BANCA D'ITALIA
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ISSN 1972-6643 (online)

Designed by the Printing and Publishing Division of the Bank of Italy

FINANCIAL WEALTH IN ITALY:
EVIDENCE FROM BANKING SUPERVISORY REPORTS

by Francesco Vercelli*

Abstract

This study analyses some distributive features of household financial wealth in Italy from 2012 to 2023, exploiting Italian Banking Supervisory Reports. For each custodian bank and geographical area, we have information on securities accounts divided into four groups according to their outstanding amounts of financial instruments (debt securities, listed shares, and mutual fund shares). We see that portfolio composition varies across amount brackets and has changed over the period of analysis. We compute indicators of inequality based on the average amounts of financial instruments by bracket, and we find that inequality increased from 2012 to 2021 and decreased thereafter. Finally, we show that the richest class obtains larger capital gains than the other classes, which may be due to higher financial education levels and/or easier access to financial advice services.

JEL Classification: D31, E21, E52, G11.

Keywords: wealth distribution, inequality, portfolio composition.

DOI: 10.32057/0.QEF.2024.0865

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1 Introduction[1]

Wealth inequality has become a major subject of debate among economists. The rising pattern observed in advanced economies has raised concerns about the determinants of such dynamics (Saez and Zucman, 2016; Kuhn et al., 2020). This strand of literature has strongly benefited from the availability of administrative data, which allow studying the top part of the distribution where wealth is highly concentrated. Household surveys, instead, generally suffer from the under-representation of the wealthiest individuals. Moreover, the issue of misreporting and under-reporting of financial assets is more critical for rich households.

An important driver of wealth concentration is the persistence of higher returns at the top of the distribution, as explained theoretically by Benhabib et al. (2011) using an overlapping generation model. Persistence may be due to different choices of portfolio composition, reflecting differences in risk-return profiles across the wealth distribution. However, Fagereng et al. (2020) provide empirical evidence that heterogeneity of returns arises even within narrow components of net wealth. Therefore, there are other relevant factors to take into account other than risk-return profiles: constraints on some forms of investments (e.g., minimum denomination requirements); financial education; access to financial advice services. For a given level of risk, wealthy clients are expected to obtain higher returns and capital gains, since they face fewer constraints on investment choices and generally have access to dedicated advice services. For the Italian case, Cannari et al. (2008) show that capital gains explain a large fraction of the growth of wealth concentration. Frost et al. (2020), using Italian micro data from 1991 to 2020, find that wealthier households achieved higher returns.

This paper exploits administrative banking data from the Italian Banking Supervisory Reports (BSR)[2] to overcome the limitations posed by survey data to a comprehensive appraisal of the distribution of financial wealth and its inequality developments from 2012 to 2023. More specifically, twice a year, custodian banks provide information on their clients, divided into four amount classes according to the amount of holdings in custody.[3] For each bank, geographical area, and amount bracket, we observe the number of clients and the outstanding amounts of financial instruments (debt securities, listed shares, and mutual fund shares) they hold in custody. The source is particularly appealing because it covers the universe of households' holdings, deposited at Italian custodian

[1]The opinions expressed and the conclusions drawn are those of the author and do not necessarily reflect the views of the Bank of Italy and the Eurosystem. I thank Giovanni D'Alessio, Luigi Infante, and Alfonso Rosolia for useful comments on a preliminary version of the paper. I thank Alessio Fiume and Matteo Spuri for help with data.

[2]In this paper we define Supervisory Reports as *administrative data*, stressing their difference from survey data.

[3]In this paper, when we use the expressions *amount class* or *amount bracket*, we refer to the amounts held in custody, which correspond to debt securities, listed shares, and mutual fund shares. These instruments represent nearly one-fourth of the financial assets held by households according to the Financial accounts statistics.

banks. Furthermore, the BSR data, notwithstanding the exclusion of important wealth items (e.g., housing, deposits), allow for distinguishing debt securities, listed shares, and mutual fund shares into around 50 categories.[4]

We analyse the portfolio composition of Italian households by amount bracket and we show that it has changed markedly in the period of analysis. Then, we compute indicators of inequality, which exhibit a significant increase from 2012 to 2021 and a decrease thereafter. Finally, we use a multivariate analysis to test if revaluations of financial instruments are different among amount classes. Consistently with the results in Fagereng et al. (2020) and Frost et al. (2020), we find that the richest class obtains higher capital gains than the other classes, presumably reflecting better financial education and/or easier access to financial advice services.

The rest of the paper proceeds as follows. Section 2 describes the administrative data used in the analysis and compares them with survey data; Section 3 provides stylized facts on portfolio characteristics among different amount classes; Section 4 displays the evolution of several indicators of inequality; Section 5 reports the multivariate analysis on capital gains across classes; finally, Section 6 concludes.

2 Data

Banks provide their clients with securities custody services to manage holdings of debt securities, listed shares, and investment fund shares (SSF, for brevity). These instruments represent nearly one-fourth of Italian households' financial assets (Figure A.1.1, Panel A).[5] Custodian services include all the operations related to the administration of clients' financial instruments, like the receipt of coupons and dividends or the transmission of orders. Italian Banking Supervisory Reports (BSR) include detailed data on securities accounts. Every month, custodian banks transmit the outstanding amounts of SSF held in custody at nominal value by ISIN code, with information on the institutional sector of the holder as well as her province of residence. Every quarter, the BSR contain the same information at market value. Twice a year,[6] at the end of June and December, banks provide the number of clients and the outstanding amounts of SSF at market value by amount bracket of clients' holdings, i.e. by distinguishing clients according to the overall amount of SSF they hold:

1) up to €50,000

3) from €50,000 to 250,000

[4] Unfortunately, granular data at the ISIN level, which would provide more precise information on the choices made by the different clients' asset classes, are not available.

[5] According to the Financial accounts statistics, between 2012 and 2023 on average one-fourth of financial assets consisted of SSF: the percentage decreased from 32% in 2012 to 20% in 2022, and then it slightly increased.

[6] Since December 2022, data are available on a quarterly frequency.

4) from €250,000 to 500,000

5) over €500,000.

Since December 2022, there is a finer partition of the richest class: from €500,000 to €1 million; from €1 million to €5 million; over €5 million. The granularity of the observations by amount class is lower than in the other custodian statistics since SSF are grouped into nearly 50 asset categories, instead of being reported at the ISIN level. The holder institutional sector is less detailed, but still, it allows identifying households.[7] The residency is grouped into 5 geographical areas: North-West, North-East, Center, South, and Isles. Data are available since 2008, but they are fully consistent only from December 2012.

Clients' holdings refer to the SSF that are in custody at the reporting bank. Therefore, if an investor holds securities accounts at different banks, she is counted as many clients as the number of banks at which she holds an account. Moreover, a joint account is not split between holders but is considered as owned by a different client. For example, if two clients have one custody account each and one joint account, the bank reports three different clients. Therefore, although the supervisory statistics are formally based on the definition of *client*, the underlying concept should not be too different from the number of securities accounts.[8] For simplicity, in this paper we generally refer to these statistics as if they were compiled at the securities account level.

Table 1 reports the number of securities accounts by amount bracket for each year between 2012 and 2023 (31st December). The total has declined since 2012, from nearly 12 million to around 9.5, with a minimum of 8.7 in 2021.[9] Most of the accounts belong to the first amount class: in 2023 61% of accounts had SSF holdings lower than €50,000, 30% between €50,000 and 250,000, 5% between €250,000 and 500,000, and 3% over €500,000. The distribution of outstanding amounts, instead, is quite different (Figure 1). According to Table 2, in 2012 accounts with more than €500,000 held 35% of aggregate SSF and the percentage rose to over 42% in 2023. The share of the first class, instead, slightly decreased from 12 to 9%. The outstanding amount of SSF in BSR data represents

[7]Non-profit institutions serving households are generally grouped with households. In the present work, these institutions were excluded in the few cases in which it was possible to identify them.

[8]For example, the two concepts would deliver different results when an individual holds two securities accounts, without any co-holders, at the same bank. This should not be a common behaviour. Indeed, in this case the holder would pay higher fixed costs since Italian banks generally charge fix commissions on securities accounts, depending on the type of financial instrument held in custody (fixed commissions are generally lower if a securities account includes only government bonds, whereas they are higher if it also includes shares). On the other side, securities account contracts also include variable costs related, for example, to the number of orders transmitted by the client. Moreover, taxation is currently computed on a proportional basis (*imposta di bollo).*

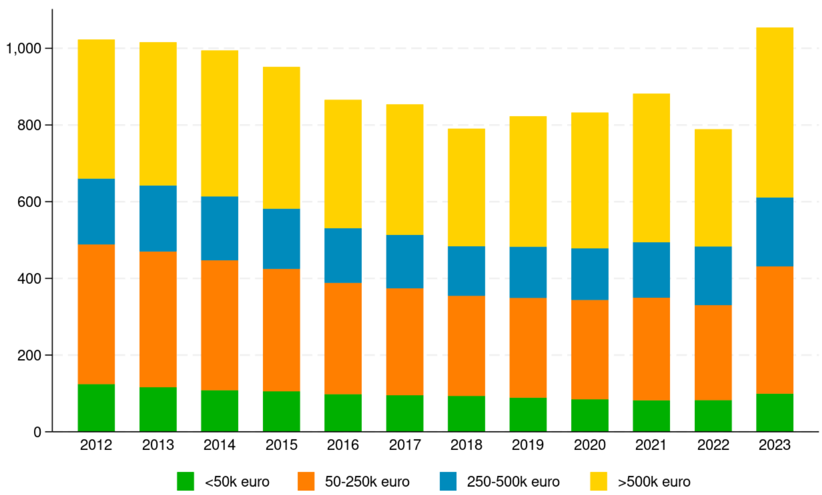
[9]Several factors may help explaining the reduction of the number of clients, which concerned most of the largest Italian banks. For example, part of the decrease may be due to M&As: the same individual is considered as two different clients if she has two securities accounts at two different banks; if the two banks are merged, than the individual is accounted as a unique client. Moreover, between 2012 and 2023 the Italian population reduced by nearly one million.

nearly 80% of the corresponding aggregate in the Financial accounts statistics (Figure A.1.1, Panel B). The difference is mainly due to the Balance of Payments estimates on financial instruments held by Italian households abroad, which do not appear in securities accounts managed by resident banks.

Table 1: Number of securities accounts by amount bracket
(*annual data; 2012-2023; thousands of clients and percentage values*)

Year	<50k	50-250k	250-500k	>500k	Total	<50k (%)	50-250k (%)	250-500k (%)	>500k (%)	Total (%)
2012	7,750	3,365	500	289	11,905	65.1	28.3	4.2	2.4	100
2013	7,257	3,262	501	297	11,317	64.1	28.8	4.4	2.6	100
2014	6,920	3,111	485	297	10,813	64.0	28.8	4.5	2.8	100
2015	6,826	2,925	456	282	10,488	65.1	27.9	4.3	2.7	100
2016	6,680	2,657	414	257	10,007	66.7	26.6	4.1	2.6	100
2017	6,370	2,545	404	255	9,575	66.5	26.6	4.2	2.7	100
2018	6,324	2,380	375	232	9,311	67.9	25.6	4.0	2.5	100
2019	6,000	2,369	388	252	9,009	66.6	26.3	4.3	2.8	100
2020	5,839	2,357	390	257	8,842	66.0	26.7	4.4	2.9	100
2021	5,591	2,405	420	277	8,693	64.3	27.7	4.8	3.2	100
2022	5,847	2,385	395	248	8,875	65.9	26.9	4.5	2.8	100
2023	5,842	2,856	508	328	9,533	61.3	30.0	5.3	3.4	100

Figure 1: SSF by amount bracket
(*annual data; 2012-2023; billions of euros*)



A major source for studying financial inequality in Italy is the Survey on Household Income and Wealth (SHIW). The survey, which has been conducted by the Banca d'Italia since 1965, consists of a probabilistic sample of around 8,000 households selected from population registers. It collects detailed information about the characteristics of the household and of its members (e.g., gender, age, education, job status, dwelling type) as

Table 2: Amounts of financial instruments in custody by amount bracket
(*annual data; 2012-2023; millions of euros and percentage values*)

Year	<50k	50-250k	250-500k	>500k	Total	<50k (%)	50-250k (%)	250-500k (%)	>500k (%)	Total (%)
2012	124,573	364,356	172,012	359,973	1,020,914	12.2	35.7	16.8	35.3	100
2013	116,254	354,570	172,233	369,554	1,012,610	11.5	35.0	17.0	36.5	100
2014	108,615	338,847	166,873	374,085	988,419	11.0	34.3	16.9	37.8	100
2015	105,689	319,446	157,060	361,666	943,860	11.2	33.8	16.6	38.3	100
2016	98,319	290,230	142,534	325,441	856,524	11.5	33.9	16.6	38.0	100
2017	93,778	278,648	139,380	329,234	841,040	11.2	33.1	16.6	39.1	100
2018	91,532	260,746	129,021	295,356	776,655	11.8	33.6	16.6	38.0	100
2019	86,520	259,890	133,587	325,876	805,873	10.7	32.2	16.6	40.4	100
2020	84,835	259,110	134,522	334,505	812,972	10.4	31.9	16.5	41.1	100
2021	82,213	267,418	144,802	361,110	855,542	9.6	31.3	16.9	42.2	100
2022	87,705	264,508	136,202	328,163	816,578	10.7	32.4	16.7	40.2	100
2023	93,203	319,635	175,184	434,756	1,022,777	9.1	31.3	17.1	42.5	100

Financial instruments refer to debt securities, listed shares and investment fund shares.

well as a wider range of financial (and non-financial) instruments than BSR. As already mentioned, according to Financial account statistics SSF represent around one fourth of household financial wealth on average in the period of analysis (Figure A.1.1, Panel B), while household portfolios include other important instruments (available in SHIW) as deposits (30%), unlisted shares and other equity (21%) and insurance products (21%). Data on asset holdings are available as continuous variables, providing information on the entire distribution, instead the BSR statistics group the SSF holdings into amount brackets.

The BSR data consider only households with strictly positive amounts of SSF, whereas the SHIW allows computing SSF inequality including also the households who do not own SSF. As reported in Table 3, in 2020 around one-fifth of Italian households held SSF, and most of them belonged to the richest wealth deciles. In Section 4 we show that including households without SSF holdings does not impact the dynamics of the inequality indicators, but only on their levels.

Table 3: SHIW: Households who hold SSF by wealth decile
(*2020; per cent*)

	Wealth decile										
	1	2	3	4	5	6	7	8	9	10	Total
Holding SSF											
Households without SSF	8.3	8.2	11.2	12.8	9.3	6.7	6.1	5.4	5.1	4.9	78.0
Households holding SSF	0.2	0.1	1.4	1.4	1.1	1.7	2.8	3.0	3.7	6.7	22.0

More importantly, we are generally interested in computing inequality measures at the household level. This is feasible using the SHIW because the sampling unit is the household. The BSR contain data by securities accounts, so the higher the number of accounts per household, the stronger the distortion in interpreting the indicators as household inequality. On one side, as shown in Table 4, the distortion should not be too large: according to the SHIW, in 2020 more than 90% of the Italian households who held SSF owned just one securities account. On the other side, the higher the amount of SSF holdings, the higher the probability of owning more than one account (Table 4).[10] So it is likely that the BSR underestimate the amounts held by the richest households, since securities accounts below €500,000 may belong to households with overall holdings over that threshold. Unfortunately, the SHIW does not provide information on how each household splits SSF across different accounts,[11] so the SHIW does not allow computing an indicator of inequality at the securities accounts level. Therefore, we cannot assess how much inequality measures differ between using household-level data or securities accounts level data, and we are not able to compute a correction term to adjust the estimates from BSR to match household inequality. Nevertheless, since the BSR underestimate the amounts held by the richest households, we can guess that the indicators based on BSR provide lower bounds for household inequality.[12]

Table 4: SHIW: Households who hold SSF by no. of securities accounts and amount bracket
(*2020; per cent*)

	classe				
	<50k euro	50-250k euro	250-500k euro	>500k euro	Total
No. securities accounts					
1	94.0	88.4	81.4	60.6	90.4
2	5.3	10.6	10.8	21.7	7.7
3 or more	0.7	1.1	7.7	17.7	1.9
Total	100.0	100.0	100.0	100.0	100.0

On the other side, BSR data display important advantages compared to the SHIW. First, the SHIW is available every two years and it is generally released nearly one year later, whereas BSR data are semi-annual and are released around one month later. Second, BSR data display a high coverage of the universe of SSF held by Italian households (around 80%) since they do not suffer from zero-reporting, under-reporting, and differential non-response, which seriously affect wealth variables in the SHIW (D'Alessio and Faiella, 2002; D'Alessio and Neri, 2015). Until the 2016 release, the coverage, i.e. the ratio of aggregates obtained from the SHIW to those observed in BSR, is around one-third in terms of the outstanding amounts.[13] As shown in Figure 2, the coverage of outstanding amounts is particularly low for the richest class. In the 2020 release, instead, thanks to methodological changes to improve the statistical coverage of high-income households, the number of securities accounts obtained through the survey is around 75% of the one observed in the BSR data, whereas in terms of outstanding amounts the two sources provide almost the same figures. The coverage for the richest class exceeds 100%, which can be consistent with the BSR underestimation of the amounts held by this class, as

[10] In the SHIW we cannot observe if these accounts are held at the same bank or not.

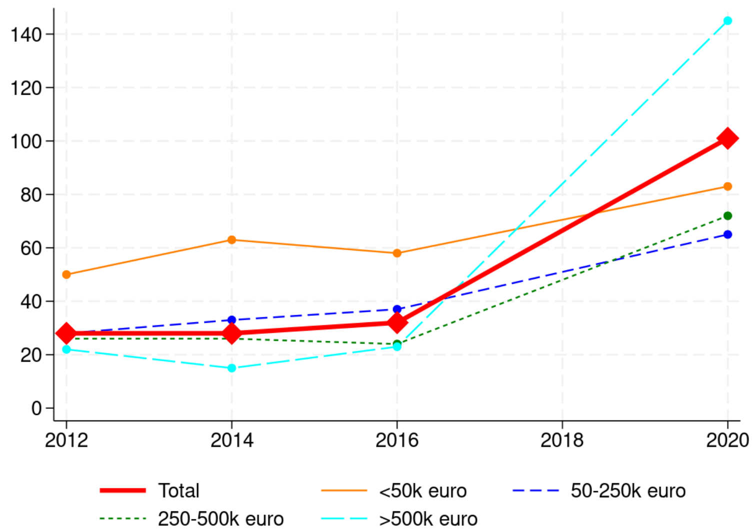
[11] Concerning deposit accounts, the 2020 release of the SHIW reports that Italian households keep more than two-thirds of their deposits in their main account. However, we cannot assume a similar percentage for securities accounts, which are less widespread among Italian households and are held for different purposes than deposit accounts.

[12] We refer to inequality measured among households having at least one securities account.

[13] The coverage is low also in terms of the number of securities accounts.

previously discussed. Therefore, although the SHIW has recently undergone relevant improvements in coverage, it remains farther than BSR from the national aggregates for most of the period under analysis.

Figure 2: SSF by amount bracket: SHIW aggregates over BSR aggregates
(*2012-2020; per cent*)



3 Household portfolios across amount classes

Although BSR data do not allow to analyse the entire portfolio of financial assets,[14] they represent a unique statistical source for studying distributional features of financial household wealth, distinguishing between several categories of financial products. In the period of analysis, the overall amount of ordinary non-government bonds held by households dropped by nearly ten times, from €300 billion to €31 billion, whereas mutual fund shares became a major component of SSF, rising from €185 billion to €474 billion (Figure 3). Government bonds decreased until 2021, and then they almost doubled in 2023. These dynamics concern all the amount classes, but with some distinctions. In 2012 most of the non-government bonds were owned by the second class, characterized by holdings between €50,000 and €250,000; since then, this class – like the first one – has markedly decreased bond holdings and has increased investments in both Italian

[14]For example, in the period of analysis households accumulated large amounts of deposits, which are not included in the BSR data used in the present study. As shown by Neri et al. (2024), deposits are quite widespread among clients in the left part of the wealth distribution. Probably, clients in the first and second classes, whose joint share of SSF reduced from 47.8% to 40.4%, may have increased deposits. Unfortunately, as already mentioned in Section 2, BSR statistics do not allow for a joint analysis of the entire household financial portfolio.

and EU investment fund shares. However, while Italian fund shares are mostly held by the second class, EU investment fund shares are mostly held by the richest one. Households in the top amount bracket also account for a large share of the government bonds, ordinary shares and other financial products.

Figure 3: SSF instruments by amount bracket
(*annual data; 2012-2023; billions of euros*)

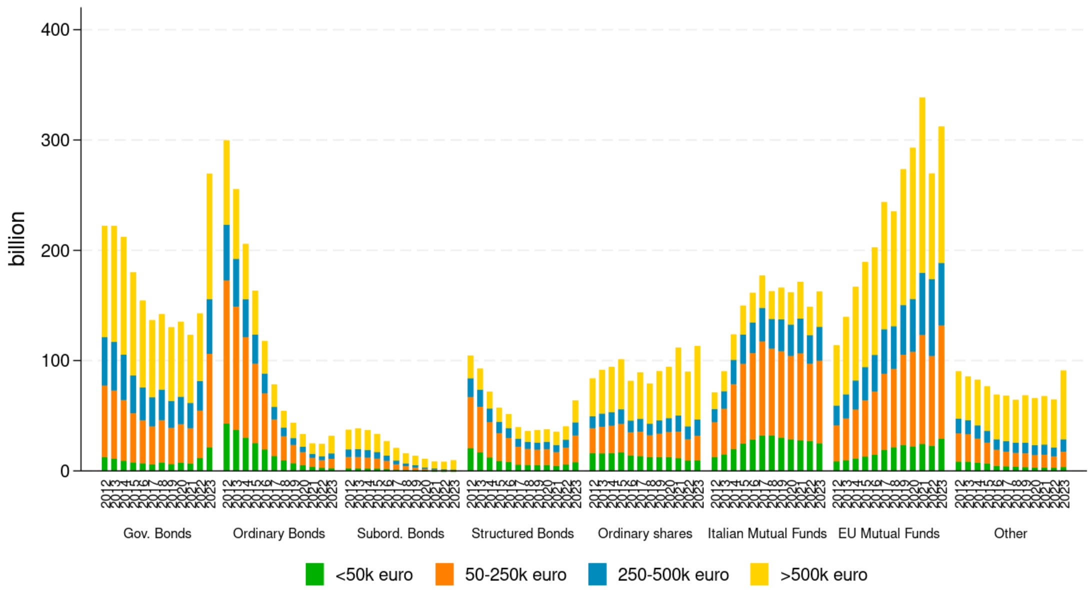
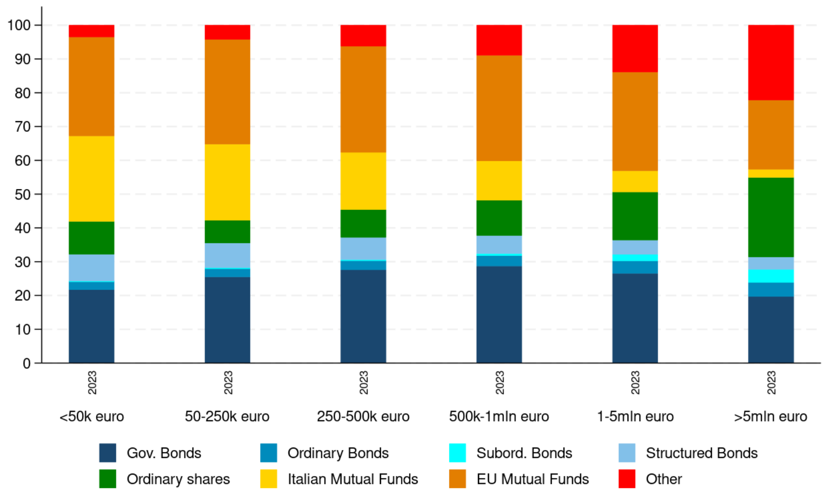


Figure 4 reports the portfolio composition by amount class in 2023, exploiting the finer breakdown of amount classes available since 2022. The relationship between the share invested in government bonds and the amount classes displays an inverted U-shaped pattern: the share increases from 21.7% for the first class (with SSF holdings below €50,000) to a maximum of 28.7% for the class with outstanding amount between €500,000 and €1 million, and then decreases to 19.7% for the class with more than €5 million. Investments in mutual fund shares decline with overall SSF holdings, from 56.1% for the first class to 30.6% for the richest class. However, this reduction concerns only Italian mutual fund shares, whereas the share invested in EU mutual funds remains around 30% until the class with SSF between €1 billion and €5 billion.[15] Ordinary shares represents a large fraction of rich households' portfolios, reaching almost one-fourth of the overall SSF for the richest class. Moreover, for this class nearly one-fifth of the portfolio consists of other financial products, like ETF (Exchange traded funds) and securitizations. A special note regards the first class, which owns more

[15]EU mutual fund shares include the so-called round-trip mutual funds, i.e. foreign funds under the control of Italian financial intermediaries. These funds are generally settled in EU countries other than Italy, especially in Luxembourg and Ireland, to exploit lighter taxation and less stringent regulation.

ordinary shares and less government bonds than the second class, contrasting with the expectation that less affluent households should prefer simple financial instruments, like bonds. Nevertheless, for the households in the lower part of the wealth distribution SSF represent only a small fraction of their financial wealth, which is mainly composed of deposits (Bank of Italy, 2022). Moreover, a part of the amounts recorded in this class may refer to richer households who hold more than one securities accounts and may use different accounts for different financial instruments. For example, since financial advice is particularly useful for riskier instruments, like ordinary shares, households may hold these investments at banks specialized in advising.

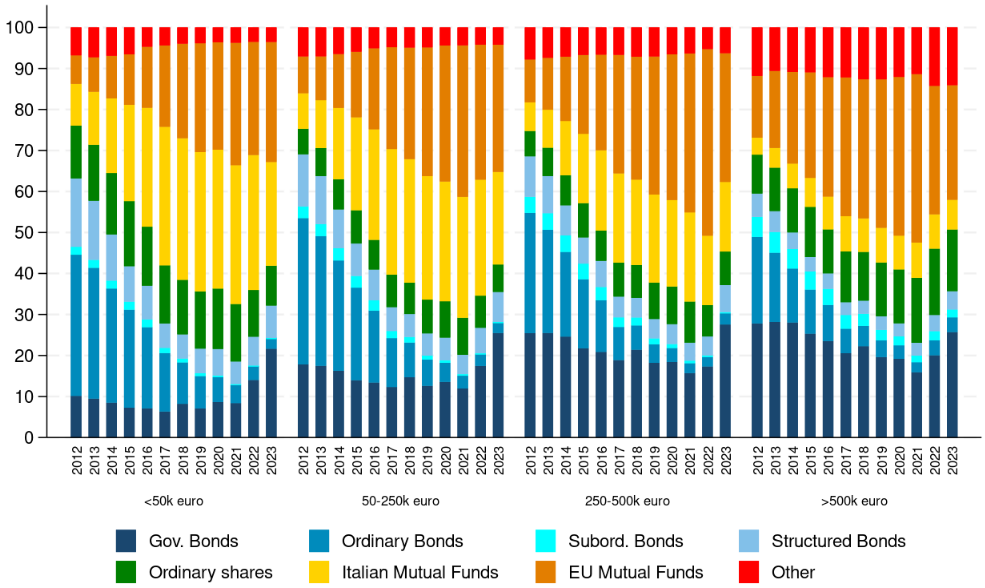
Figure 4: Portfolio composition by amount bracket
(*2023; per cent*)



The portfolio composition by amount class has changed in the period of analysis (Figure 5). Debt securities other than government bonds represented more than half of the portfolio of the first two classes in 2012; the percentage dropped impressively until 2021, to around 10%, a similar level for all the amount classes. They were substituted by investment fund shares, whose ratio to SSF tripled for the first two classes in few years, between 2012 and 2018. This substitution between debt securities and investment fund shares emerges in the richer classes as well. Until 2020, the first class has devoted a larger fraction of SSF to ordinary shares (14.5% on average) than the other classes, especially the second and the third ones. However, while in this period the percentage was almost stable for the first class, it has increased for the other classes, especially for the richest one (from 10.2% in 2012 to 13.6% in 2020). Then, in 2023 the ratio of ordinary shares to SSF dropped below 10% for the first class, like for the second and the third ones, while it further increased to 15.5% for households with SSF outstandig amounts over €500,000.

Figure A.1.2 reports the portfolio composition of other institutional sectors, according to SHS data, using the same asset categories of Figure 5. The high percentage of EU mutual fund shares, as well as of government bonds at the beginning of period analysed, makes the portfolio composition of the richest class more similar to that of other institutional sectors, like investment funds, insurance companies and pension funds. This seems to suggest that the richest households are able to align the risk-return profile of their investments to the one of institutional investors, for example thanks to better financial education and easier access to financial advice services, like individually managed portfolios.

Figure 5: Portfolio composition by amount bracket
(*annual data; 2012-2023; per cent*)

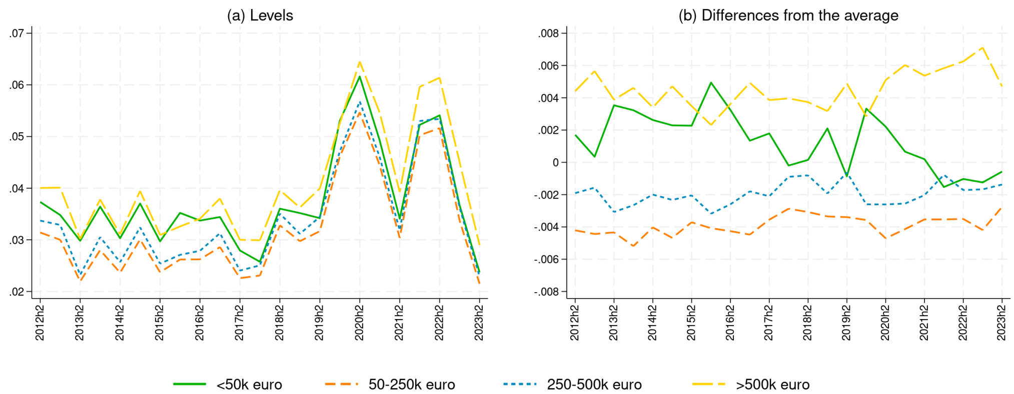


In order to assess portfolio riskiness, we compute an indicator of price volatility by amount bracket. In particular, we obtain the coefficient of variation of the prices underlying the financial instruments held by each class, as described in Appendix A.2, by exploiting the Centralised Securities Database (CSDB)[16]. As shown in Figure 6, the coefficient of variation displays a similar pattern for all the classes, with two spikes, the first related to the Covid-19 pandemic and the second to the tighter monetary policy stance in 2022 (Panel A). Visually, to compare the coefficient of variation across classes, for each semester we show the difference between the coefficient of variation of a class

[16]The CSDB is managed by the European System of Central Banks and contains granular information at the ISIN level on the main characteristics of securities, such as the issued amount, the issuing sector, the dates of emission and reimbursement. Among the available variables, the CSDB allows keeping track of the evolution of prices for each security.

and the average among the classes (Panel B). It comes to light that the class with more than €500,000 displays the riskiest portfolios, followed by the first class with less than €50,000. For the richest class it could suggest lower risk aversion, and for the first one higher difficulty in achieving risk diversification due to the low level of the invested amounts. Nevertheless, as previously explained, since households in the lowest part of the wealth distribution devote a larger fraction of their portfolio to deposits than richer ones Neri et al. (2024), the high riskiness of the SSF portfolio of the first class may be counterbalanced through holdings of other safer instruments like deposits. More importantly, the high level of riskiness observed for the first class may be due to the amounts belonging to richer people with more than one securities accounts.

Figure 6: Portfolio volatility by amount bracket: Coefficient of variation of prices (weighted average)
(*semi-annual data; 2012-2023*)



4 The evolution of SSF inequality

The estimate of inequality generally requires the availability of household surveys. Each interviewed household is associated with a sampling weight that allows the assessment of inequality in a target population. In the literature on world income distribution, because of the absence of harmonized surveys across all the countries, researchers have developed alternative strategies to study inequality. Bourguignon and Morrisson (2002) observe GDP, population, and national income shares. Thanks to this information, they compute the number of people and their per capita incomes by country and income quantile. In other words, they obtain a dataset in which the unit of observation is the income quantile of a country, the observed quantity is the average income and the observation weight is the number of people belonging to that quantile. They compute measures of world income inequality using this dataset, in a similar way to what they would have done using survey data.

Our exercise is similar to the one by Bourguignon and Morrisson (2002). As explained in Section 2, for every reporting bank and geographical area we observe the number of securities accounts in a specific amount bracket and the aggregate of SSF held in custody in those accounts, so that for each bracket we can compute the average holdings of SSF by account. Therefore we construct a dataset where the unit of observation is an amount class for a reporting bank and a geographical area, the observed quantity is the average amount of SSF holdings and the weight associated with this observation is the number of securities accounts. Using this dataset we compute several inequality indicators, weighing each observation by the respective number of accounts. Under the assumption that Italian households have at most one securities account, these indicators are proxies of SSF household inequality. As explained in Section 2, this assumption is quite reasonable since, among Italian households with positive amounts of SSF holdings, the percentage of those who own just one securities account is very high (more than 90% in 2020). Nevertheless, we expect that the indicators obtained through BSR data provide a lower bound of household inequality because rich households generally own more than one securities account.[17]

Figure 7 shows the nine indicators of SSF inequality that we calculate:

- the Gini coefficient;
- the percentile ratio between the 90th percentile and the 10th (p90/p10);
- the percentile ratio between the 75th percentile and the 25th (p75/p25);
- four Generalized Entropy (GE) Indices ($\alpha = -1; 0; 1; 2$);[18]
- two Atkinson Indices ($\epsilon = 0.5; 2$).[19]

[17] It represents a lower bound also with respect to the inclusion of households without any holdings of SSF.

[18] The members of the Generalized Entropy class follow this general formula:

$$I_\alpha(x) = \left(\frac{1}{\alpha(\alpha-1)}\right)\left[\left(\left(\frac{1}{N}\right)\sum_{i=1}^{N}\left(\frac{x_i}{\mu}\right)^{\alpha}\right) - 1\right]$$

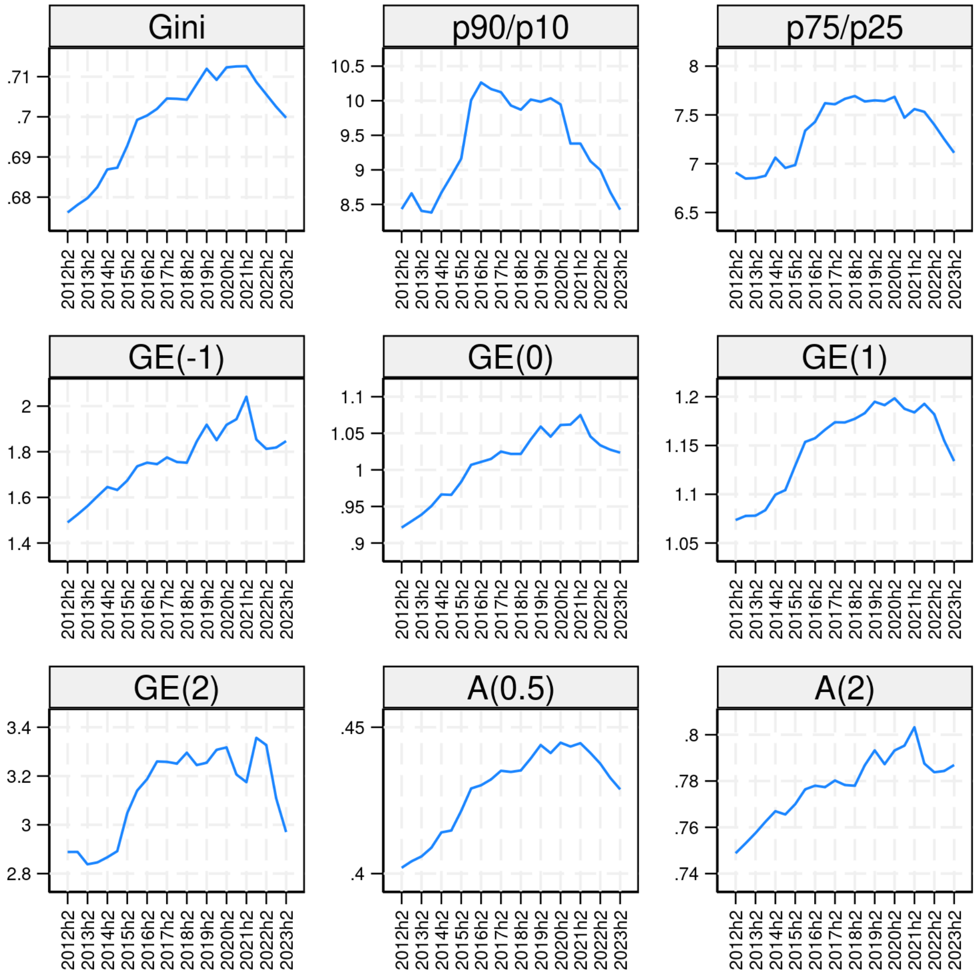
where N is the total population, x_i is the income of individual i and μ is the mean income. The parameter α represents the weight given to distances between incomes at different parts of the distribution and it can take any real value. Low values of α give more importance to differences in the lower tail of the distribution, whereas high values stress the dispersion in the upper tail. The Generalized Entropy indexes correspond to: the Theil's L index (mean logarithmic deviation) when α tends to 0; the Theil's T index when α tends to 1; half the square of the coefficient of variation when α is equal to 2.

[19] The formula of the general Atkinson Index is:

$$A_\epsilon(x) = 1 - \left[\left(\frac{1}{N}\right)\sum_{i=1}^{N}\left(\frac{x_i}{\mu}\right)^{1-\epsilon}\right]^{\frac{1}{1-\epsilon}}$$

where N is the total population, x_i is the income of individual i and μ the mean income. ϵ, taking values between 0 and $+\infty$, represents the degree of inequality risk-aversion; the higher it is, the more people are averse to inequality.

Figure 7: SSF inequality
(*semi-annual data; 2012-2023*)

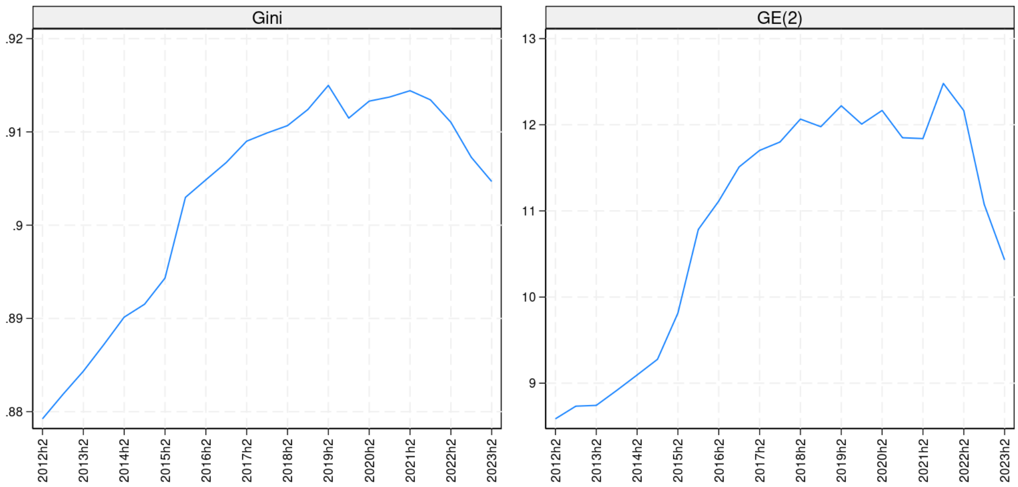


All the indicators show an increasing pattern between 2012 and 2021, which is generally almost linear, followed by a decline starting in 2022. Three measures – p90/p10, p75/p25, and GE(2) –, instead, display a slightly different pattern. They rise fast between 2014 and 2016, they remain almost stable for few years, and then they drop markedly. These three indicators are more sensitive to changes at the top of the distribution and so can be more affected by the structure of the available data, grouped by amount brackets. Indeed, inequality is affected both by the average value of SSF holdings in each amount bracket and by the number of accounts used as weights in the computation of the inequality indicators. The average amount in each of the first three classes tends to be quite stable since the brackets are bounded, whereas the fourth one (over

€500,000) displays stronger variability since it's unbounded. Changes in the bottom and the central parts of the distribution mostly depend on the variation in the number of accounts in each class, whereas the top of the distribution may capture changes both in average holdings and number of accounts. This explains why the p90/p10, the p75/p25, and the GE(2) may provide a slightly different pattern with respect to the other measures.

The inequality indicators computed above only consider households with strictly positive amounts of SSF holdings. According to the SHIW, in 2020 around 78% of Italian households do not hold SSF. As a rough exercise, we include these households in the computation of the Gini indicator and the GE(2), which are suited for including observations with zero values (Figure 8). As expected, for both indicators the levels of inequality are higher than the estimates in Figure 7, but the rising dynamics are similar, with a more gradual increase of GE(2) between 2014 and 2018.

Figure 8: SSF inequality: including Italian people without SSF holdings
(*semi-annual data; 2012-2023*)

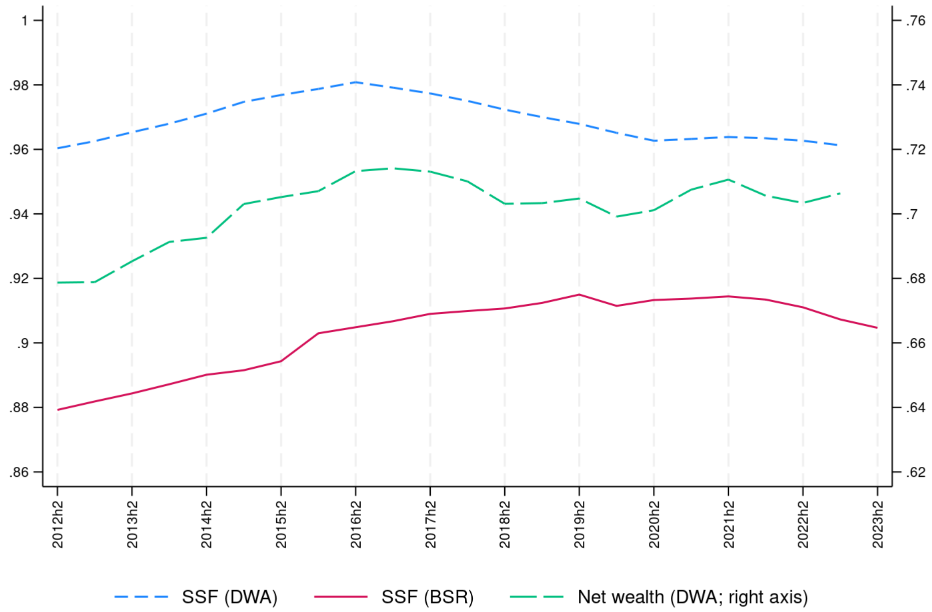


First, we compare our results with the evidence from the SHIW (Figure A.1.3). We compute the same nine indicators of inequality using the SHIW and applying the same definition of SSF (debt securities, listed shares, and investment fund shares). While all the indicators increase in the period of analysis as in the estimates based on the BSR data, the pattern is different. Most of them display a reduction of inequality between 2012 and 2014 and a subsequent rise, particularly marked in 2020. The contrasting results obtained from the SHIW may reflect the issues of zero-reporting, under-reporting and differential non-response outlined in Section 2, which do not affect administrative data like the BSR.

Second, we compare our estimates with the new experimental statistics of the Distributional Wealth Accounts (DWA), compiled by the Bank of Italy since January 2024 (Neri et al., 2024). The DWA provide quarterly information on the distribution of household wealth, combining national accounts aggregates from balance sheets with survey data from the Household Finance and Consumption Survey (HFCS) – the harmonized survey on household finances in the euro area countries, which incorporates the Bank of Italy's SHIW. The DWA methodology tries to face the issues of under-reporting and differential non-response, which affect micro surveys. The DWA include information on the portfolio composition by decile of the net wealth distribution, as well as some inequality indicators like the Gini index in terms of net wealth (Figure 9). By exploiting the microdata underlying the DWA statistics, it is possible to compute the Gini indicator in terms of SSF. These instruments are more concentrated than the overall net wealth (around 0.97 and 0.70, respectively). The Gini index computed using BSR data – adjusted for including observations with zero holdings of SSF – is very high too (around 0.90). The level is slightly lower than in the DWA and this confirm the expectation suggested in Section 2 that BSR data provide lower bounds for household inequality, since they underestimate the amounts held by the richest households. According to the DWA, the Gini index increased until 2016, reaching a maximum of 0.98, then declined to 0.96 in 2020 and it stabilized around that level. The dynamics according to the BSR data are slightly different, with an increase more intense until 2019, and a decline starting in 2022. It is worth noting that the DWA series after the last available release of the HFCS only reflect the dynamics of macroeconomic aggregates.[20]

[20]Furthermore, the DWA methodology estimates both the overall net wealth of the richest households (the so called *added rich*), which are not always captured in surveys, and its composition. More details can be found in Neri et al. (2024).

Figure 9: Gini index: BSR vs DWA
(*2012-2023*)



Using BSR data it is possible to analyse the evolution of SSF inequality also from a geographical perspective. In Figure A.1.4 we decompose inequality into the between geographical area inequality component and the within component. We focus on 6 indicators, those allowing for perfect decomposition of inequality (Generalized entropy indices and Atkinson indices). The between component is very low, generally around 0.5-1.0% of total inequality: most of the overall inequality is explained by the within geographical area differences. Both components display an increasing pattern, with some specificities. Using the Generalised entropy indices, the between component has a roughly linear increasing pattern, with a decrease starting in 2022. The rapid growth of GE(2) displayed in Figure 7 after 2014 is driven by the within component. Using the Atkinson indices the rise of the between component is faster after 2017. Financial inequality rises in the period of analysis in each geographical area, before starting decreasing in 2022 (Figure A.1.5). In terms of levels, however, there are differences across areas and indicators. Most indicators reveal higher inequality in the North-West and the Center, and lower in the North-East and the South. Instead, the GE(2), which is better able to capture changes at the top of the distribution, shows higher levels for the Center. However, it markedly suffers from the BSR data structure, as it happens for the p90/p10 and the p75/p25.[21]

[21] In particular, the quantiles used for computing these measures are more volatile when focusing on a lower number of observations, as it happens when studying distinct geographical areas.

The BSR data provide information by amount class at the bank and geographical level. In Figure A.1.6 we show how the estimates of inequality would change if we had less granular information, for example with different levels of aggregation of the amount brackets. The benchmark level of aggregation is the most granular available, where classes are observed by time, bank, and geographical location as in Figure 7. The least granular estimation is obtained by collapsing all the observations by amount bracket and time so that for each semester we only observe four data points (one for each bracket at the national level). The other two aggregation levels are obtained by collapsing observations by time and geographical area or by time and reporting bank. If we collapse all observations by bracket and time, the level of the Gini coefficient is lower than in the benchmark case, but the dynamics are identical. The geographical variability has almost no impact on the estimates, whereas bank granularity determines higher levels of inequality. The Gini coefficient mostly captures variations in the middle part of the distribution, which depends less on the fourth bracket in BSR data. Since the average SSF holdings of the first three brackets are similar across different reporting banks, granular data do not add relevant information for the computation of this indicator. A similar reasoning applies to the other measures, except to those that strongly depend on the top part of the distribution, like p90/p10, p75/p25, and GE(2). For these three measures, using granular data at the bank level crucially changes the inequality dynamics.

Our estimation method attributes average values of SSF to the securities accounts belonging to the same amount bracket. Ideally, we would like to derive a more realistic distribution of SSF within each bracket. In the literature on world income inequality, the method by Bourguignon and Morrisson (2002) has been improved using either parametric (Chotikapanich et al., 2012) or non-parametric (Sala-i-Martin, 2006) techniques. In our case, since we are studying the distribution of financial assets instead of incomes, we might expect that the right tail could be approximated by the Pareto distribution after a certain threshold. However, it is not straightforward to obtain reliable estimates of the Pareto curve with the available bank data at the bracket level. Moreover, the usage of average amounts of SSF may be less stringent in our exercise than in Bourguignon and Morrisson (2002) because our dataset includes almost 5,000 observations per period on average, while the world distribution of income is estimated using fewer observations (quintiles at the country level).[22]

5 Capital gains across amount classes

The changes in the outstanding amounts underlying the observed increase of inequality (Figure 7) are due either to transactions (savings invested in financial instruments) or to other price changes, in particular capital gains (revaluations). The flow of savings invested in financial instruments may differ across the wealth distribution, as well as the ability to select financial products with higher revaluations. As reported in the

[22] On the other side, income shares are better indicators of location than groups based on fixed brackets.

Introduction, there is empirical evidence that capital gains explain a large fraction of the growth of wealth concentration in Italy and that wealthier households achieve higher returns (see Cannari et al., 2008; Frost et al., 2020).

The BSR data by bracket only report outstanding amounts at market values, without any information on transactions and revaluations. We obtain 6-month percentage price revaluations at the ISIN level from the CSDB and we compute the weighted average of these percentages at the bracket level using as weight an estimate of the portfolio share invested in each single ISIN, following the same procedure adopted for the price volatility indicator in Section 3. We interpret this average as an aggregate index of revaluation at the bracket level. The results are shown in Figure 10. The first class generally reports more extreme revaluations, both positive and negative, especially between 2014 and 2018. Instead, the richest class generally obtains higher revaluations than the average, in line with Frost et al. (2020). Since 2019, the capital gains obtained by the richest class have mostly been higher than those obtained by the other classes.[23]

Figure 10: Semi-annual percentage capital gains/losses (revaluations) by amount bracket
(*semi-annual data; 2012-2023*)

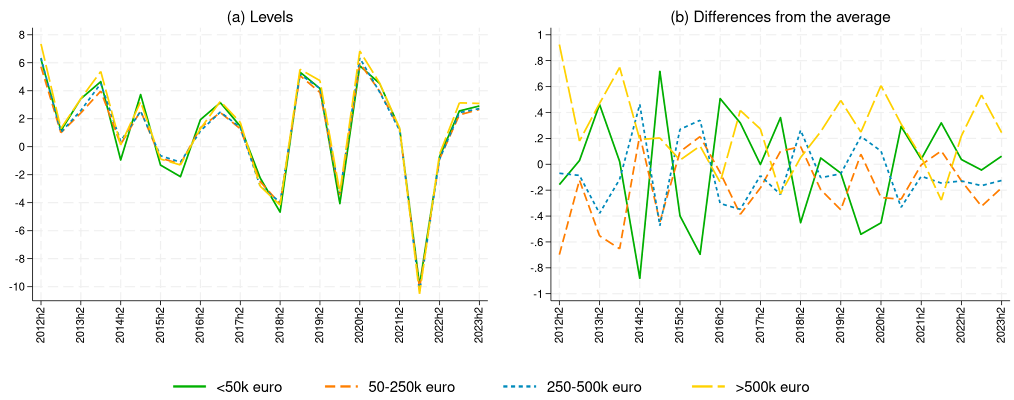


Figure 10 does not provide a clear result on the ability of the different classes to obtain positive capital gains. Moreover, higher capital gains may reflect different attitudes towards risk, as suggested by the coefficients of variation in Section 3. Therefore, in the same spirit of Fagereng et al. (2020), we adopt a multivariate analysis to investigate more carefully how percentage price revaluations vary across amount brackets. We regress the percentage average 6-month revaluations at the most granular level (reporting bank, geographical area, amount bracket) on dummies for the four asset classes.

[23]Higher capital gains do not directly reflect actual higher returns to households because they do not include commissions and fees. As previously explained in Section 2, commissions on securities accounts generally differ depending on the types of financial products held in custody. Differences in commissions and fees are particularly relevant when analysing the performance of mutual funds.

The omitted dummy on clients' classes is the one identifying the richest class (greater than €500,000) so a negative coefficient on the other dummies indicates lower returns than in the richest class. We control for macroeconomic effects through time dummies. We use the random effects estimator to allow for individual unobserved heterogeneity, such as the time-invariant component of the risk profile[24]. We control for portfolio characteristics through the lagged portfolio shares of different types of assets (government bonds, other bonds, listed shares, mutual fund shares). In this way, the coefficients on the class dummies are not influenced by differences in portfolio composition but reflect the revaluations obtained by choosing specific instruments among these broad types of assets. For example, a rich client may be able to select specific mutual fund shares with higher performance thanks to financial advice services.

The main results are reported in Column (1) of Table 5. The coefficients on the first, second, and third class dummies are negative and statistically significant, indicating that these classes have been less able to invest in the assets with the best price performances than the richest one. Since we are broadly controlling for the risk profile and the portfolio composition, possible explanations of this result include that the richest clients have higher financial education and/or easier access to financial advice services.[25] Based on these explanations, we might expect that the relationship between capital gains and SSF holdings is positive and monotone. Instead, the estimates show a U-shaped curve, with the first class obtaining higher capital gains than the second one. However, this might reflect that part of the amounts recorded in the first class actually refer to richer households, who hold more than one securities accounts.

In Column (2) we add the indicator of price volatility introduced in Section 3 to provide an additional control for the risk profile. The coefficient is positive, indicating that higher risk is associated with higher capital gains. The coefficients on the dummy variables reduce in absolute values but remain negative and statistically significant, confirming that the richest class is more able to attain higher holding gains. In this specification, the coefficients on portfolio composition related to listed shares and government bonds turn negative.[26] In Column (3) we split the ratio of mutual fund shares to total SSF into two components, Italian mutual funds, and EU mutual funds. As described in Section 3, the mutual funds held by the richest class mainly consist of EU mutual funds, whereas the opposite holds for the first two classes (Figure 5). All else equal, we find that the holding gains are larger for EU mutual fund shares than for the Italian ones.[27] In Column (4) we include all the interactions between time and port-

[24] The Breusch-Pagan LM test suggests that the RE estimator is preferred to the OLS one. Anyway, the OLS coefficients are coherent with the results obtained through RE.

[25] Of course, we would like to control also for other demographics, as in Fagereng et al. (2020). However, the BSR data do not contain other information on clients except for the bank at which they hold a securities account, the area of residence, and the amount class.

[26] Both the percentage revaluation and the price volatility indicator are built using the CSDB prices, which may create some concerns on using the latter variable among the controls.

[27] As already explained, capital gains do not directly reflect actual returns because they do not consider commissions and fees.

Table 5: Determinants of revaluations

	(1)	(2)	(3)	(4)	(5)
	6m reval	6m reval	6m reval	6m reval	6m reval
	b/se	b/se	b/se	b/se	b/se
<50k euro	-0.1565***	-0.1098***	-0.1298***	-0.1107***	
	(0.0278)	(0.0247)	(0.0281)	(0.0288)	
50-250k euro	-0.2095***	-0.1081***	-0.1973***	-0.1694***	
	(0.0253)	(0.0223)	(0.0254)	(0.0256)	
250-500k euro	-0.1241***	-0.0752***	-0.1109***	-0.0984***	
	(0.0258)	(0.0223)	(0.0258)	(0.0257)	
Mutual Funds (% portf.) (lag)	0.0117***	0.0066***			0.0116***
	(0.0004)	(0.0004)			(0.0004)
Gov. Bonds (% portf.) (lag)	-0.0013***	-0.0040***	-0.0024***		-0.0012***
	(0.0004)	(0.0004)	(0.0004)		(0.0004)
Listed shares (% portf.) (lag)	0.0147***	-0.0000	0.0139***		0.0147***
	(0.0008)	(0.0007)	(0.0008)		(0.0008)
Price volatility (12 months)		23.7596***			
		(0.7887)			
IT Mutual Funds (% portf.) (lag)			0.0011		
			(0.0007)		
EU Mutual Funds (% portf.) (lag)			0.0150***		
			(0.0006)		
Mean assets (log) (lag)					-0.3607***
					(0.1121)
Mean assets (log; squared) (lag)					0.0168***
					(0.0047)
Constant	0.6655***	0.1332***	0.7210***	0.7959***	2.4064***
	(0.0298)	(0.0332)	(0.0298)	(0.0279)	(0.6575)
R^2	0.565	0.577	0.564	0.676	0.564
Time F.E.	YES	YES	YES	NO	YES
Bank-Area F.E.	YES	YES	YES	YES	YES
Time-Portaf interactions	NO	NO	NO	YES	NO
No. Banks/Area	7563	7563	7563	7563	7561
Observations	98668	98668	98668	98668	98651

Variables are symmetrically winsorized at the 2.5% level by year.
*, ** and *** denote respectively a 10, 5 and 1 per cent significance level.

folio composition to control for any time-varying impact of clients' investment choices. The coefficients on the class dummies remain negative and statistically significant. In Column (5) we substitute the class dummies with log mean assets, including a quadratic term: the relation is confirmed U-shaped because the lowest revaluations are observed in the central part of the distribution (especially for the class ranging from €50,000 to €250,000).

6 Conclusions

In this paper we investigate distributive features of financial wealth in Italy from 2012 to 2023, exploiting administrative data from the Italian Banking Supervisory Reports (BSR). We observe for each custodian bank and geographical area the number of securities accounts and the outstanding amounts of financial instruments (SSF, i.e. debt securities, listed shares, and mutual fund shares) held in custody divided into amount brackets. Although survey data allow for studying the joint distribution of a larger set of instruments (e.g., housing, deposits) without grouping observations by bracket, the BSR data are highly reliable, especially for the top distribution, and are available at a higher frequency.

We show that the portfolio composition varies along the distribution of SSF holdings and markedly changed between 2012 and 2023. For example, the richest class invests more in listed shares, whereas the fraction of the portfolio devoted to mutual funds decreases with SSF holdings. The increasing relevance of mutual funds observed in the financial accounts since 2012 and the corresponding drop of debt securities have involved all the amount classes. We find that inequality on SSF instruments has increased until 2021 and then started decreasing. The levels of inequality are generally higher in the North-West and the Center, but the dynamics are similar across geographical areas. Finally, we find that the richest class obtains larger holding gains than the other classes, which may be due to higher financial education and/or easier access to financial advice services.

The administrative data from securities accounts by amount bracket described in this paper may turn useful in refining the compilation of the Italian Distributional Wealth Accounts (DWA), which combine survey data and national accounts to provide distributional statistics on overall household wealth. To correct under-reporting issues that affect the survey data, calibration techniques based on BSR data may be used to improve DWA statistics. This is left for future research.

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Appendix

A.1 Tables and figures

Table A.1.1: SSF by asset range: a comparison between BSR and the SHIW
(*millions of euros and per cent*)

Year	Asset range	SHIW		BSR		SHIW/BSR
		€million	per cent	€million	per cent	per cent
2012	<50k €	62,706	22	124,572	12	50
	50-250k €	103,362	36	364,356	36	28
	250-500k €	44,220	15	172,011	17	26
	>500k €	77,532	27	359,973	35	22
	Total	287,820	100	1,020,912	100	28
2014	<50k €	68,769	25	108,615	11	63
	50-250k €	113,346	41	338,847	34	33
	250-500k €	42,606	15	166,872	17	26
	>500k €	54,666	20	374,085	38	15
	Total	279,387	100	988,419	100	28
2016	<50k €	57,384	21	98,319	11	58
	50-250k €	107,733	39	290,229	34	37
	250-500k €	33,702	12	142,533	17	24
	>500k €	75,711	28	325,440	38	23
	Total	274530	100	856,521	100	32
2020	<50k €	70,791	9	84,834	10	83
	50-250k €	169,581	21	259,110	32	65
	250-500k €	96,978	12	134,523	17	72
	>500k €	485,214	59	334,506	41	145
	Total	822,564	100	812,973	100	101

Figure A.1.1: Comparison with Financial account statistics
(*annual and semi-annual data; 2012-2023*)

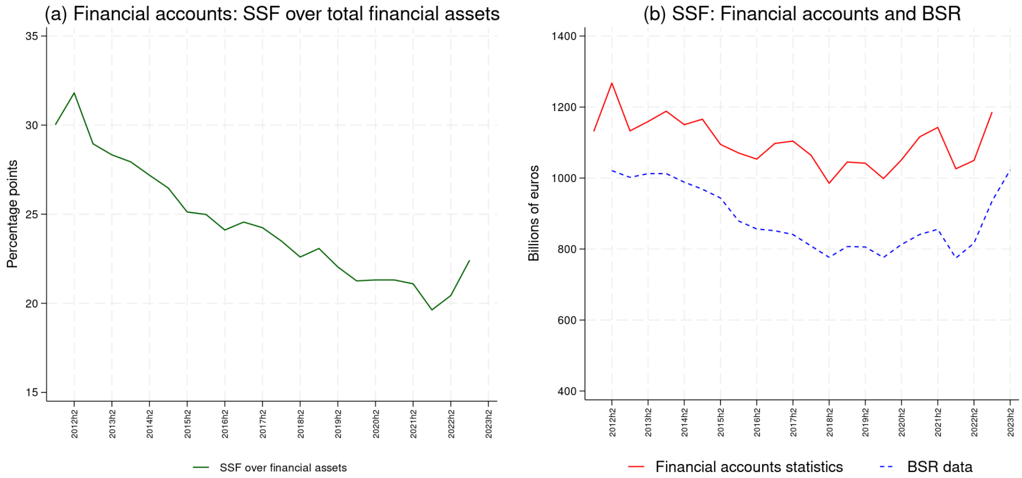


Figure A.1.2: Portfolio composition by institutional sector (SHS data)
(*annual data; 2012-2023; per cent*)

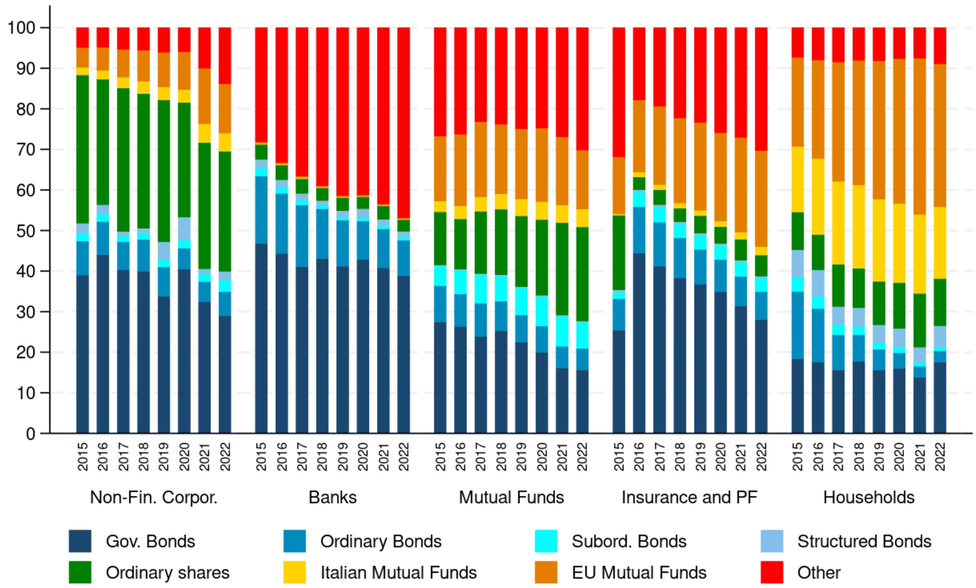


Figure A.1.3: SSF inequality according to SHIW
(*biannual data; 2010-2020*)

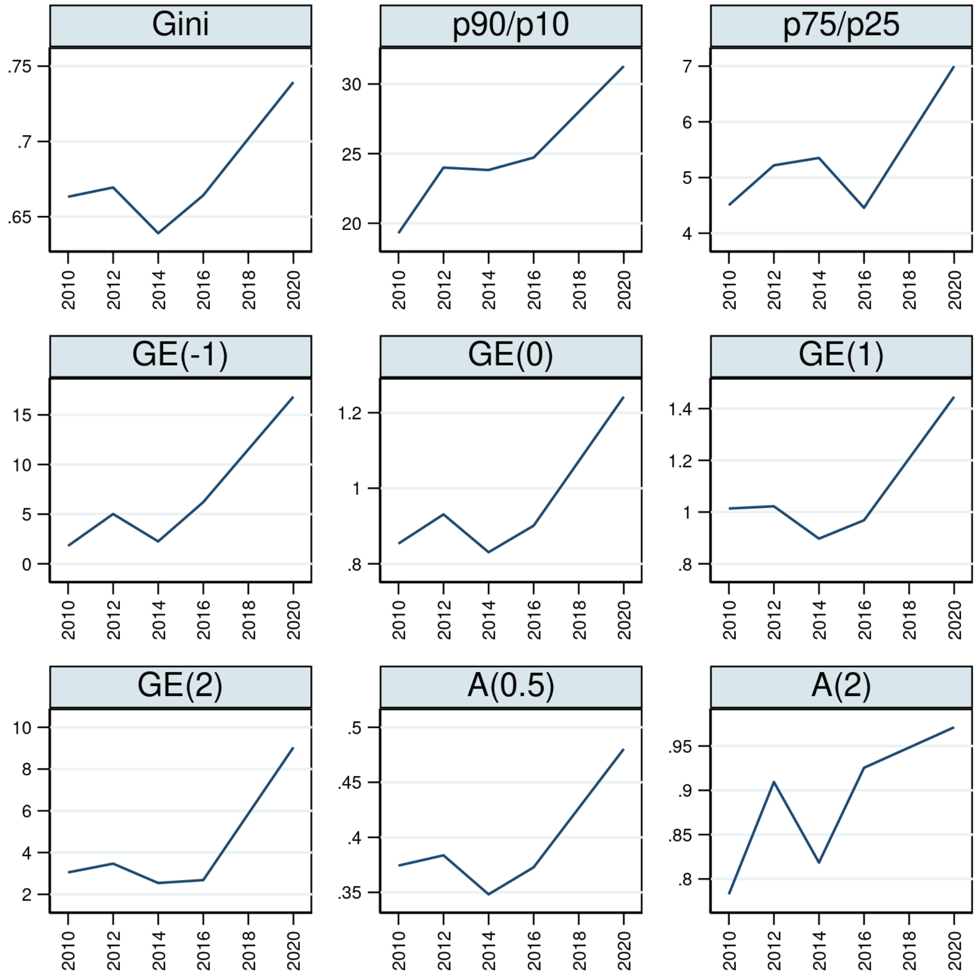


Figure A.1.4: SSF inequality: between and within geographical area components
(*semi-annual data; 2012-2023*)

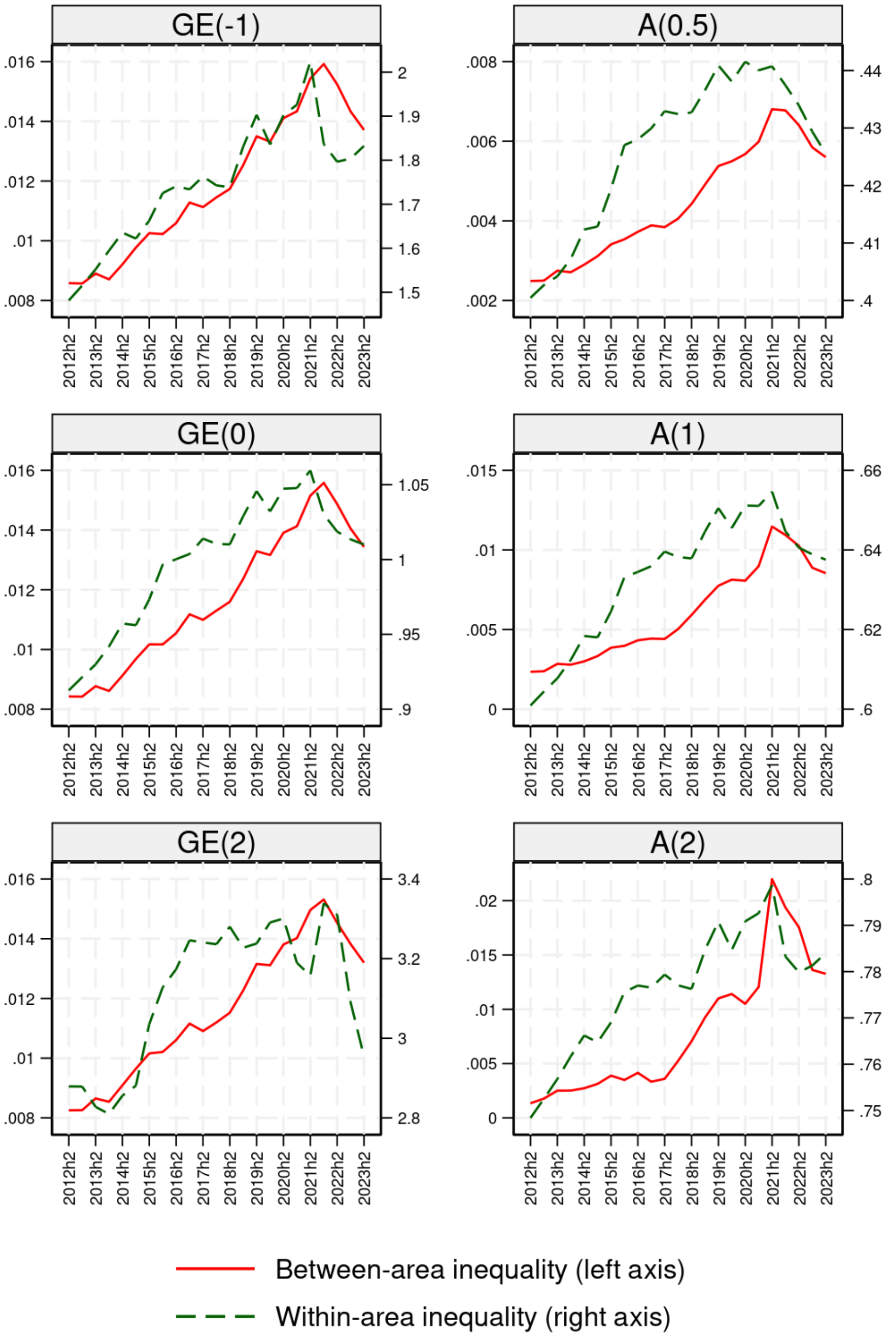


Figure A.1.5: SSF inequality by geographical area
(*semi-annual data; 2012-2023*)

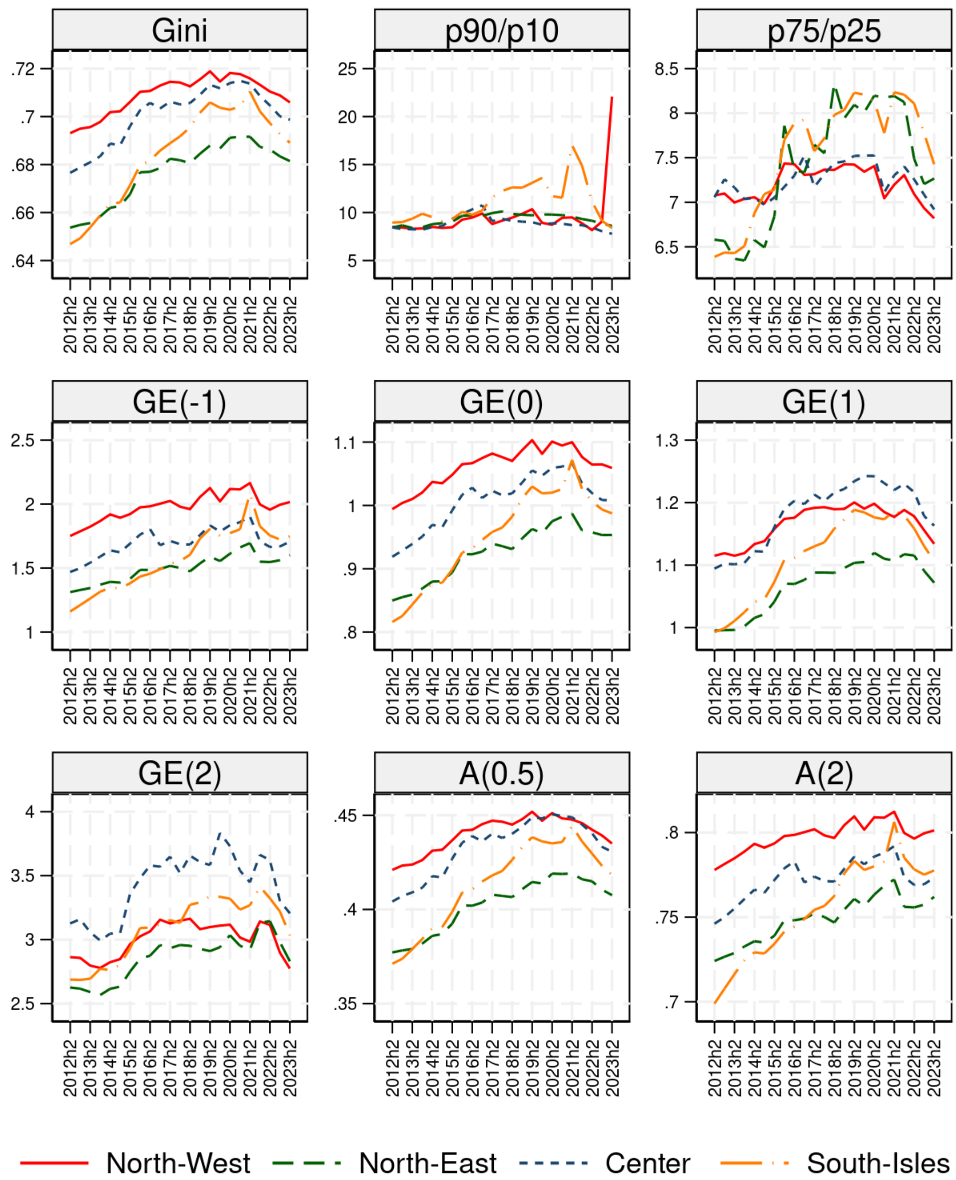
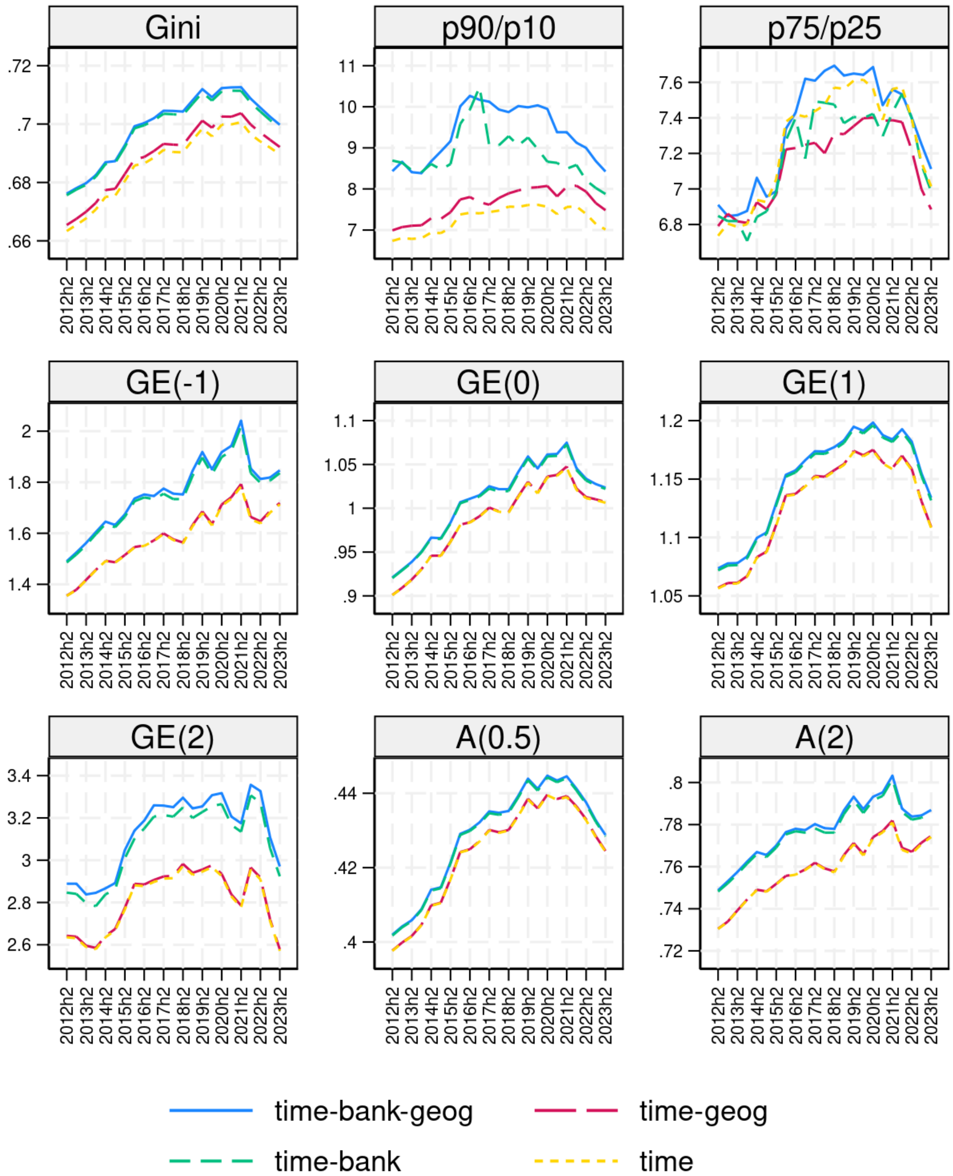


Figure A.1.6: SSF inequality: different aggregations of BSR data
(*semi-annual data; 2012-2023*)



A.2 Calculation of price volatility by amount class

In Section 4 we report the coefficient of variation of the prices underlying the financial instruments held by each amount class. The CSDB allows to keep track of asset prices at the ISIN level, so that it is possible to compute a 12-month coefficient of variation of prices for each ISIN. Then, we would like to match this coefficient of variation at the ISIN level with the specific composition of the portfolio of each class. Unfortunately, as explained in Section 2, SSF outstanding amounts in the BSR statistics by amount class are grouped into nearly 50 categories of financial instruments and not by ISIN code.[28] Data by ISIN, geographical area and reporting bank are available only without the distinction by amount class. Therefore, we have to combine the different sources in order to construct a proxy of portfolio volatility by size bracket at the bank-geography level.

The procedure to obtain the volatility indicator by size bracket at the bank-geography level in a specific period follows five steps. First, for each ISIN appearing in custodian bank statistics we compute the coefficient of variation of CSDB prices related to the previous 12 months.[29] Second, we match the coefficient of variations by ISIN with the outstanding amounts of financial instruments at the ISIN level available in the custodian bank statistics, which do not contain the distinction by amount class. Third, we need to compute a coefficient of variation for each category of financial asset defined in the custodian statistics by amount class. Therefore, we use the outstanding amounts of SSF held in custody by ISIN as weights to compute a weighted average of the coefficients of variation for every reporting bank, geographical area and financial category. Fourth, we match the weighted coefficients of variation at the bank-geography-category level with custodian bank statistics by amount class. Finally, for each class, geographical area and reporting bank, we compute the weighted average of the coefficients of variation using the outstanding amounts by financial category as weights.

In formulas, let v_j be the coefficient of variation of the financial product with ISIN j obtain in the first step. As described in the second step, let $x_{j,c,b,a}$ be the amount of a financial product with ISIN j, belonging to financial category c held in custody at bank b by clients resident in geographical area a (available data by ISIN, bank, geographical area, but not by amount class). In the third step, we define the coefficient of variation of category c for securities accounts of bank b belonging to clients resident in area a, as the weighted average:

$$CV_{c,b,a} = \sum_{j \in c} v_j \cdot \left(\frac{x_{j,c,b,a}}{\sum_{j \in c} x_{j,c,b,a}} \right)$$

In the fourth step, we match $CV_{c,b,a}$ with custodian bank statistics by amount class (available data by class, instrument category, bank, geographical area, but not by ISIN).

[28] According to Fagereng et al. (2020), individuals display heterogeneity in returns even within narrow asset classes. Therefore, we would like to analyse data at the ISIN level.

[29] In case of newly issued instruments, we compute the coefficient of variation if there are at least 7 observations (all the months of previous semester).

Finally, we compute the coefficient of variation for clients of bank b, residents in area a and belonging to the amount class w, $CV_{b,a,w}$, as the weighted average:

$$CV_{b,a,w} = \sum_{c \in C} CV_{c,b,a} \cdot \left(\frac{x_{c,b,a,w}}{\sum_{c \in C} x_{c,b,a,w}} \right)$$

where C denotes all the financial product categories and $x_{c,b,a,w}$ the outstanding amount of financial products of category c held in custody at bank b, referred to clients resident in area a and belonging to the class w.