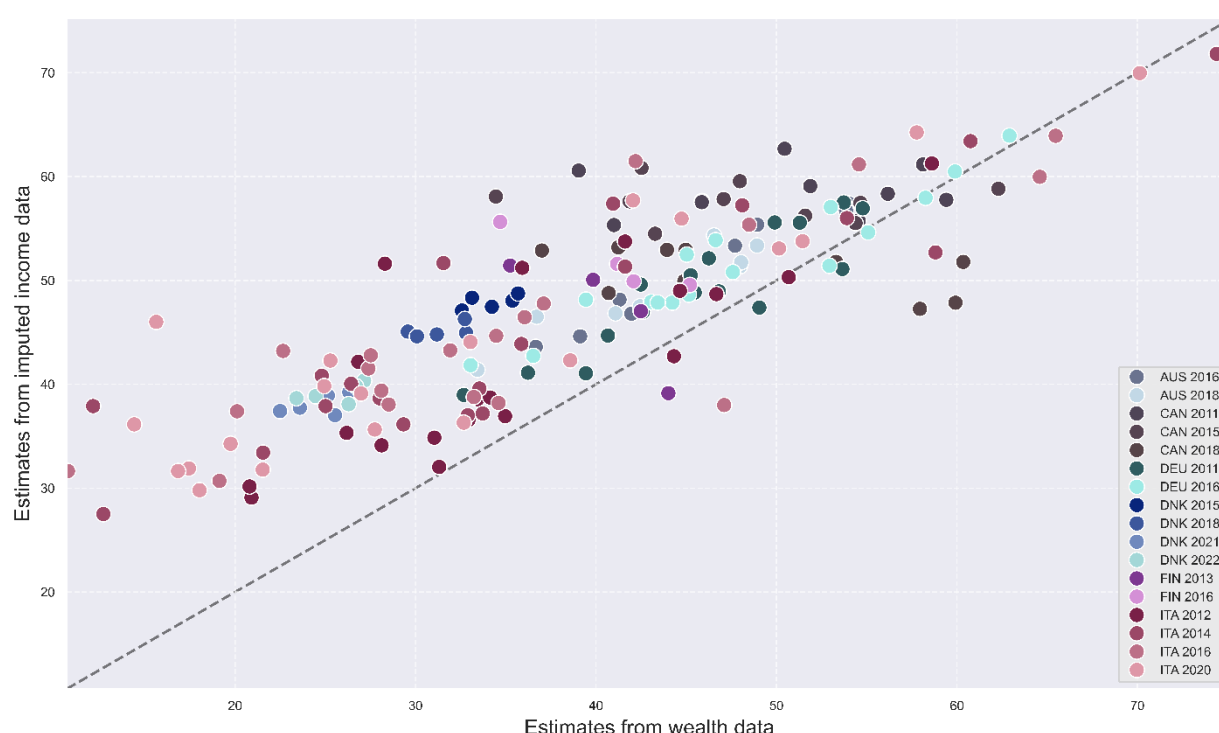
The multiple parametric method also performs relatively well in some countries with respect to the Gini (Figure 5, Panel B), maintaining the original variance, although showing a relatively large bias in Japan (27%). However, as expected, mean-based methods deliver considerable biases, with underestimations surpassing 20% in many cases. As explained earlier, these methods are designed to reduce the variance of the model and tend to perform well in terms of out-of-sample prediction capacity. Indeed, as shown in Table C.3, Random Forest and Extreme Gradient Boosting compete to be the best-performing methods in (out-of-sample) Root Mean Square Error. However, this compression of the variance that enhances prediction capacity comes at the cost of reducing variability in the outcome, thus provoking a severe underestimation of inequality.

Panel A in Figure 5 showing the FF estimates conveys the same idea. The percentage deviation with respect to the original estimate lies around zero in Germany, Finland, and Denmark, with some

overestimation observed in Australia and France. Multiple parametric imputation systematically overestimates FF, with all associated values being positive and reaching values as high as like 75% in Italy and 53% in Germany. These results come from overfitting, which overdistributes households in the lower part of the distribution. Group-wise mean algorithms again reduce the variance of the imputed values, concentrating them around the mean. This comes at the cost of severely underestimating FF rates.

In light of these results, our preferred method is the random hot-deck, which we use to match the LIS and LWS and re-estimate FF. Figure 6 assesses the concordance between regional FF rates estimated from LWS and those derived after imputing income on the LIS using this method. Each point corresponds to a single region-year observation, color-coded by country and survey year, plotted against a dashed 45° identity line. Proximity to this line indicates minimal bias introduced by the imputation process, whereas deviations quantify the magnitude and direction of estimation error.

Figure 6. Financial fragility estimates comparison



Note: This figure shows the comparison between the regional financial fragility estimates from wealth data obtained with LWS data and those from wealth data imputed on LIS data. Imputation is performed using a random hot-deck algorithm. Each point represents a region within a given country and year dataset. Individuals are considered as financially fragile if they live in a household with financial assets below 25% of the national income poverty line. Financial assets are calculated as the market value of financial investments, deposit accounts, cash and other financial assets owned by household members. Disposable household income is calculated as current household income net of income taxes and social security contributions paid. Gross income is calculated as current household income before income taxes and social security contributions. All income and wealth measures are equivalised by dividing by the square root of the household size.

Source: Authors' calculations based on Luxembourg Wealth Study (LWS) Database (2025^[23]) and Luxembourg Income Study (LIS) Database (2025^[26]).

Most regions lie close to the bisector, demonstrating that the imputed income data reproduce the spatial pattern of FF observed in the wealth-based estimates. Indeed, while the correlation across both sets of estimates reaches a value of 0.847, the slope of a linear regression of the LWS estimates over the LIS estimates reaches a value of 0.846.¹⁰ Nevertheless, a non-negligible scatter persists, with regions at both

ends of the distribution exhibit systematic over- or underestimation, suggesting that the imputation model captures central tendencies more reliably than extreme values.

More in detail, some regions in Italian survey waves (2012, 2014, 2020) display a consistent upward bias, with imputed LIS estimates exceeding the original LWS-based rates by several percentage points, especially in the poorest subnational units, where deviations surpass 20 percentage points. At the other extreme of the distribution, the 2018 wave in Canada seems to deliver downward biased estimates in several regions, producing a bias over 15 percentage points. By contrast, countries such as Denmark (2015, 2018, 2021, 2022), Canada (2011, 2015) and Germany (2011, 2016) exhibit tight clustering around the identity line, indicating high fidelity of the imputation in contexts with more homogeneous wealth-income relationships. Still, even some Canadian regions are affected by a persistent bias, in some cases surpassing 12 percentage points.

Future work could consider several avenues for fixing this persistent bias in the estimation on the tails:

- Model enrichment, including more household covariates or regional information in the regression (Korinek, Mistiaen and Ravallion, 2007^[23]; Blanchet, Chancel and Gethin, 2022^[24]; Torres López, Monroy-Gómez-Franco and Vélez-Grajales, 2025^[25]; Torres López, Monroy-Gómez-Franco and Vélez-Grajales, 2025^[25]; Balestra and Oehler, 2023^[14])¹.
- Post-imputation calibration, like ranking or regression adjustments. This correction approach could be used, for instance, to reweight imputed values to align with external benchmarks.

4 Discussion and conclusions

This paper has provided, for the first time, estimates of financial fragility and asset poverty across OECD regions in 11 countries with available data. The findings highlight the significance of sub-national perspectives, as asset poverty rates vary widely within countries. These variations depend on the measurement approach—whether based on financial assets or net wealth—highlighting the need for further research into how wealth portfolio composition and financial literacy differ across regions.

The paper also explores methods to impute regional financial fragility estimates using income data, offering a potential solution in cases where regional identifiers are missing. The results show that a hot-deck imputation approach provides a reasonable approximation of regional financial fragility rates when compared to estimates derived from wealth data with geographic detail. However, there is substantial variation in the performance of different methods, and in countries with high regional dispersion, the method struggles to capture the extremes of the distribution.

These findings suggest that imputation-based analyses can be useful for computing regional estimates in countries with relatively uniform regional characteristics. For example, they may be valuable for extending time series in such contexts. Before producing estimates for countries with available income but no wealth regional identifiers (e.g. Spain, United States and United Kingdom), it would be necessary to explore solutions to the regression to the mean issue, including the ones suggested in the paper.

In conclusion, direct estimates from survey or administrative sources with regional identifiers should remain the preferred standard for official statistics. This implies that household wealth surveys should be designed to accurately represent sub-national levels, including regions and local areas, and that geographical identifiers of households should be made accessible to researchers.

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Notes

¹ For example, aggregate economic losses in Southern European regions are estimated to be several times greater than those in their northern counterparts (Gagliardi, Arévalo and Pamies--Sumner, 2022^[32]). In this respect, the OECD measurement framework for vulnerability to environmental hazards highlights variations on the impact of environmental hazards across population groups and places. However, it does

not yet consider financial vulnerability and/or variations in regional wealth and assets due to lack of available estimates (OECD, 2025^[34]).

² In principle, the measurement of household income and wealth across regions should adjust for differences in living standards by accounting for regional variations in the cost of living—for example, through the use of regional Purchasing Power Parities (PPPs). When such adjustments are made, regional poverty lines can provide meaningful benchmarks for individuals who remain in the same region, while national poverty lines may be more appropriate for individuals who move across regions. However, regional PPPs are currently available for only a limited number of countries, and existing data do not allow for distinguishing between movers and stayers. Additionally, income poverty rates for OECD regions are typically calculated using national poverty lines (OECD, 2024^[11]).

³For more information on cross-survey imputation techniques see for instance Balestra and Oehler (2023^[21]) and Torres López, Monroy-Gómez-Franco and Vélez-Grajales (2025^[42]).

⁴ Sample sizes for regions can be found in the METIS website of the Luxembourg Income Study (Luxembourg Income Study, 2025^[15])

⁵ This method has recently been shown to perform well when imputing missing incomes (Brunori, Hufe and Mahler, 2023^[35]).

⁶ We initially considered pooling data across all countries to enhance the performance of machine learning-based models through a larger training dataset. However, this approach proved infeasible due to computational limitations within the LISSY remote-execution system used to access LIS and LWS data.

⁷ The housing ownership rate in Denmark is 56.2%, above Germany (51%), and Austria (53.9%), but below France (60.6%), Australia (68.2%), Canada (69.2%), Italy (71.3%), Finland (72.2%), Slovenia (80.6%) and Slovak Republic (90.6%). Households tend to hold their wealth in financial assets while residing in rented accommodations, many of which are part of public housing schemes.

⁸ Nevertheless, this correlation does not control for demographic composition, which may vary significantly across regions. For instance, regions with a higher proportion of younger households tend to exhibit both lower ownership rates and lower net wealth. Future work could further explore this relationship.

⁹ Results available upon request.

¹⁰ We run this regression with no constant. The results from including the constant are:1.19.

Annex A. Data sources and processing

We rely on two harmonised microdata sources: the Luxembourg Income Study (LIS) (Luxembourg Income Study (LIS) Database, 2025^[26]) and the Luxembourg Wealth Study (LWS) (Luxembourg Wealth Study (LWS) Database, 2025^[27]).¹ LIS is the largest repository of harmonised income microdata, currently encompassing over 930 datasets from around 52 countries across Europe, the Americas, Asia, and Africa. LWS, coordinated by the same research institution, offers harmonised wealth microdata for 22 countries. The LWS data is designed to be compatible with LIS in terms of variable definitions and documentation (Sierminska, Brandolini and Smeeding, 2006^[28]).²

We focus on OECD countries with information available on region of residence. This includes 11 countries (Australia, Austria, Canada, Denmark, France, Finland, Germany, Italy, Japan, Slovak Republic, Slovenia) for 2010 to 2022 (most recent year available). See Table A.1. for a complete list of the data used. The unit of analysis is the household, from which we take information on economic outcomes and socioeconomic covariates. LIS and LWS data provide household weights (*hpopwgt*) calibrated to national population distributions by age, sex, and, where possible, region composition (Gornick and Milanovic, 2022^[29]).

Financial fragility (FF)

The definition of FF is based on financial assets from the LWS Household Financial Assets (*haf*) variable, i.e. assets that can be liquidated relatively easily if needed. This measure reflects the market value of all financial assets like bonds, stocks, cash, deposits, investment funds and others, excluding pensions. These wealth components align with those in the OECD Wealth Distribution Database (WDD). Financial Assets (F) include: Currency and deposits (F1), Bonds and other debt securities (F2), Mutual funds and other investment funds (F3), Net equity in own unincorporated enterprises (F4), Stocks (F5), Unlisted shares and other equity (F6) and Other non-pension financial assets (F7).

Our definition of financial assets differs from that in the OECD Wealth Distribution Database (WDD) (OECD, 2025^[30]) as we do not include voluntary individual life insurance and private pension funds (F8). The reason for this discrepancy is that some datasets (Australia and Japan) do not collect private pension funds separately (Australia) or at all (Japan).

Asset poverty (AP)

To calculate AP we use the LWS Disposable Net Worth (*DNW*) variable. This variable contains the total value of both financial and non-financial assets (excluding pensions and other long-term savings), minus total liabilities. Non-Financial Assets (NF) include the Principal residence (NF1), Other estate property (NF2), Vehicles (NF3), Valuables (NF4) and Other non-financial assets like consumer durables or intellectual property (NF5). Liabilities (L) include principal residence loans (L1), Other residence and real estate loans (L2), Other loans (L3). Net Wealth (NW) is defined as Non-Financial Assets (NF) + Financial Assets (F) – Liabilities (L). The NW definition excludes pension schemes related to employment like occupational pension plans with account balance.

Disposable income

The definition of disposable income used in this paper follows that of the LIS/LWS Disposable Household Income (DHI) variable. It includes $DHI = E$ (employee income) + KI (capital and property income) + SEI (income from self-employment) + $TRROT$ (current transfers received from non-profit institutions and other private households) + $TRRER$ (current transfers received from employment-related social insurance

schemes) + TRRSS (current transfers received from social security) – TA (direct taxes) – TRPER (contributions paid by households to employment-related social insurance schemes). It differs from the OECD Income Distribution Database (IDD) definition in that it does not subtract TRPOT.

Gross income

The definition of Gross income is based on the LWS Total Current Income (HITOTAL) variable. $HITOTAL = E + KI + SEI + TRROT + TRRER + TRRSS$. It differs from the OECD Income Distribution Database (IDD) definition in that it does not subtract TRPOT and TRPER.

Common variables

The variable *rural* is defined in LWS based on one or both of the following criteria:

- Locality size – typically measured by the number of inhabitants.
- Type of area – often determined by population density.

In general, rural areas are defined as localities with low population density and/or a small population, usually fewer than 2 000 inhabitants. Denmark is an exception to this definition, where a rural area is more narrowly defined as a locality with fewer than 200 inhabitants.

We apply some additional transformations to enhance the consistent use of the data:

- For *own*, we recode tenure status into four categories: values 100 or 110 are mapped to *owned or owned outright*, value 120 to *owned with mortgage*, values 200 to 212 to *rented*, and values 220 to 224 to *other*. All other values, including unclassified responses, are assigned to *other*, while missing values remain missing. Household size (*nhhmem*) is top-coded at 5 members.
- The *age* of the household head is grouped into five brackets: under 25, 25-34, 35-49, 50-64, and 65 or older.
- Educational attainment and employment information are also reduced to standardised categories. For example, employment status (*status1*) is recoded into mutually exclusive categories capturing dependent employment, self-employment, employer status, cooperative membership, and family business participation.
- Similarly, labour force status (*lfs*) is mapped to a six-category variable distinguishing between employment, unemployment, disability/inactivity, retirement, education, and homemaking. For all employment-related variables, classifications are computed based on the household head only ($relation == 1000$).
- Total disposable income (*hitotal*) is transformed into quintile categories to reduce sensitivity to outliers and facilitate imputation. More information about the cleaning and data management process is available upon request.

Table A.1. List of datasets used and available data

Country	Year	Region available in LWS	Region available in LIS	Disposable income available in LWS	Voluntary life insurance accounts available in LWS	Voluntary private pension accounts available in LWS
Australia	2020, 2018, 2016, 2014, 2010	Yes	Yes	Yes	Yes	No
Austria	2021, 2017, 2014, 2011	2021, 2017*	Yes	No	Yes	No
Canada	2019, 2016, 2012	Yes	Yes	Yes	Yes	No
Denmark	2022-2015	Yes	Yes	Yes	Yes	No
Finland	2019, 2016, 2013	Yes	Yes	Yes	Yes	2019, 2016
France	2020, 2017, 2014	Yes	Yes	Yes	Yes	No
Germany	2017, 2012	Yes	Yes	Yes	Yes	No
Italy	2020, 2016, 2014, 2012, 2010	Yes	Yes	Yes	Yes	Yes
Japan	2021, 2020, 2019, 2018, 2017, 2016, 2015, 2014, 2011	Yes	Yes	Yes	No	No
Slovak Republic	2021, 2017, 2014, 2010	2021, 2017*	Yes	No	Yes	Yes
Slovenia	2021, 2017, 2014	2021, 2017*	Yes	No	Yes	Yes

* Region data extracted from matched HFCS

Source: Authors' elaboration based on Luxembourg Wealth Study (LWS) Database (2025_[23]) and Luxembourg Income Study (LIS) Database (2025_[26]).

Table A.2. List of regions used, by country

NUTS1		TL2		TL3	
Country	Region Name	Country	Region Name	Country	Region Name
FRA	Île-de-France	AUT	Burgenland	SVK	Bratislava Region
FRA	Bassin parisien	AUT	Lower Austria	SVK	Trnava Region
FRA	Nord	AUT	Vienna	SVK	Trencin Region

FRA	Est	AUT	Carinthia	SVK	Nitra Region
FRA	Ouest	AUT	Styria	SVK	Žilina Region
FRA	Sud-Ouest	AUT	Upper Austria	SVK	Banská Bystrica Region
FRA	Centre-Est	AUT	Salzburg	SVK	Prešov Region
FRA	Méditerranée	AUT	Tyrol	SVK	Košice Region
FRA	Départements d'Outre-Mer	AUT	Vorarlberg		
		AUS	New South Wales		
		AUS	Victoria		
		AUS	Queensland		
		AUS	South Australia		
		AUS	Western Australia		
		AUS	Tasmania		
		AUS	Northern Territory		
		AUS	Australian Capital Territory		
		CAN	Newfoundland and Labrador		
		CAN	Prince Edward Island		
		CAN	Nova Scotia		
		CAN	New Brunswick		
		CAN	Quebec		
		CAN	Ontario		
		CAN	Manitoba		
		CAN	Saskatchewan		
		CAN	Alberta		
		CAN	British Columbia		
		CAN	Yukon		

CAN	Northwest Territories
CAN	Nunavut
DEU	Baden-Württemberg
DEU	Bavaria
DEU	Berlin
DEU	Brandenburg
DEU	Bremen
DEU	Hamburg
DEU	Hesse
DEU	Mecklenburg-Vorpommern
DEU	Lower Saxony
DEU	North Rhine-Westphalia
DEU	Rhineland-Palatinate
DEU	Saarland
DEU	Saxony
DEU	Saxony-Anhalt
DEU	Schleswig-Holstein
DEU	Thuringia
DNK	Capital City Region
DNK	Zealand
DNK	Southern Denmark
DNK	Central Jutland
DNK	Northern Jutland
EST	North
EST	Northeast
FIN	Western Finland

		FIN	Helsinki-Uusimaa		
		FIN	Southern Finland		
		FIN	Northern and Eastern Finland		
		ITA	Piedmont		
		ITA	Aosta Valley		
		ITA	Liguria		
		ITA	Lombardy		
		ITA	Abruzzo		
		ITA	Molise		
		ITA	Campania		
		ITA	Apulia		
		ITA	Basilicata		
		ITA	Calabria		
		ITA	Sicily		
		ITA	Sardinia		
		ITA	Province of Bolzano-Bozen + Trento		
		ITA	Veneto		
		ITA	Friuli-Venezia Giulia		
		ITA	Emilia-Romagna		
		ITA	Tuscany		
		ITA	Umbria		
		ITA	Marche		
		ITA	Lazio		
		JPN	Hokkaido		
		JPN	Tohoku		
		JPN	Kanto		

		JPN	Hokuriku+Toukai		
		JPN	Kinki		
		JPN	Chugoku		
		JPN	Shikoku		
		JPN	Kyushu, Okinawa		
		SVN	Eastern Slovenia		
		SVN	Western Slovenia		

Notes

¹ We complement LWS data with data from the Household Finance and Consumption Survey (HFCS). The HFCS is coordinated by the European Central Bank and contains detailed household-level data on assets, liabilities, income, and consumption in euro area countries, with four waves collected since 2010.

² See <https://www.lisdatacenter.org/> for more information about the institution, data sources, definitions, and harmonisation methodology.

Annex B. Benchmark matching methods

Group-wise mean

In this approach, missing incomes in the recipient dataset are replaced by the average income observed in the donor dataset for each combination of categorical covariates x^{c1} .

$$\mu_g = \frac{1}{n_g} \sum_{i: g(i)=g} y_i$$

the sample mean of y_i (income) across all donor observations in group g , where $g(i)$ is the group index determined by the levels of x^{c1} , and n_g is the number of donors in that group. Then every recipient unit j belonging to group g is assigned:

$$\hat{y}_j = \mu_g$$

Because each $\hat{y}_j$ is a fixed, deterministic function of the donor data, this single-imputation preserves the group means exactly but underestimates the within-group variance (all recipients in the same group get identical values). Unlike multiple parametric imputation, there is no built-in mechanism to reflect sampling uncertainty—every imputed value is simply the group average.

Multiple Parametric

This method consists of imputing income values on the recipient dataset with values generated using a regression model run on the donor dataset. The most common approach is based on multiple parametric imputation, which departs from a log-linear regression model where the target outcome in the donor dataset is regressed against the set of covariates in x^{c1} :

$$\log(y_i) = \alpha + \beta x_i^{c1} + \varepsilon_i$$

The estimated parameters are used to compute the fitted values in the recipient dataset:

$$\hat{y}_j = \exp(\hat{\alpha} + \hat{\beta} x_j^{c1})$$

With sample-based surveys, single imputations may deliver accurate means, but the predicted variance is expected to be inaccurate, as the model relies on just one draw of data. For this reason, it is usually recommended to draw several bootstrapped samples that reflect the potentially different realizations of the data. The resulting $\hat{y}_j$ is hence obtained after averaging the predictions for each bootstrapped model, generating a “multiple imputation” (see Raghunathan et al. (2001_[31]) for a review). We average five bootstrapped repetitions, and check that the Smearing correction or running a regularized regression (LASSO) including all pairwise interactions does not meaningfully alter the performance of this approach.

Random Forests

Conditional Inference Random Forests build upon Conditional Inference Regression Trees, which are algorithms designed to predict an output variable out-of-sample (Hothorn, Hornik and Zeileis, 2006_[21]). The method divides the observed dataset into non-overlapping subgroups based on exhaustive partitions of the regressors' space. The predicted output for each subgroup is the average observed value of the output variable within each subgroup. The binary splitting mechanism employed in growing regression trees makes them particularly effective for modelling non-linear data generation processes (Hastie, Tibshirani and Friedman, 2009_[31]).

While regression trees exhibit low bias, they often suffer from high variance. This issue can be mitigated through Random Forests. Random Forests improve prediction accuracy by generating a large ensemble of decision trees. Each tree is built from a random subset of the original data, and the variables used for each split are randomly selected from the full set of available covariates. This method aggregates the predictions from multiple trees, each utilizing different subsets of data and variables, to produce a final prediction based on the average of all individual tree predictions.

As with other predictive models, the Random Forest approach begins by training the model on a donor dataset. Predictions for the recipient dataset are then generated based on common covariates shared between the two datasets.

Extreme Gradient Boosting

Extreme Gradient (EG) Boosting (Chen and Guestrin, 2016^[22]) is an implementation of gradient boosting machine learning algorithms that constructs a robust ensemble model by combining the predictions of several decision trees. Unlike Random Forests, which rely on multiple independently grown trees, EG Boosting builds its model sequentially, with each tree grown to correct the errors of its predecessors.

EG Boosting introduces several optimisations that distinguish it from other boosting techniques. It uses a regularised learning objective that integrates a loss function (the mean squared error for regression tasks) with a complexity penalty to reduce overfitting. Moreover, it employs second-order gradient boosting, which leverages both first- and second-order derivatives of the loss function, enhancing accuracy and enabling faster convergence.

Random hot-deck

The Random Hot-Deck method involves finding observations in the donor sample that closely match those in the recipient sample. The matching is performed based on observed covariates, x^{c1} , which serve as non-parametric predictors of the outcome variable. In this study, we adapt the Predictive Mean Matching (PMM) method proposed by Rubin (1986^[22]). First, we match groups endowed with identical covariates in both samples. Then, instead of assigning the predicted expected outcome, as in parametric approaches, we select a random outcome realization from the group in the donor dataset. The value of y_i from the selected donor observation is then imputed into the incomplete case of the recipient sample, thus delivering y_j .

Annex C. Summary statistics and benchmark results

Table C.1. Summary statistics of key outcome variables by country-year in LWS

Country	Year	Sample size financial assets	Sample size net wealth	Mean financial assets	Mean net wealth	Median financial assets	Median net wealth	Zero values financial assets	Zero values net wealth	Negative values financial assets	Negative values net wealth	SD financial assets	SD net wealth	Gini financial assets	Gini net wealth
AUS	2020	15 011	15 011	71 039.3	30 937.4	8 665.8	169 442.4	428	1	43	510	368 773	692 621	0.846	0.637
AUS	2018	14 060	14 060	79 797.2	320 940.2	7 274.3	168 012.9	165	1	15	377	452 669	702 378	0.872	0.647
AUS	2016	17 768	17 768	66 310.8	296 091.5	6 550.6	165 378.9	296	5	12	411	741 544	940 273	0.867	0.629
AUS	2014	14 162	14 162	63 445.2	270 855.9	6 215.2	148 960.7	204	3	13	273	401 373	617 884	0.861	0.625
AUS	2010	18 071	18 071	56 333.5	279 316.5	4 367.6	162 257.5	738	0	8	322	370 401	887 126	0.882	0.612
AUT	2021	11 465	11 465	36 177.1	236 658.3	14 010.5	113 081.5	218	43	0	396	103 135	486 784	0.685	0.676
AUT	2017	15 360	15 360	30 279.2	220 363.9	12 952.2	9 7483.1	562	154	0	699	70 547	853 061	0.666	0.702
CAN	2019	10 182	10 182	47 480.1	298 701.7	6 832.7	129 859.8	303	1	69	568	217 049	605 932	0.837	0.679
CAN	2016	12 349	12 349	46 807	283 025.9	5 931.1	123 206.7	417	5	83	673	219 456	595 144	0.847	0.682
CAN	2012	11 933	11 933	37 934.4	241 090.8	4 953.2	107 629.1	548	3	0	629	147 617	465 075	0.838	0.672
DEU	2017	79 095	79 095	29 863.9	170 568.6	6 256.4	67 908.4	27690	6938	0	6 790	120 697	549 044	0.786	0.718
DEU	2012	74 355	74 355	26 323.4	135 630.9	6 504.5	46 460.5	23710	12189	0	9 488	89 584	420 696	0.772	0.759
DNK	2022	300 514	300 514	92 397.5	158 463.7	12 530.1	46 022.4	4102	2248	1	53 667	1 241 161	1 291 444	0.861	0.859
DNK	2021	297 348	297 348	98 472.4	167 757.6	13 687.3	46 375.7	3781	1967	0	56 466	1 050 517	1 122 269	0.857	0.865

DNK	2020	294 379	294 379	81 867.6	144 519.5	13 105.6	38 733.7	3367	1543	0	59 300	1 197 899	1 234 992	0.842	0.874
DNK	2019	292 246	292 246	44 610.7	106 597.6	9 738.3	33 609	4476	1952	0	60 028	563 124	649 399	0.779	0.847
DNK	2018	290 616	290 616	39 604.4	100 150.9	9 015.4	31 158.3	4697	2118	0	61 624	439 383	614 446	0.769	0.869
DNK	2017	288 398	288 398	40 018.9	97 862	8 484.1	28 633.1	4657	1926	0	63 263	310 328	473 233	0.778	0.876
DNK	2016	286 388	286 388	38 230.8	90 966.6	8 163.1	25 402.6	4775	1846	0	68 395	543 053	630 353	0.776	0.912
DNK	2015	284 083	284 083	37 621.5	87 553.7	7 642.3	23 227.1	4897	1798	2	70 354	375 240	500 717	0.782	0.939
FIN	2019	9 474	9 474	39 890.5	168 299.4	7 378.6	89 665.1	88	19	0	640	160 809	331 603	0.802	0.661
FIN	2016	10 210	10 210	33 195.4	162 064.5	6 072.6	90 230.8	104	27	0	670	140 563	297 277	0.805	0.64
FIN	2013	11 030	11 030	28 408.5	154 757.5	5 703.7	9 2611	137	30	8	718	235 646	350 229	0.792	0.625
FRA	2020	10 253	10 253	31 101.6	206 336.4	8 252.3	97 341.6	83	0	0	144	261 654	542 605	0.757	0.664
FRA	2017	13 685	13 685	26 689.9	183 225.4	6 074.3	93 502.1	173	0	0	243	270 935	714 982	0.781	0.658
FRA	2014	12 035	12 035	24 394	177 951.5	5 484.4	90 179	81	0	0	215	195 070	458 779	0.781	0.656
ITA	2020	6 239	6 239	30 004.6	197 570.6	5 370.7	111 094.1	460	0	0	45	205 816	505 444	0.812	0.62
ITA	2016	7 420	7 420	23 147.7	193 202.2	4 602.2	121 661.1	1233	33	0	63	94 117	300 670	0.8	0.584
ITA	2014	8 156	8 156	20 719.5	197 833.7	4 388.2	125 093.2	1414	1	0	81	79 090	314 089	0.793	0.586
ITA	2012	8 151	8 151	20 615.7	224 832.4	3 907.5	134 265.9	1647	2	0	97	78 761	434 214	0.805	0.614
ITA	2010	7 951	7 947	21 867.4	250 072.8	5 592	158 176.1	1472	2	0	55	84 913	464 090	0.769	0.592
JPN	2021	4 505	0	49 171		14 199.4		1301		0		104 157		0.742	
JPN	2020	5 192	0	42 405.9		9 814.7		1614		0		94 411		0.761	
JPN	2019	5 876	0	39 521.5		7 359.2		2014		0		92 523		0.776	
JPN	2018	4 053	0	46 924.6		12 322.8		1190		0		104 154		0.756	
JPN	2017	4 359	0	50 855.6		15 241.6		1190		0		100 243		0.728	
JPN	2016	4 589	0	53 087		19 372.6		978		0		102 601		0.71	
JPN	2015	4 914	0	54 022		17 662.1		1040		0		100 647		0.72	
JPN	2014	5 218	0	52 467.1		17 442.9		1119		0		93 894		0.712	
JPN	2011	5 677	0	49 471.8		14 530.1		1248		0		104 300		0.731	

SVK	2021	10 870	10 870	8 165	107 708.3	2 924	82 422.9	1220	145	0	103	19 269	123 585	0.711	0.463
SVK	2017	10 895	10 895	7 315.2	101437.5	1 736.5	70 307.8	1572	223	0	237	20 869	165 354	0.76	0.521
SVK	2014	10 675	10 675	4 738.9	64289.9	1 609	51 142.6	1892	235	0	236	10 835	112 461	0.72	0.489
SVK	2010	10 285	10 285	6 592.1	84157.6	1 880.6	62 216.2	790	85	0	239	17 229	88 278	0.725	0.446
SVN	2021	9 755	97 55	12 877.7	185598.3	1 492.7	112 975.9	1347	116	0	178	37 520	299 602	0.819	0.574
SVN	2017	10 070	10 070	8 787.2	148913.3	913.5	92 314.8	1453	86	0	273	31 552	296 451	0.837	0.586
SVN	2014	12 765	12 765	8 533.7	140639.6	675.7	84 047.4	1026	149	0	476	39 686	412 936	0.853	0.601

Source: Authors' calculations based on Luxembourg Wealth Study (LWS) Database (2025_[23]).

Table C.2. Summary statistics of key outcome variables by country-year in LIS

Country	Year	Sample size disposable income	Sample size gross income	Mean disposable income	Mean gross income	Median disposable income	Median gross income	Zero values disposable income	Zero values gross income	Negative values disposable income	Negative values gross income	SD disposable income	SD gross income	Gini disposable income	Gini gross income
AUS	2020	15 011	15 011	40 166.1	49 581.3	34 865.9	40 452.3	148	148	0	0	28 031	43 027	0.325	0.374
AUS	2018	14 060	14 060	39 150	48 728.2	33 334.5	39 367.4	94	93	0	0	36 186	60 079	0.331	0.382
AUS	2016	17 768	17 768	38 751.3	47 781.6	32 959	38 468.1	78	78	0	0	29 138	45 345	0.327	0.376
AUS	2014	14 115	14 115	39 352.2	48 224.3	33 399.6	38 781.3	69	69	0	0	41 625	59 015	0.332	0.384
AUS	2010	18 008	18 008	36 670.1	43 353.4	31 053.9	35 295	88	88	0	0	28 017	37 311	0.334	0.373
AUT	2021	0	11 465		42 236.7		39 402.7		5		0		23 386		0.269
AUT	2017	0	15 360		44 319.2		38 934.6		0		0		61 701		0.297
CAN	2019	10 029	10 029	40 830	49 320.4	36 627.2	41 795.1	50	37	0	0	29 194	44 060	0.322	0.364
CAN	2016	12 349	12 349	39 447.7	47 683.9	34 006.7	39 210.3	21	10	0	0	32 911	49 412	0.338	0.381
CAN	2012	11 933	11 933	37 363.8	44 568.8	32 128.4	36 454.8	18	11	0	0	28 682	41 314	0.336	0.378
DEU	2017	85 605	85 605	33 385.3	46 016	29 215.9	38 304.6	365	275	0	0	24 028	39 503	0.295	0.349
DEU	2012	81 985	81 985	31 544.8	43 063.9	27 555.2	35 389	120	90	0	0	22 017	36 117	0.288	0.344
DNK	2022	30 0514	300 514	35 572	58 105.8	31 144	49 526.4	1863	1712	0	0	103 997	196 165	0.297	0.342
DNK	2021	29 7348	297 348	37 005.9	60 331.4	32 727.7	51 889.9	1689	1497	0	0	44 767	77 569	0.29	0.336
DNK	2020	29 4379	294 379	36 081.5	58 727.2	32 291.6	51 056.7	1571	1366	0	0	31 562	56 953	0.281	0.33
DNK	2019	29 2246	292 246	34 963.8	57 097.5	31 111.3	49 265.5	1850	1593	0	0	43 333	83 374	0.286	0.335
DNK	2018	29 0616	290 616	34 405.2	55 775.6	30 837.5	48 654.2	1880	1651	0	0	37 074	64 164	0.282	0.33
DNK	2017	288 398	288 398	33 617.2	54 956.6	30 155.4	48 088.3	1906	1665	0	0	34 870	61 276	0.281	0.33
DNK	2016	286 388	286 388	33 800.4	55 359.1	29 776.6	47 327.1	2211	1964	0	0	234 865	470 731	0.293	0.344
DNK	2015	284 083	284 083	32 684.6	53 206.6	29 400.2	46 594.9	2113	1926	0	0	39 972	75 899	0.278	0.328
FIN	2019	9 474	9 474	32 454	43 338.1	28 656	36 774.8	6	4	0	0	20 633	31 912	0.273	0.321

FIN	2016	10 210	10 210	31 194	41 741.9	27 863.5	35 925	2	0	0	0	18 074	28 704	0.261	0.31
FIN	2013	11 030	11 030	30 851.3	40 921.8	27 866.4	35 708.5	5	5	0	0	19 176	28 818	0.263	0.308
FRA	2020	10 244	10 244	30 530.6	33 675.6	26 377.9	27 654.4	75	40	0	0	27 767	37 594	0.321	0.353
FRA	2017	11 197	11 732	33 321.4	35 302.5	29 525.5	30 247.1	44	31	0	0	21 102	26 851	0.276	0.312
FRA	2014	12 035	12 035	28 143	32 280.8	24 706.2	27 228	67	50	0	0	21 598	28 669	0.301	0.331
ITA	2020	6 236	6 239	23 113.6	30 706.1	20 174.2	24 590.5	31	30	0	0	17 553	30 158	0.336	0.394
ITA	2016	7 420	7 420	22 332.1	29 788.1	19 503.7	23 750.5	136	135	0	0	16 065	27 709	0.34	0.4
ITA	2014	8 151	8 156	21 480.3	28 528.9	18 922.1	23 216.5	125	123	0	0	15 310	25 540	0.332	0.389
ITA	2012	8 151	8 151	21 695.5	21 695.5	18 863.4	18 863.4	31	31	0	0	15 219	15 219	0.334	0.334
ITA	2010	7 951	7 951	23 994.6	23 994.6	20 974.3	20 974.3	48	48	0	0	16 080	16 080	0.323	0.323
JPN	2021	4 484	4 487	29 023.5	35 980.9	25 992.2	31 024.2	2	4	0	0	17 330	25 010	0.304	0.332
JPN	2020	5 157	5 161	28 094.4	35 060.3	25 006	29 927.3	7	7	0	0	17 310	25 525	0.308	0.337
JPN	2019	5 777	5 783	27 753.2	34 508.7	25 082.3	29 882.7	6	7	0	0	16 705	24 345	0.306	0.334
JPN	2018	4 085	4 089	28 590	35 341.3	25 388.8	30 384	6	7	0	0	16 205	22 414	0.296	0.321
JPN	2017	4373	4 385	28 201.9	34 930.3	25 139	30 205.4	3	6	0	0	16 082	22 502	0.297	0.325
JPN	2016	4774	4 779	28 668.1	35 278.8	25 732	31 106.3	8	10	0	0	16 343	22 758	0.288	0.315
JPN	2015	5125	5 127	28 578.2	35 141.9	25 398.8	30 525.1	3	5	0	0	16 711	23 238	0.292	0.316
JPN	2014	5471	5 477	28 221.4	34 729.8	25 416.5	30 114.3	6	10	0	0	16 764	23 415	0.295	0.321
JPN	2011	5969	5 970	30 184.7	36 696.4	27 165.9	31 691.4	7	5	0	0	17 230	23 774	0.292	0.316
SVK	2021	0	10 870		21 524.8		19 246.1		15		0		12 416		0.296
SVK	2017	0	10 895		20 701.5		17 269.8		45		0		26 125		0.338
SVK	2014	0	10 675		15 910.5		13 968.6		120		0		13 476		0.323
SVK	2010	0	10 285		14 836.5		13 035.8		35		0		10 813		0.293
SVN	2021	0	9 755		32 178.4		28 504.3		172		0		20 399		0.324
SVN	2017	0	10 070		24 408.9		20 928.6		318		0		19 965		0.391
SVN	2014	12765	12 765	21078	21 078	17 857.2	17 857.2	137	137	0	0	17 373	17 373	0.361	0.361

Source: Authors' calculations based on Luxembourg Wealth Study (LWS) Database (2025_[23]).

Table C.3. Benchmark results

Country	Method	OOS RMSE	Mean	Median	Gini	Financial Fragility Rate (%)
AUS	Original	0	80 520	9 857	0.82	39%
AUS	Group-wise mean	193 600	82 396	22 041	0.74	23%
AUS	Random hot-deck	212 930	81 490	10 000	0.82	43%
AUS	Multiple parametric	202 063	46 500	4 438	0.8	54%
AUS	Random forest	165 182	85 433	33 836	0.66	11%
AUS	EG Boosting	187 073	84 276	27 490	0.66	15%
CAN	Original	0	35 660	9 502	0.77	38%
CAN	Group-wise mean	62 979	28 192	11 593	0.65	16%
CAN	Random hot-deck	69 169	28 782	6 187	0.77	39%
CAN	Multiple parametric	62 047	14 236	4 186	0.7	39%
CAN	Random forest	55 978	28 358	14 167	0.59	7%
CAN	EG Boosting	56 843	27 766	15 412	0.58	0%
DEU	Original	0	21 752	4 243	0.79	43%
DEU	Group-wise mean	89 222	24 110	9 603	0.68	24%
DEU	Random hot-deck	113 176	30 348	5 380	0.82	42%
DEU	Multiple parametric	86 542	6 783	579	0.81	67%
DEU	Random forest	75 602	2 3274	12 278	0.6	15%
DEU	EG Boosting	73 840	23 227	16 840	0.55	0%
DNK	Original	0	295 824	72 934	0.74	42%
DNK	Group-wise mean	443 036	295 344	137 308	0.6	19%
DNK	Random hot-deck	605 774	296 096	74 534	0.73	42%
DNK	Multiple parametric	506 367	170 990	59 116	0.66	45%
DNK	Random forest	472 911	298 696	150 392	0.58	17%
DNK	EG Boosting	453 542	298 479	144 251	0.58	18%
FIN	Original	0	36 144	8 764	0.77	45%
FIN	Group-wise mean	66 254	28 429	11 085	0.66	23%
FIN	Random hot-deck	71 118	27 820	6 693	0.76	44%
FIN	Multiple parametric	65 015	14 381	3 787	0.71	54%
FIN	Random forest	58 571	28 423	13 904	0.6	17%
FIN	EG Boosting	62 171	28 175	12 566	0.57	0%
FRA	Original	0	80 520	9 857	0.82	41%
FRA	Group-wise mean	193 600	82 396	22 041	0.74	23%
FRA	Random hot-deck	212 930	81 490	10 000	0.82	43%
FRA	Multiple parametric	202 063	46 500	4 438	0.8	54%
FRA	Random forest	165182	85 433	33 836	0.66	11%
FRA	EG Boosting	187 073	84 276	27 490	0.66	15%
ITA	Original	0	22 038	5 000	0.76	35%
ITA	Group-wise mean	33 467	16 594	4 500	0.72	22%
ITA	Random hot-deck	37 208	16 377	3 536	0.76	36%
ITA	Multiple parametric	37 002	11 988	1 158	0.8	61%
ITA	Random forest	33 352	17 022	4 618	0.7	16%
ITA	EG Boosting	33 866	16 872	4 633	0.7	18%
JPN	Original	0	6 687 142	2 121 320	0.73	31%
JPN	Group-wise mean	12 308 425	6 675 041	3 216 167	0.62	13%

JPN	Random hot-deck	12 391 300	6 722 142	2 121 320	0.73	31%
JPN	Multiple parametric	22 850 077	3 466 898	78 725	0.93	68%
JPN	Random forest	10 880 887	6 892 655	4 418 139	0.51	1%
JPN	EG Boosting	12 062 303	6 716 330	4 275 153	0.50	0%

Note: Rows with 'Original' in Method represent the actual estimates from LWS datasets. The other rows show the estimates from the imputed data. Mean and median reflect estimates of financial assets in current prices and national currencies. Financial fragility rate represents the estimated percentage of individuals living in households with financial assets below 25% of the national income poverty line. For AUS we pooled the 2020, 2018, 2016, 2014 and 2010 datasets; for AUT 2021 and 2017; for CAN 2019, 2016 and 2012; for DEU 2017 and 2012; for DNK 2021, 2020, 2019, 2018, 2017, 2016, 2015; for FIN 2019, 2016, 2013; for FRA 2020, 2017, 2014; for ITA 2020, 2016, 2014, 2012; for JPN 2021, 2020, 2019, 2018, 2017, 2016, 2015, 2014, 2011.

Source: Authors' calculations based on Luxembourg Wealth Study (LWS) Database (2025^[23]).