WORKING paper

BANQUE DE FRANCE
EUROSYSTÈME

Unravelling Household Financial Assets and Demographic Characteristics: a Novel Data Perspective

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February 2026, WP 1034

ABSTRACT

This paper presents a novel dataset that combines granular information on financial assets from the Security Holdings Statistics (SHS) with household characteristics from the Household Finance and Consumption Survey (HFCS). We illustrate one of its potential uses by studying the link between portfolio returns and risk with education. First, we provide a non-parametric exercise taking Ireland as a case study and report a robust link between education levels and returns. Moreover, we find that more educated households exhibit higher risk tolerance and portfolios structured to realise greater gains in periods of elevated positive risk, albeit being more susceptible to losses in challenging times. Second, we expand the illustrative example to a country panel setting and address the previous question following non-parametric as well as parametric methods. Interestingly, the previous results for education and returns also emerge in this setting. These are robust to the inclusion of unobserved conditioning factors and macro-financial controls. We outline avenues for potential research and analysis that our novel dataset may contribute to in the future.

Keywords: Household Finance, International Macroeconomics, Portfolio Return, Investment Risk

JEL classification: G50, G11, E22, F21

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We would like to thank Daragh Clancy, Thomas Conefrey, Martin O'Brien, participants at the Irish Economics Association Conference 2024 and the ECB-BIS-BdE External Statistics Conference 2024, as well as seminar participants at the European Central Bank, the Central Bank of Ireland, and Trinity College Dublin for useful comments. We are grateful to Apostolos Serletis and two unknown referees for valuable comments and suggestions. We also thank the CSO for access to granular HFCS data. The data have been cleared by the Eurosystem for non-disclosure of confidential data. The views expressed are those of the authors and do not necessarily reflect those of the Banque de France, the Central Bank of Ireland or the European System of Central Banks. Arrigoni, Bénétrix, and Romelli were research affiliates of the Central Bank of Ireland during the conduct of this project.

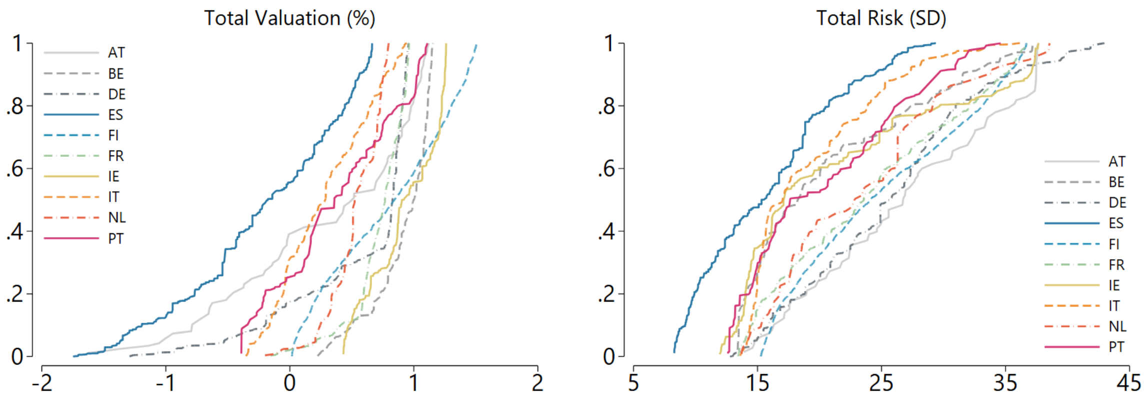
Non-Technical Summary

Financial asset holdings vary substantially across countries and over time. However, most existing research analyses these patterns at the aggregate country level. As a result, less is known about sectoral characteristics and heterogeneity in asset holdings, and even less attention has been paid to the household sector. This leaves a relevant gap, as household decisions affect the macroeconomy and households hold a non-negligible share of total financial assets.

A key reason behind the persistence of this gap in the literature is the limited availability of detailed data on household financial investments. Outside a few countries, administrative data are generally not widely accessible in the euro area, preventing cross-country comparisons. This paper contributes to the literature by developing a methodology that links two rich yet underused datasets available for euro area countries. The Security Holdings Statistics (SHS) provide detailed information on domestic and cross-border financial investments at the aggregate level, capturing how and how much the household sector invests, while the Household Finance and Consumption Survey (HFCS) collects granular information on individual household characteristics. We match country-level valuation and risk measures computed from the SHS to household portfolios in the HFCS to construct household-specific return and risk figures.

This augmented dataset allows us to study how households' investment returns and risk exposures vary both between and within countries. To visualise the derived household-level return and risk metrics, the figure below plots the cumulative distributions of total valuation effects and risk for a sample of euro-area countries. Household return-risk profiles differ substantially between countries, with some (e.g., Spain) showing low return and low risk, while others (e.g., Ireland, Finland) show both high return and high risk. Within each country, the dispersion of household outcomes also varies substantially, as highlighted by the width and shape of the CDFs. Since our analysis focuses on households holding at least two out of the three financial instruments, the results effectively describe the diversification patterns of households that participate in risky asset markets.

Figure. CDFs of total valuation (left) and risk (right)



Note: Cumulative Distribution Functions (CDFs). Cumulative share of households on the y-axis. CDFs of total valuation (total risk) are computed using average valuations (standard deviations of returns) of each instrument type. Sources: SHS, HFCS, and authors' calculations.

To illustrate the framework's potential, we examine how education relates to investment outcomes for a panel of euro area countries between 2019 and 2022. Using descriptive comparisons between groups and panel regressions, we show that more educated households are not only more likely to experience positive investment returns but also exhibit a higher tolerance for risk. Because education is correlated with financial wealth, part of this relationship operates through wealthier households having more scope to diversify into risky assets. This aligns with established evidence that risk tolerance rises with wealth (e.g., Calvet and Sodini, 2014; Liu, Yang, Cai, 2016). These patterns may also reflect other factors, such as the presence of illiquid business wealth among some households. Interestingly, we find that differences in return and risk primarily come from portfolio composition and market price movements, rather than from exchange rate fluctuations.

The broader implications extend beyond this single example. Disaggregated information on household financial asset holdings enables researchers and policymakers to detect emerging risks, understand how shocks propagate across household types, and design policies that support both welfare and financial stability. The insights of our paper are directly relevant for current European policy debates. Because European households hold markedly less risky portfolios than those in the United States, the Savings and Investments Union (SIU) initiative aims to foster greater participation in capital markets by broadening investment options and improving financial literacy. Indeed, financial education is one lever to increase participation, illustrating why detailed household-level data such as the one we use is essential for effective policy design and evaluation.

Analyser les actifs financiers des ménages et leurs caractéristiques démographiques : une nouvelle approche des données

RÉSUMÉ

Cet article présente des données inédites qui combinent des informations détaillées sur les actifs financiers issues des Security Holdings Statistics (SHS) avec les caractéristiques des ménages provenant de l'Household Finance and Consumption Survey (HFCS). Nous illustrons l'une de ses utilisations potentielles en étudiant le lien entre les rendements et le risque des portefeuilles et le niveau d'éducation. Dans un premier temps, nous proposons une analyse non paramétrique en prenant l'Irlande comme étude de cas et mettons en évidence une relation robuste entre le niveau d'éducation et les rendements. De plus, nous constatons que les ménages les plus instruits présentent une tolérance au risque plus élevée. Ils ont également des portefeuilles structurés leur permettant de réaliser des gains plus importants en période de risque positif élevé, tout en étant plus exposés aux pertes en période difficile. Dans un second temps, nous étendons l'exemple illustratif à un panel de pays et abordons la question précédente en utilisant des méthodes non paramétriques et paramétriques. Fait intéressant, les résultats précédents concernant l'éducation et les rendements apparaissent également dans ce cadre. Ces résultats sont robustes à l'inclusion de facteurs de conditionnement non observés et de contrôles macro-financiers. Enfin, nous présentons des pistes de recherche et d'analyse auxquelles notre donnée inédite pourrait contribuer à l'avenir.

Mots-clés : finance des ménages, macroéconomie internationale, rendement de portefeuille, risque d'investissement

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1 Introduction

International financial integration, measured through cross-border positions, varies between countries and over time. This is due to differences in the depth of financial systems, the scale of balance sheets, the structure (type of investments, currency of denomination, location, maturity, etc) and the role played by macro-financial factors affecting these systems (exchange rates, stock markets, interest rates, inflation, etc). The various ways in which these elements are linked with international gross positions, net positions, flows and valuation effects have been extensively documented in the relevant literature. However, most of these characterisations take an aggregate country perspective. Little is known about the link between international financial integration and sectoral characteristics, in particular for the household sector. To the best of our knowledge, the sectoral heterogeneity in asset holdings literature is small (Giofré, 2013; Roque and Cortez, 2014; Galstyan et al., 2016; Galstyan and Velic, 2018; Boermans and Vermeulen, 2020). Among these papers, even fewer focus on the household sector.

Household finances are important in assessing the macroeconomy, as decisions taken by households affect aggregate outcomes. Household income determines aggregate private spending (Deaton, 2017; Muellbauer, 1994). Saving decisions play a role in the transmission of monetary policy (Lane, 2019). Household indebtedness can drag on or support aggregate output, depending on the relative value of household assets and debt, i.e., their net wealth (Kim et al., 2015). During business cycle turning points, household finances can play a role in financial stability. For instance, the role of mortgages was of great importance during the global financial crisis (Mian and Sufi, 2018). The financial behaviour of households at the top of the wealth distribution compared to those lower down in the distribution may contribute to persistent wealth inequality trends (Bach et al., 2020).

However, many of the insights into the interactions between household finances and the macroeconomy are generated by information on real assets, outstanding debt, labour income and/or ownership of small firms. Instead, the role of households in the macroeconomy through their holdings of financial assets is less well understood (Santoso et al., 2009). This is despite the substantial holdings of financial assets by this sector. In 2021, euro area households held 20.1% of their gross wealth as financial assets (ECB-HFCN, 2023).

To bridge this gap, the focus of this project is to use microdata and multiple information sources to study the link between international financial integration and the household sector. To accomplish this, we propose a methodology to combine two key sources for the analysis: financial information on domestic and cross-border investments from the Security Holdings Statistics (SHS) database and household-level data from the Household Finance and Consumption Survey (HFCS). The SHS dataset is a Eurosystem database with information on securities held by selected categories of euro area investors, broken down by country of residence. These data are collected by national central banks directly from reporting investors and indirectly from custodians. The HFCS collects cross-sectional household-level data on wealth (real and financial assets, liabilities, and credit constraints), income, consumption, saving and other household characteristics. In a nutshell, while SHS provides a detailed picture of what households, on aggregate, do with their investments, HFCS allows us to analyse how household types within each country differ regarding these investments. The primary objective of the paper is to provide a framework that enables the analysis of investment positions (primarily cross-border) through the lens of microdata.

We use this augmented dataset to illustrate the potential research and policy applications arising from the combined insights into financial assets and the characteristics of their holders. We showcase the power of this augmented data by examining the role of education in household financial returns. A compelling narrative emerges, revealing that households with higher levels of education exhibit a distinctive investment behaviour that significantly impacts their portfolios. More educated households not only display a greater likelihood of positive returns but also a higher risk tolerance. This might be expected, but interestingly we find that this result derives from market price changes rather than exchange rate fluctuations. This underlines the pivotal role of education in shaping investment strategies and risk management among households.

Disaggregated information on the financial asset holdings of households will be useful on several dimensions. For example, facilitating the identification of risks and imbalances within the sector concerning financial assets. Moreover, it enables a comprehensive examination of the impact of shocks on households through the financial system. Together, these insights will be informative for policy design and impact including supporting household welfare.

Figure 1 compares financial participation in financial assets and their significance in total financial portfolios across euro area countries. Notably, 80% to 100% of households have deposits, making it the most common financial asset. Participation rates in investment assets are lower, yet they constitute a significant portion of households' financial portfolios in terms of value. To align the instrument coverage in the security database (SHS) with the household survey (HFCS), this paper focuses on Investment Funds (IF) and Money Market Funds (MMF) shares, Quoted Shares, and Debt Securities. On average, these assets collectively represent 22% of the total gross financial

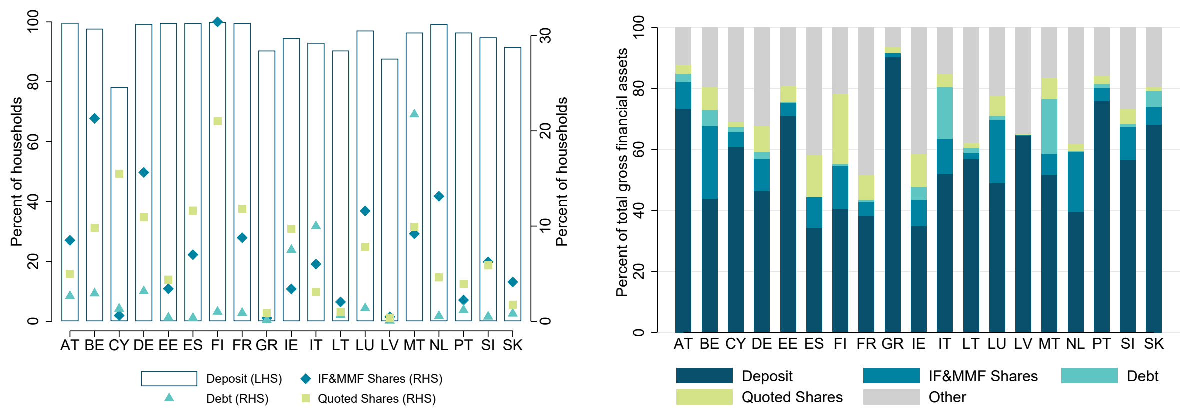

FIGURE 1: Financial participation (left) and financial portfolios (right)

Source: HFCS (Wave 3 – 2017/18).
Notes: The left panel illustrates household participation in financial assets, by instrument type. The right panel shows the composition of financial portfolio, using the total by instrument type over the total of gross financial assets. “Other” includes non self-employment private business, managed accounts, money owed to households, voluntary pension/whole life insurance, and other financial assets.

assets held by households in euro area countries, with almost one in five households owning at least one of these investment assets. Deposits, not included in the financial assets explored in this paper, account for 44% of total gross financial wealth in euro area countries, on average.[1]

The remainder of this paper is organised as follows. Section 2 describes the two main data sources in detail, while Section 3 explain how we merge the information from these sources to create an augmented dataset. Section 4 provides two applications to showcase the use of the augmented dataset. Section 5 concludes.

2 Data

This Section describes in detail the two datasets used in our analysis. Before providing further details, we explain why these two datasets are the best choice for the aims of this paper. The primary objective of the paper is to provide a framework that enables the analysis of investment positions (primarily cross-border) through the lens of micro-data. By merging the SHS and HFCS, our goal is to combine financial and demographic information for a large set of countries. The innovation of the dataset lies in the fact that no existing dataset provides this information for euro area countries, aside from administrative data in a few cases. Our framework aims to overcome this data limitation, which arises from the lack of or inaccessibility of administrative data. We seek to contribute to the literature by providing a case study for Ireland and the euro area,

[1] Apart from deposits and investment assets, households hold “other” financial assets. This includes non self-employment private business, managed accounts, money owed to households, voluntary pension/whole life insurance, and other financial assets.

with the aim of illustrating one of the potential uses of the merged dataset, examining education as a conditioning factor.

For this purpose, the choice of which financial and demographic data to merge depends on the level of granularity and cross-country availability. For financial holdings data in the euro area household sector, SHS is unequivocally the best option. This dataset provides detailed, disaggregated, and official reports on security holdings. When it comes to household demographics, there are several options, particularly for individual countries. For instance, the DIW's Socio-Economic Panel (SOEP) is an excellent source of information on German households. However, HFCS has the unique advantage of offering detailed, disaggregated, and harmonised data for all euro area countries. Additionally, it is primarily a survey on household finances, which enhances the accuracy of the information relevant for merging with SHS. In a nutshell, while SHS provides a detailed picture of what households, on aggregate, do with their investments, HFCS allows us to analyse how different households within each country differ regarding these investments. For these reasons, combining the HFCS and the SHS datasets allows us to create the optimal dataset for our analysis.

2.1 Security Holdings Statistics (SHS)

The Security Holding Statistics (SHS) dataset is a Eurosystem database that provides information on securities held by selected categories of euro area investors, broken down by country of residence. These data are collected by national central banks directly from reporting investors and indirectly from custodians.

The database consists of two different data sources that we link using the unique common International Securities Identification Number (ISIN) identifier of each instrument:

- *Centralised Securities DataBase (CSDB)*. This data set provides information on the *issuer* of securities, compiled on the basis of ECB Guideline ECB/2022/25 and ECB Recommendation ECB/2022/26.
- *Securities Holdings Statistics by Sector (SHS-S)*. This data set provides information on the *holder* of securities (euro area investors), broken down by country of residence. SHS-S data are collected on the basis of the ECB Regulations ECB/2012/24 and ECB/2013/7 (including amendments).

While SHS collects data for various economic sectors, for the purpose of our paper we focus on the household sector.[2] Data at the security level are grouped into the following instrument types:[3]

- *Investment Funds & Money Market Funds Shares (F.52)*
  - *Non-MMF Investment Funds Shares (IF, F.522)*: shares and units are issued by investment funds and trust funds, respectively, other than MMFs.
  - *Money Market Funds Shares (MMF, F.521)*: shares issued by MMFs, i.e. collective investment schemes that raise funds by issuing shares or units to the public.
- *Debt Securities (F.3)*
  - *Short-Term Debt Securities (STD, F.31)*: debt securities with original maturity of at most one year and debt securities repayable on demand of the creditor.
  - *Long-Term Debt Securities (LTD, F.32)*: debt securities with original maturity of more than one year or with no stated maturity.
- *Quoted Shares (F.511)*: shares listed on a stock exchange, either a recognised stock exchange or any other form of organised secondary market.

These are available at quarterly frequency starting from 2013Q4. The SHS sample covers euro area countries and four additional participating non-euro area countries (Bulgaria, Czech Republic, Denmark, and Romania). The data are expressed in terms of market value. Information on the stock position, as well as the flow and valuation components are provided.

SHS provides two area concepts: *holder* area and *reference* area. Holder area is the country of residence of the holder, while reference area is the reporting country. This means that two types of holdings are available. On the one hand, securities held by a resident household that are reported by domestic custodians (i.e. where holder area = reference area). On the other hand, securities holdings by non-financial residents from euro area or participating non-euro area countries which are in custody in another euro area or participating non-euro area country (i.e. third party holdings, where holder area is different than reference area). An example of the latter would be a security held by an Irish household via a German custodian. To provide a more complete view of investment positions and given that for the household sector, double reporting is not an issue (see Boermans et al., 2022, for a extensive discussion on the issue), we include

[2]The household sector consists of individuals or groups of individuals (consumers and entrepreneurs), provided that the production of goods and services is not by separate entities treated as quasi-corporations (S.14). It also includes the non-profit institutions serving households (S.15), which are separate legal entities that serve households under voluntary contributions.

[3]Stock positions are consistent with the criteria from the IMF-BIS-ECB Handbook on Securities Statistics and the European System of Accounts (ESA 2010). Definitions are taken from these Handbooks.

both observation types. This choice is in line with the guidelines provided in the ECB's SHSS User Guide.

2.2 Household Finance and Consumption Survey (HFCS)

The Household Finance and Consumption Survey (HFCS) collects cross-sectional household level data on wealth (real and financial assets, liabilities and credit constraints), income and consumption. Alongside these economic dimensions, HFCS provides a rich set of demographic characteristics. Among the most relevant for household portfolio decisions, which is the focus of this paper, are education level, age, labour status, and housing tenure status. This European System of Central Banks survey is coordinated by the European Central Bank (ECB) and conducted at the national level by the national central banks of the Eurosystem and several national statistical institutes.

So far, four waves of the survey have been completed. The fieldwork for the first HFCS survey (2010 wave) was conducted for most countries in 2010 and 2011, the second wave (2014) took place between 2013 and the first half of 2015, the third (2017) wave was conducted between the last quarter of 2016 and the last quarter of 2018, while the fourth (2021) wave was carried out between the first half of 2020 and the first half of 2022. Anonymised microdata from these four waves was made available to researchers in April 2013, December 2016, March 2020, and July 2023 respectively. For this paper we will use data from the third wave.

The set of questions asked in the HFCS survey are ex-ante harmonised across euro area countries. The household sample is designed to ensure representativeness of each country population and a probabilistic sample design is applied. The latter means that the ex-ante probability that each household in the target population takes part in the survey is non-zero (see ECB-HFCN, 2021b). However, to account for the high concentration of financial instruments towards the top of the wealth distribution, an oversampling of wealthy households is implemented.

For the purpose of our analysis, we consider the following instruments to match information from SHS:[4]

- *Mutual Funds (DA2102)*: all types of mutual funds – equivalent to IF&MMF Shares in SHS.
- *Debt (DA2103)*: securities other than shares excluding financial derivatives.
- *Quoted Shares (DA2105)*: publicly traded shares, i.e. shares that are listed on a

[4]Differently from SHS, HFCS does not disaggregate Mutual Funds and Managed Accounts into Investment and Money Market Funds shares nor Debt into short and long term. For details on the questions please see ECB-HFCN (2021a).

stock exchange or other form of secondary market.

Note that households are asked to report both domestic and international investments in these instruments. However, the data does not distinguish between these types of holdings.

3 Combining SHS and HFCS

Before describing how we merge the information provided by SHS and HFCS, we want to assess the comparability of the two datasets. For this purpose, we compute portfolio shares by country in both datasets and compare them. In SHS we sum over all holdings by country and asset class in the period that overlaps with the specific fieldwork for that country in HFCS. In HFCS we take the total of reported holdings in wave 3. Figure 2 illustrates the comparison. From this exercise it emerges that for the vast majority of the countries households' portfolio aggregates are similar among the two databases. Although there are level differences between totals in the two data sources, portfolio shares appear to be consistent. This information is relevant for the paper because our exercise will be based on portfolio shares. Moreover, we can see that there is large heterogeneity between countries. While between country heterogeneity is a feature of both datasets, the merged database will allow us to explore within country heterogeneity as well. This is one relevant dimension of our contribution. It is worth noting that for the majority of countries, the composition of portfolios is not substantially different between the two databases. However, some countries do show differences. Take Ireland, for example. The financial portfolio in the SHS shows a larger share of quoted shares compared to the HFCS, which instead shows a larger share of debt securities. One possible reason for this discrepancy could be related to the technical definition of reporting in the two databases. In the HFCS, households are asked about their holdings of instruments and related amounts, and they should report them regardless of whether they are held through euro area or non-euro area custodians. In contrast, the SHS, being an administrative dataset, only requires the reporting of household holdings by euro area custodians, while non-euro area custodians provide data voluntarily. In fact, Irish households sometimes use custodians based in the United Kingdom due to historical links. While these holdings can be reported in the HFCS, they may not necessarily appear in the SHS. However, there may be other reasons for the discrepancy, and different explanations may apply to other countries. Although we acknowledge these differences, an in-depth examination of the factors influencing them lies outside the boundaries of this paper.

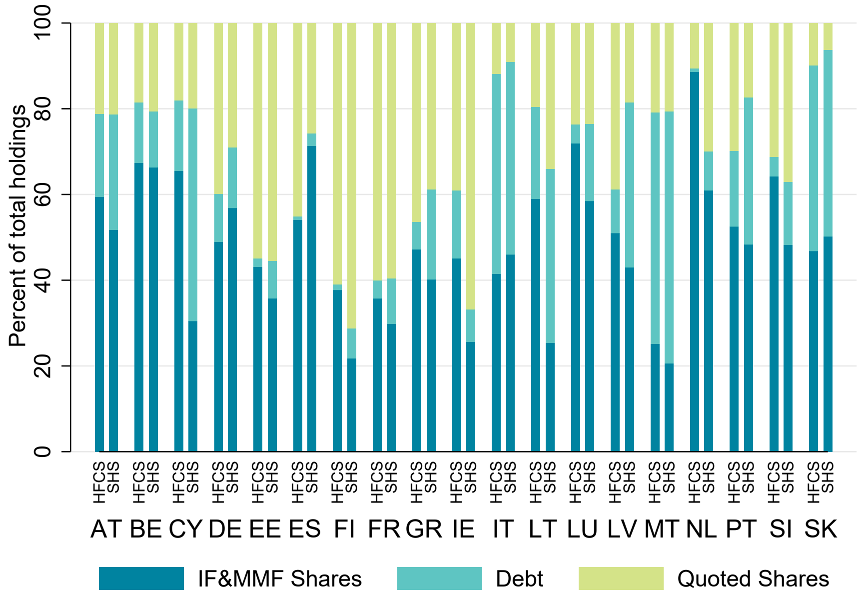

FIGURE 2: Portfolio composition by holder country

Source: SHS, HFCS (Wave 3).
Notes: Percent of total holdings by country for each asset class. We match the full SHS sample with HFCS using the average of the quarters in which HFCS fieldwork was conducted in each country.

3.1 Data cleaning in SHS

We perform a set of data cleaning procedures on the full SHS dataset before proceeding to merge with HFCS. Many of these procedures follow Boermans et al. (2022), which suggest a set of cleaning rules specific to this database, while others are tailored to our exercise.

We exclude securities that fall into one or more of these categories: unknown instrument type, short positions, missing stock amount, issued by tax heavens countries or with an ISIN related to a tax haven, unallocated or unknown issuer country, issued by institutions, issued by Luxembourg or with Luxembourg as a reference area.[5]

3.2 Combining SHS and HFCS: an augmented dataset

To combine the SHS data with the HFCS data, we proceed in three steps. First, we compute quarter-on-quarter valuation rates at the security level using SHS data over

[5]Positions are defined as short when the stock amount is lower or equal to zero. Tax heavens are United States Virgin Islands, Curaçao, Cayman Islands, The Bahamas, Bermuda, British Virgin Islands, Isle of Man, Marshall Islands, Guernsey, Gibraltar, Jersey, Liechtenstein. Reference area is the nationality of the custodian the household used to invest in.

the period 2019Q1-2022Q4 as follows:[6]

$$Valuation\ Rate_{v,s,t} = \left(\frac{Valuation\ Amount_{v,s,t}}{Stock\ Amount_{v,s,t-1}}\right) \times 100 \qquad (1)$$

where v is the valuation type, s denotes the unique security as identified by the ISIN, and t is the quarter. We distinguish three valuation types, based on the richness of information offered by SHS. *Market price* valuation refers to changes in the value of end-period positions that occur because of holding gains or losses. *Exchange rate* valuation is due to movements in the exchange rates of the currency of denomination of the security against the euro, while *total* valuation is the sum of the two.

Panel (A) of Figure 3 shows the distribution of valuation rates for each valuation type. The sample includes euro area countries, excluding Luxembourg. Commenting on the magnitude, we can see that valuation changes due to market prices are larger than valuation changes due to exchange rates. As a result, total valuation rates reflect the former more than the latter. Moreover, the distribution of total and market prices valuation changes are more volatile than those of valuation changes due to exchange rates. On average, the standard deviation for total and market prices valuation is three times higher than that for exchange rates.[7] These two descriptive pieces of information follow the fact that stock prices are generally, and in our period as well, more volatile than exchange rates. This means that valuation gains and losses connected to changes in stock prices, i.e., market prices valuation, would tend to be larger on average than those derived from changes in exchange rates vis-à-vis the currency of denomination. As an example, following the outbreak of the Covid-19 pandemic, the S&P500 lost around 20% in the first quarter of 2020, while the EUR/USD exchange rate only fell by 1.9%. These facts are supported by Panel (B) of Figure 3, which shows the decomposition of the total valuation rates presented in the first distribution plot in Panel (A) into their components arising from changes in market prices and exchange rates. Market prices are indeed the main driver of asset valuation, while the contribution of exchange rates is more ambiguous in terms of sign and marginal in magnitude across the entire distribution.

It is important to note that 70% of the observations in our sample for total valuation

[6]Valuation rates/returns, as used in this context, encompass any capital gains or losses arising from fluctuations in market prices and exchange rates. The selected time frame for computing returns corresponds to the aftermath of the HFCS Wave 3 fieldwork, considering the last country in the sample. Separately, when looking at each type of valuation, we only keep securities for which that type of valuation is non-zero and non-missing. To reduce the impact of sensitive outliers, we remove observations outside the 1-99 percentile range, computed on the entire sample of countries.

[7]For example, using data over the same horizon of interest, the coefficient of variation (Standard Deviation/Mean x 100) of the S&P500 is 17, compared to 5 for the EUR/USD exchange rate. A larger coefficient of variation denotes higher volatility of the underlying time series.

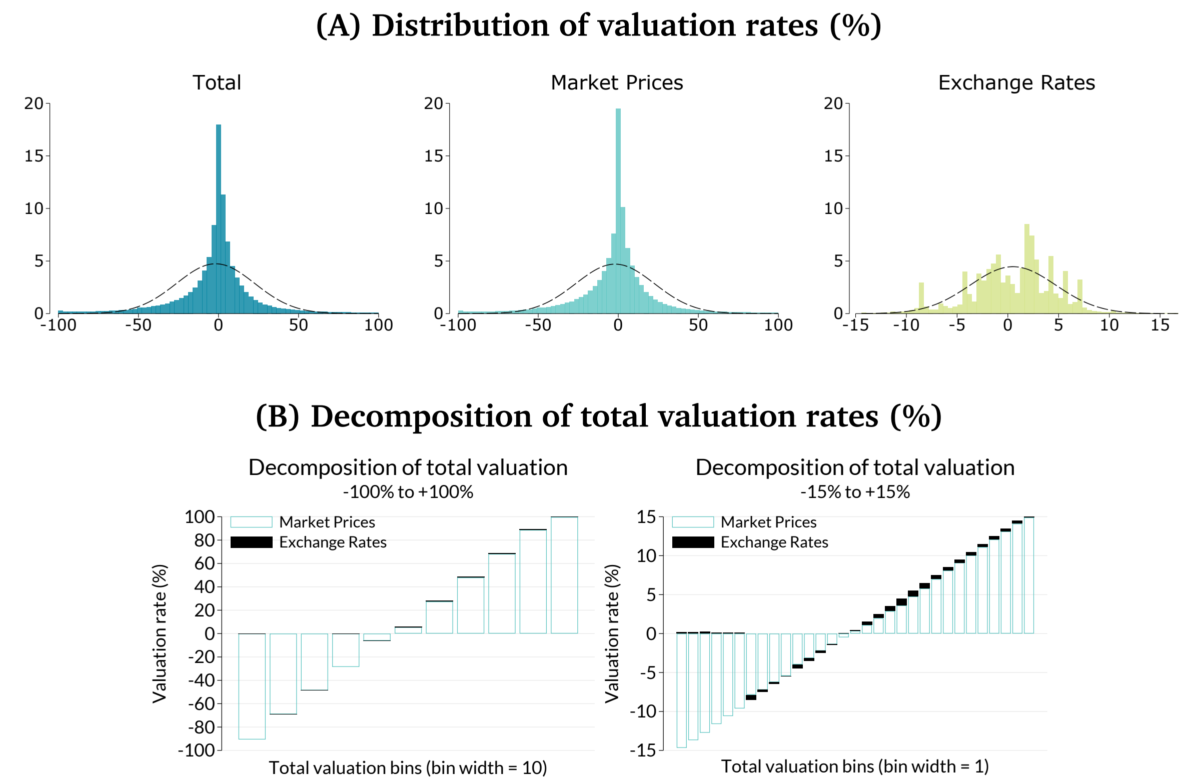

FIGURE 3: Distribution and decomposition of valuation rates from SHS

Source: SHS and authors' calculations.
Notes: Quarter-on-quarter valuation rates computed over the period 2019Q4-2022Q4 using all securities. (A) Percent on the y-axis, valuation rates in percent on the x-axis. The black dashed line is a standard normal distribution. (B) The figures decompose the total valuation rate shown in the first distribution plot in Panel A into its components arising from changes in market prices and exchange rates. The figure on the left breaks down total returns between -100% and +100% to match the range of the distribution plot. The figure on the right zooms in on total returns between -15% and +15% to better highlight the role of exchange rates. On the x-axis, total valuation rates are sorted in ascending order and grouped into bins.

are not issued by the holder country, which means they are cross-border (including other countries in the euro area). Except for Spain and Germany, for which this ratio is less than 50%, for the remaining 16 countries it is over 85%. 27% of these are denominated in USD, and 22% of observations are issued by the United States. This data is also heterogeneous by country.

Turning to the distributions of the valuation rates themselves, none of them is normally distributed. This is in line with the stylised facts of financial returns (see Fan and Yao (2017), for a summary). In particular, financial returns tend to display heavier tails compared to normal distributions, with asymmetry, i.e., returns are often negatively skewed, and a larger mass concentrated around the mean.[8] It is worth noticing that these stylised facts apply to all the countries in the sample (see Appendix Figures A1, A2, A3).

Second, we compute summary statistics of these valuation rates, namely the mean,

[8]In addition, one must keep in mind that the period over which we compute valuation effects has been characterised by a series of exogenous shocks, such as the Covid-19 pandemic, the war in Ukraine, and the return of high inflation.

median, standard deviation, 5th and 95th percentiles. Then, we merge them with the HFCS data. Given that the two databases have different units of analysis – security in SHS and household in HFCS – it is essential to make an assumption in order to link them. Our merging assumption is that every household invests in the same pool of international securities within a given instrument type. In this case, heterogeneity arises from the portfolio allocations across instruments for each household, which are available from HFCS. While this remains an assumption, using HFCS we observe that household participation in risky assets – quoted shares, mutual funds, and debt securities – increases with net wealth but their share in total financial assets remains relatively constant (Figure 4). This suggests that the household risk profile does not vary substantially alongside the wealth distribution, making it plausible to assume that households invest in the same pool of securities within these assets, but with different intensities. Note that this assumption does not require all households in HFCS to hold every available instrument. For a household in HFCS that does not have any holdings of a certain instrument, its return will come from the other instruments it holds.[9]

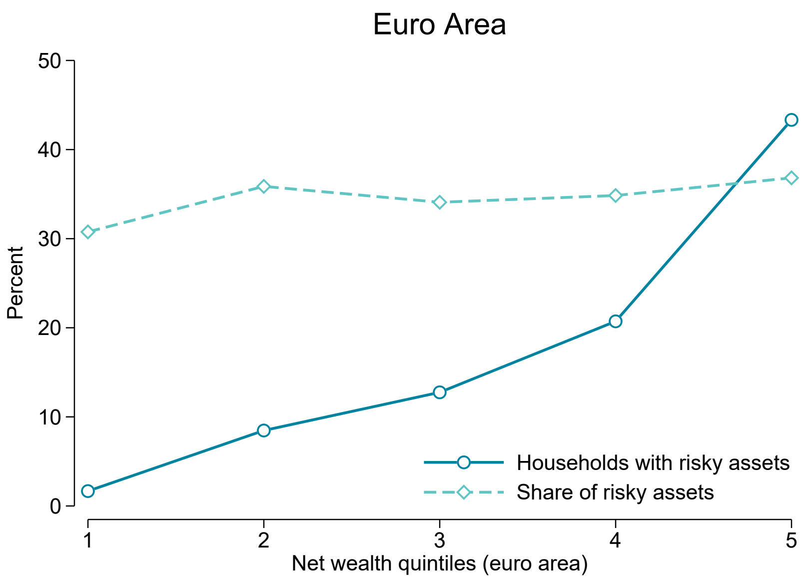

FIGURE 4: Risky assets alongside the net wealth distribution

Source: HFCS (Wave 3) and authors' calculations.
Notes: Risky assets include quoted shares, mutual funds, and debt securities. The solid line indicates the proportion of households holding risky assets, while the dashed line represents the conditional average share of risky assets in gross financial wealth.

Figure 5 provides a visual representation of the merge methodology described above.

Third, we compute household-level valuation rates for each country as a weighted

[9] In other words, it can indeed be the case that a household in HFCS holds 50 in IFMMF shares, 20 in Debt, and 0 in Shares. Thus, with our merging methodology we do not assume that all households hold all the available instruments and only differ in their intensive margins. What will happen in this case is that the return rate in HFCS of that household will be based on the IFMMF shares and Debt amounts only, using the respective returns computed with SHS.

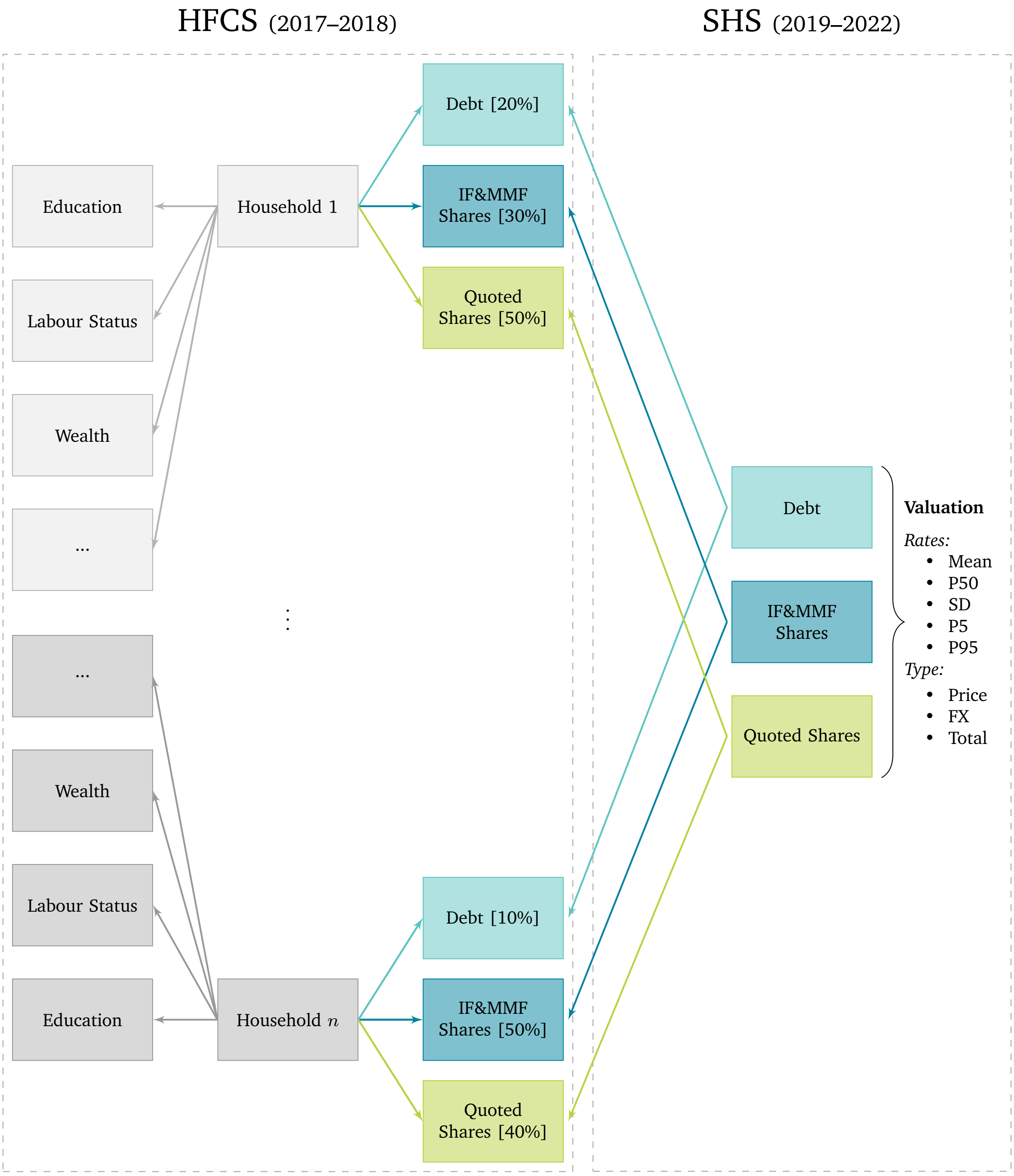

FIGURE 5: Visual HFCS-SHS merging scheme for country c

Source: Authors' own elaboration.
Notes: HFCS is at the country-household level and refers to Wave 3. SHS is at the country-security level and refers to the period 2019Q1-2022Q4.

average of the SHS summary statistics using household-specific portfolio shares (w_i^c) as weights:

$$Return_{i,v} = \frac{1}{\sum_c w_{i,v}^c = 1} \sum_c \underbrace{w_i^c}_{HFCS} \underbrace{Mean(Valuation\ Rate_{v,s,t}^c)}_{SHS} \tag{2}$$

$$Return^{median}_{i,v} = \frac{1}{\sum_c w^c_i = 1} \sum_c \underbrace{w^c_i}_{HFCS} \underbrace{P50(Valuation\,Rate^c_{v,s,t})}_{SHS} \tag{3}$$

where i is the household identifier, v is the valuation type (total, market prices, and exchange rates), s denotes the unique security as identified by the ISIN, t is the quarter, and c denotes the asset class (IF&MMF Shares, Debt, Quoted Shares). The mean return will be our baseline measure of return. Note that there is no time subscript in the return metrics, as we compute them at the time of the HFCS fieldwork for wave 3, using ex-post valuation rates.[10]

Alongside returns, in a similar way, we compute two types of risk. One is based on realised volatility (standard deviation, SD) to measure the capacity of households to diversify risk on an ongoing basis. The other one is based on the tails of the distribution, representing the tail risk associated with big shocks. The justification for this secondary category of risk stems from the concept of Value-at-Risk (VaR), a risk management metric pioneered by JP Morgan in 1996. VaR quantifies the potential profit or loss in the value of a portfolio within a specified confidence interval. Specifically, we designate the 5th percentile (P5) to represent significant valuation losses and the 95th percentile (P95) for substantial valuation gains.

$$Risk_{i,v} = \frac{1}{\sum_c w^c_i = 1} \sum_c \underbrace{w^c_i}_{HFCS} \underbrace{SD(Valuation\,Rate^c_{v,s,t})}_{SHS} \tag{4}$$

$$Negative\,Tail\,Risk_{i,v} = \frac{1}{\sum_c w^c_i = 1} \sum_c \underbrace{w^c_i}_{HFCS} \underbrace{P5(Valuation\,Rate^c_{v,s,t})}_{SHS} \tag{5}$$

$$Positive\,Tail\,Risk_{i,v} = \frac{1}{\sum_c w^c_i = 1} \sum_c \underbrace{w^c_i}_{HFCS} \underbrace{P95(Valuation\,Rate^c_{v,s,t})}_{SHS} \tag{6}$$

We exclude from our analysis households that do not report investing in any of the three asset classes we consider. While financial participation from the survey is generally high, most of the households either have all their savings in bank accounts or invest in only one of the three assets we are considering for our exercise. Given that our goal is to investigate investment diversification, we narrow our analysis to the subset of households that report holding at least two of the three types of instruments. On average in the euro area, 10.2%, 3.2%, and 8.6% of households hold mutual funds, bonds, and shares respectively ECB-HFCN (2020). These holdings account for an average of around 5% of the aggregate household net wealth and are mostly owned by wealthier

[10]To exploit the largest information set from HFCS, we average over the values of all five implicates provided for each household.

households. Therefore, our sample includes a restricted number of households (5,266) and we focus on countries with at least 50 households, i.e., Austria, Belgium, Germany, Spain, Finland, France, Ireland, Italy, Netherlands, Portugal.[11]

Before using the augmented dataset for our empirical analysis, we provide a visualisation of the dataset. We generate Cumulative Distribution Functions (CDF), to highlight how valuation rates and the risk associated with them evolve alongside the household distribution.[12] The CDF provides the share of households (probability) for which the variable of interest, i.e., the valuation rate or the risk measure, is less than or equal to a certain value x (on the x-axis). Figure 6 shows the cumulative distributions of total valuation effects and risk across households for our sample of euro area countries. The distribution of valuation rates is somewhat convex, while risk evolves in a concave form across households. The shape of the valuation rate suggests positive skewness in the distribution of portfolio valuations and the steeper increase at the right side of the CDFs suggest a higher likelihood of observing valuation rates that are higher than the average. Instead, the CDFs of risk suggest a negative skewness in the distribution of realised risk of valuation rates. The slower increase at the end of the distribution of the CDF reflects a higher likelihood of lower-risk outcomes.

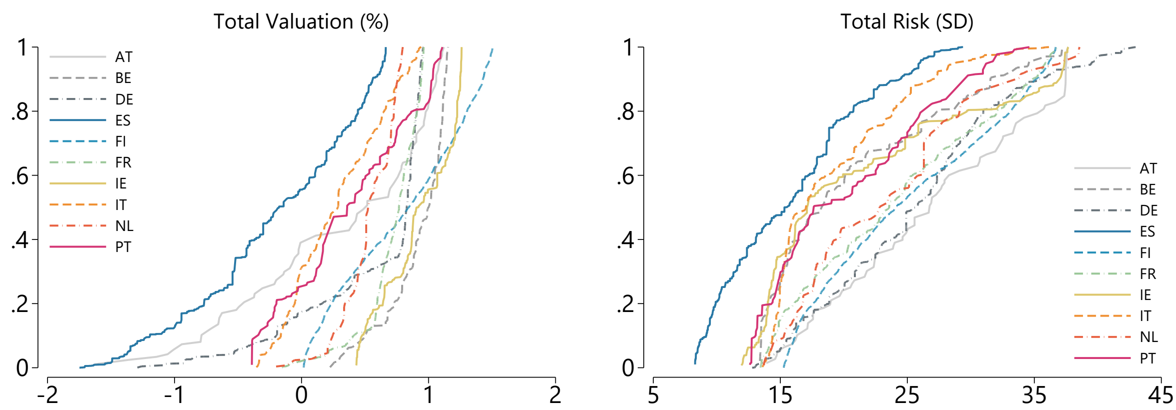

FIGURE 6: CDF of total valuation (left) and risk (right)

Source: SHS, HFCS, and authors' calculations.
Notes: Cumulative share of households on the y-axis. CDFs of total valuation are computed using average valuations of each instrument type.

The visual comparison reveals substantial heterogeneity in both *between* and *within* countries. Heterogeneity between countries is highlighted by the fact that countries have different return and risk profiles. Spanish households for example have the lowest return and risk. In contrast, countries like Ireland and Finland have the highest return

[11]The household sample by country is as follows: Austria 75, Belgium 171, Germany 701, Spain 754, Finland 1782, France 1068, Ireland 239, Italy 281, Netherlands 92, Portugal 103.

[12]All statistics derived from HFCS data are weighted using household weights that are representative of the country's population.

and risk. Other countries show a mixed profile. Austrian households for example do not receive particularly high return, but have the highest risk profile. Heterogeneity within countries can be assessed by the shape and the length of the CDF. For example, Spanish households' mean returns span from negative to positive on a range of 3 percentage points, while Irish households only show positive mean returns and the difference between the lowest and the highest household is within 1 percentage point.

To link this visualisation with our earlier discussion and to better contextualise the cross-country differences, Appendix Figure A4 reports the cumulative distribution functions (CDFs) for risk and return, decomposed by valuation type: exchange rates and market prices. In line with the stylised facts and the distribution shown in Figure 3, we observe that, in general, most of the variation in both return and risk stems from changes in market prices. Exchange rates appear to contribute relatively little. Also, the within-country variation in the CDFs is wider for market prices compared to exchange rates. The case of Spain merits further discussion. As noted above, Spanish households stand out due to lower returns and higher risk. When decomposed, this pattern is also evident in market price valuations, though in a less striking manner. Instead, the exchange rate component exhibits outlier behaviour in terms of both risk and return. An analysis of the raw data reveals three contributing factors. First, Spanish households in our dataset hold a substantial share of their portfolios in quoted shares. On average, these assets yielded the lowest returns in all countries in the sample. Second, although the overall currency composition of investments in quoted shares does not show marked differences in exposure to foreign currencies, the average return by currency tells a different story. Spanish portfolios experienced more negative returns compared to other countries, largely due to the depreciation of the Turkish Lira, the Argentine Peso, the Brazilian Real, and the Colombian Peso. Third, the CDFs for the valuation metrics in Figures 6 and A4 are constructed using average valuation rates. When median valuation rates are used instead, Spain appears far less of an outlier. This reinforces the importance of considering different valuation metrics, as we do throughout this paper and our analysis.

4 Empirical analysis: the role of education

In this Section, we provide two empirical exercises that showcase how the augmented dataset constructed above can be used for both non-parametric and parametric empirical analysis to assess how portfolio performances are related to household characteristics.

More specifically, our empirical applications focus on one of the main determinants of household investments, i.e., their education level. HFCS provides a wide range of household demographics, which makes this approach straightforward to implement on several other dimensions, e.g., labour status, age, housing tenure status, wealth, income, gender, and so on.[13] As a starting point, we focus on education because it allows us to explore the connection between financial literacy and investment decisions.

We split our sample between households with high and low levels of education, exploiting the education level of the reference person in the household. The reference person in HFCS is designated as the most financially knowledgeable person within the responding household. *Low education* households are defined as those with no education/early childhood, primary, lower secondary, upper secondary, or post-secondary non-tertiary education, while the *high education* ones have a short-cycle tertiary education, a Bachelor, a Master, or Doctoral studies. While the goal of this paper is to provide an idea of what can be done with these augmented data taking education as an example, we acknowledge that education might be correlated with other factors which in turn are associated with portfolio performance.

4.1 A non-parametric analysis through conditional CDFs

The first application of our dataset is to produce cumulative distribution functions conditional on the education level. We take Ireland as an illustrative example and then compare results with a panel of euro area countries. According to the latest data from the Eurobarometer, Ireland demonstrates a relatively high level of financial literacy compared to the EU27 average.[14]

We comment on the results on two dimensions, i.e., return and risk. In each case, we use the properties of the CDF to explain our results. When comparing two CDFs that are strictly increasing and differentiable, one (F) is said to first-order stochastically dominate the other one (G) if, for *any outcome* x, F returns a probability of receiving x which is at least as high as the one given by G ($P[F \geq x] > P[G \geq x]$). Graphically, this would be highlighted by a CDF being lower or equal to the other for all possible outcomes. We opted to start with a non-parametric approach to present findings from the augmented data because this enables us to convey results that do not rely on a singular statistical measure, such as the mean or median household, but rather capture the entire distribution of outcomes. We believe that this approach helps in mitigating estimation uncertainty and bias more effectively than a narrow focus on a specific point

[13] For illustration purposes on the potential of our methodology, Figure A5 in Appendix shows the heterogeneity of financial participation and the composition of financial portfolios across various household characteristics.

[14] A detailed report of the results from the Eurobarometer is available here.

within the distribution.

Figure 7 reports the CDFs of mean and median returns conditional on household education level being low or high.[15] A compelling narrative emerges. The CDF for households with high education levels *first-order* stochastically dominates the CDF of those with low education levels (top-left panel). This suggests that the likelihood of observing positive valuation rates is consistently higher for households with higher education. The message is consistent when looking at the two sub-components of the total return as well, with market prices showing the largest difference among the two groups (centre- and bottom-left panels). This evidence corroborates the intuition behind different investment decisions. Remember that our exercise assumes that households invest in the same pool of securities (from SHS), but in different amounts (from HFCS).

Thus, we can rationalise our finding suggesting that higher-educated households exhibit a greater ability to diversify their portfolios towards asset classes characterised by higher returns. For instance, on average, lower-educated households tend to allocate a larger share of their portfolios to debt securities (31% compared to 23% for high-educated households). In contrast, higher-educated households show a more substantial investment in quoted shares and IF&MMF shares (43% and 34%, respectively, for the high-education group, compared to 40% and 29% for the low-education group). This implies that, in the low education group, the total valuation returns lean more towards debt, which typically has a lower rate (0.43%). Conversely, households in the high-education group benefit from higher returns attributed to investments in quoted shares and IF&MMF shares (0.88% and 1.26%, respectively). This evidence suggests that education levels are associated with portfolio diversification, impacting the distribution and composition of returns across different asset classes.

The CDFs of the *median* return complement the findings and rationales discussed above (right panels). Our data show that households with high education levels exhibit a lower probability of negative rates and a higher probability of positive median rates. Households with higher education levels tend to outperform those with lower education when median returns are positive. Instead, lower-educated households have a higher likelihood of getting negative valuation rates.

Figure 8 visually depicts the dimension of risk, with each row in the panel offering insights into different risk metrics for various valuation types. The left side shows the distribution of risk in terms of standard deviation, offering a conventional understand-

[15]While the two groups are unbalanced, their means are not statistically different in terms of net total wealth, gross and net financial wealth – the focus of our analysis – and gender. Instead, their means are statistically different in terms of other household characteristics such as income, labour, and housing status. We assess mean differences using household-weighted adjusted Wald tests.

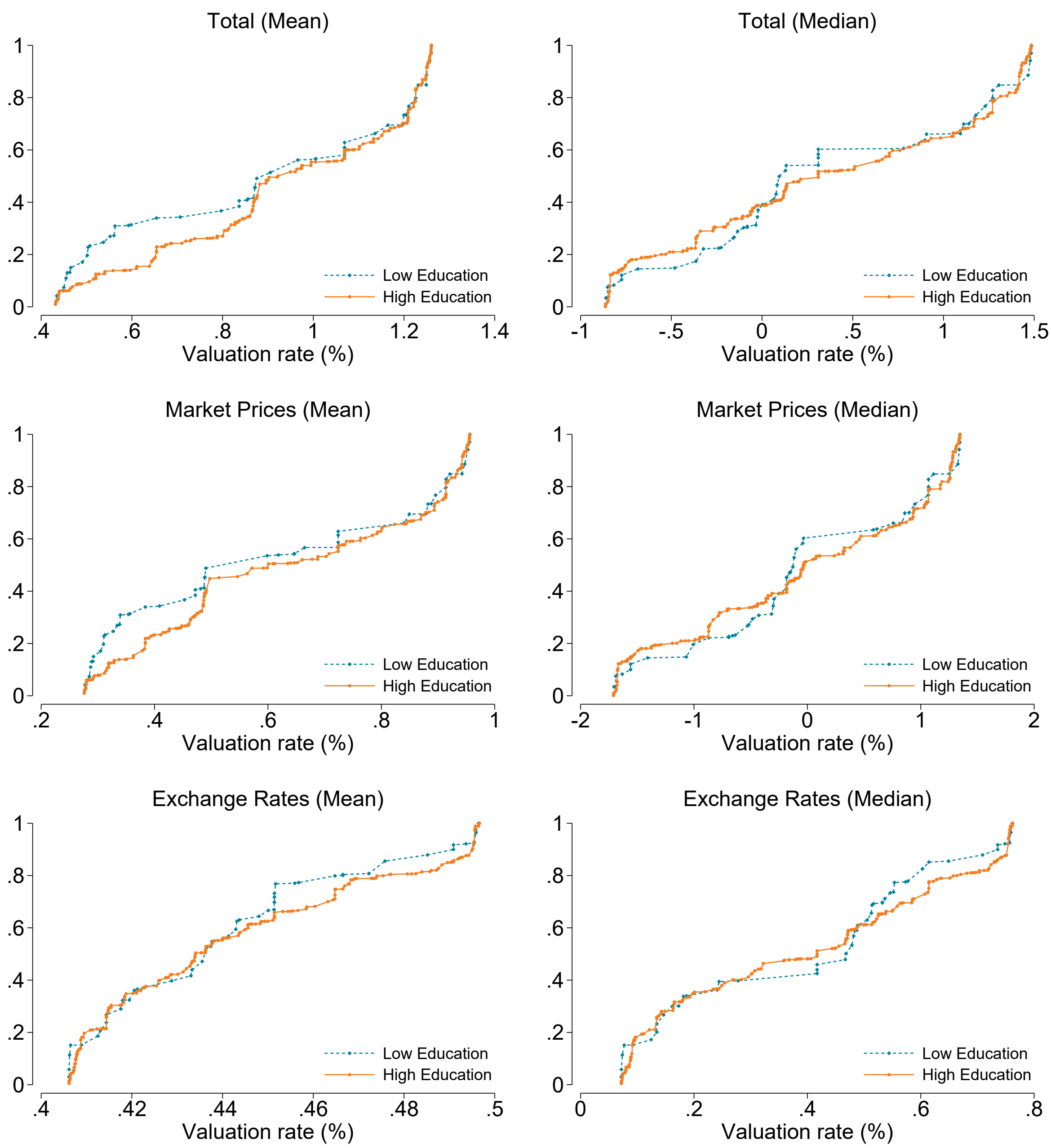

FIGURE 7: CDFs of return, by valuation type (Ireland)

Source: HFCS and authors' calculations.
Notes: Cumulative share of households on the y-axis. Education level of the reference person in the household. Low Education is defined as no education/early childhood, primary, lower secondary, upper secondary, or post-secondary non-tertiary education. High Education is defined as short-cycle tertiary education, Bachelor, Master, or Doctoral.

ing of risk. Meanwhile, the middle and right sides delve into negative and positive tail risks, respectively. While interpreting standard deviation is relatively straightforward, we aim to offer a more detailed explanation of the other two risk metrics. The focus is on the cumulative distribution of the tails of returns, providing a detailed perspective on how households experience non-standard times. This emphasises the returns received during periods characterised by negative and positive outliers, shedding light on the broader spectrum of risk scenarios. The frequency of these scenarios can help us

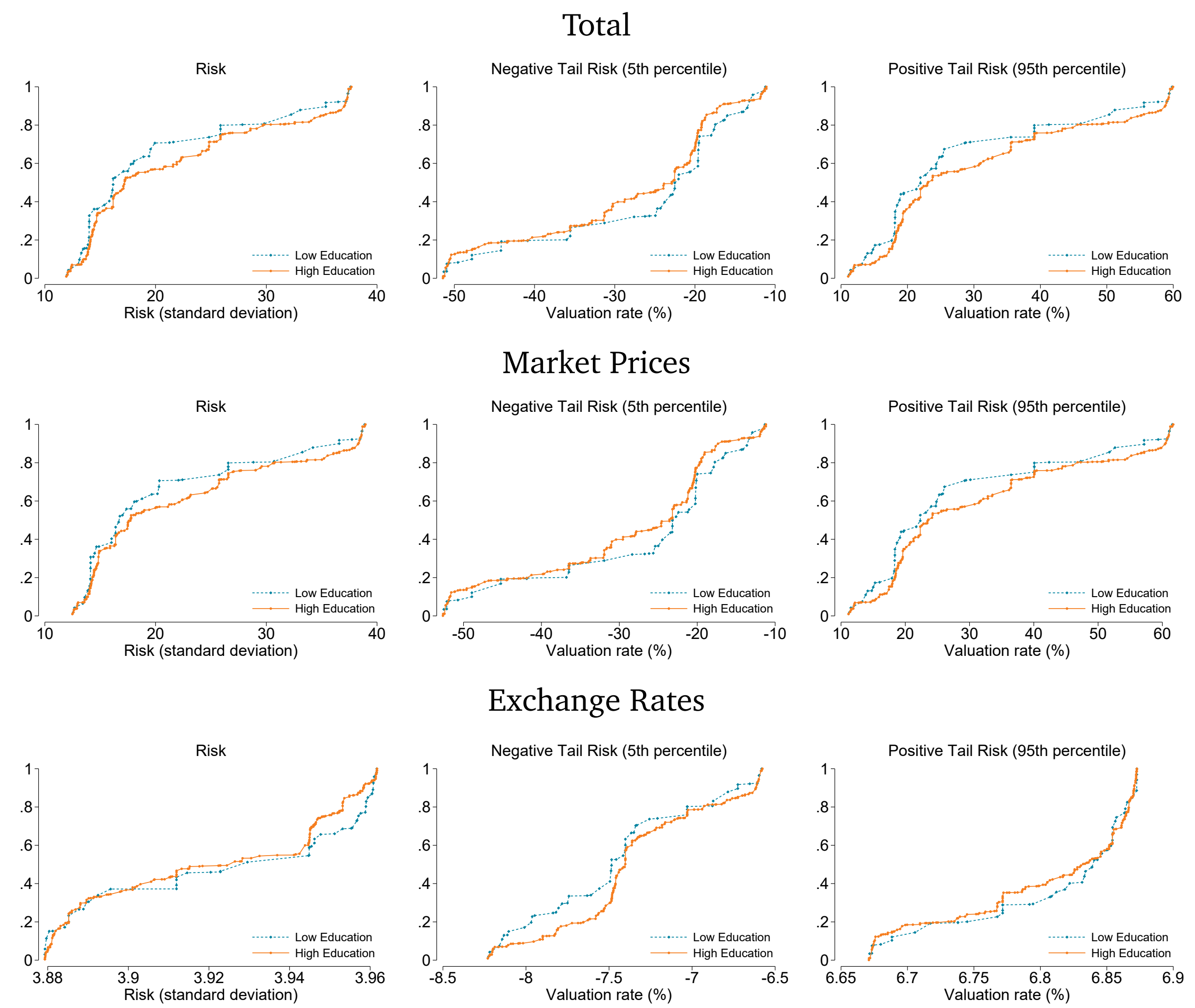

FIGURE 8: CDFs of risk, by valuation type (Ireland)

Source: HFCS and authors' calculations.
Notes: Cumulative share of households on the y-axis. Education level of the reference person in the household. Low Education is defined as no education/early childhood, primary, lower secondary, upper secondary, or post-secondary non-tertiary education. High Education is defined as short-cycle tertiary education, Bachelor, Master, or Doctoral.

rationalise our findings.

When examining total risk, three messages emerge. First, households with higher levels of education exhibit higher exposure to risk across the entire distribution (top-left panel). This relates to the concept of risk tolerance. As education and financial literacy are correlated (Kaiser and Menkhoff, 2017), we can expect higher-educated households to display higher willingness and ability to embrace investment risk. Second, in the event of major negative shocks, higher-educated households are impacted more severely than lower-educated households (top-centre panel). Third, higher-educated households realise greater returns in situations of elevated positive risk (top-right panel).

Examining the individual components, much like we did for returns, the primary source of risk arises from fluctuations in market price valuations rather than shifts in exchange rates. Notably, in the context of high-low education comparisons, market

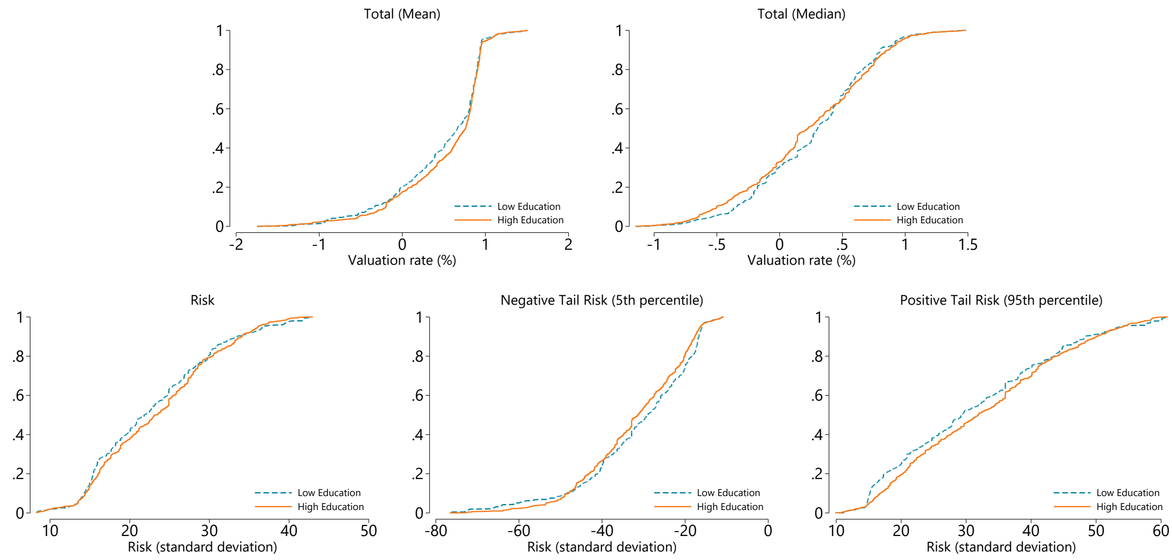

FIGURE 9: CDFs of return and risk, by valuation type (euro area)

Source: HFCS and authors' calculations.
Notes: Cumulative share of households on the y-axis. Education level of the reference person in the household. Low Education is defined as no education/early childhood, primary, lower secondary, upper secondary, or post-secondary non-tertiary education. High Education is defined as short-cycle tertiary education, Bachelor, Master, or Doctoral. Countries included are Austria, Belgium, Germany, Spain, Finland, France, Ireland, Italy, Netherlands, Portugal. We use country-level household weights as representative of the euro area aggregate.

price valuation exhibits similar behaviours to total valuation, while for exchange rate valuation the story of tail risks seems to be reversed. Higher-educated households experience larger losses in the face of negative tail risk but also realise greater gains when significant positive shocks occur. This might be explained by the fact that hedging exchange rates possibly requires less knowledge than hedging market prices or that exchange rates only explain a minor part of the variance in total valuation.

We have discussed the results of this non-parametric approach using Ireland as an illustrative example. Is Ireland an outlier? Or do euro area countries display a similar pattern? To bridge this first analysis with the second, Figure 9 shows the CDFs for the euro area aggregate, using all the households and countries in our sample. The key messages are consistent with what we have discussed with the Irish examples. Compared to their lower-educated peers, more educated euro area households display greater returns and exhibit higher risk tolerance. Figures A6 and A7 in Appendix show the disaggregation into market prices and exchange rates.

4.2 A parametric analysis through panel regressions

The empirical exercise discussed in the previous section allowed us to look at the link between education and portfolio returns and risk from a non-parametric perspective, i.e., looking at the entirety of the distribution. While this methodology is different (and more powerful) than parametric approaches, it might not be the best approach when jointly studying the differences between the two groups for a panel of countries once additional conditioning factors are included. Thus, as a second exercise - and to generalise our analysis to euro area countries - we focus on point estimates as opposed to the overall distribution. As previously discussed, the sample includes 10 euro area countries: Austria, Belgium, Germany, Spain, Finland, France, Ireland, Italy, Netherlands, and Portugal. We use the same data methodology used above. The only difference here is that, alongside the country and household dimensions, we exploit the time dimension as well. This means that return and risk measures are computed at quarterly frequency, using SHS summary statistics computed each quarter and HFCS data for wave 3, which remains constant over time. Therefore, our panel is defined as 10 countries, 5,266 households, and 16 quarters (2019Q1-2022Q4). We estimate the following equation, using OLS:

$$Return_{c,i,t} = \alpha + \beta Education_{c,i,t} + \gamma X_{c,t} + \delta_c + \theta_i + \eta_t + \epsilon_{c,i,t} \tag{7}$$

$Return_{c,i,t}$ is the return measure computed using the augmented dataset methodology, for each valuation type (total, market prices, exchange rate), for household i of country c in quarter t. $Education_{c,i,t}$ is the level of education of the household's reference person as described in the previous section (1=high education, 0=low education). $X_{c,t}$ is a set of macro-financial controls at the country level.[16]

We have two sets of controls. The first group captures the dynamics of the local financial system. This includes the quarterly growth rate of domestic market capitalisation, credit to the household sector as a percentage of GDP, and households' deposits to GDP. The second set accounts for macroeconomic conditions and features the nominal effective exchange rate (NEER), 10-year government bond yields, quarterly GDP growth, and the inflation rate.[17] Time fixed effects allow us to account for global factors that change over time but are common to the countries in our sample. See Table A1 in the Appendix for details on data sources and descriptions.

We include country, household, and quarter fixed effects ($\delta_c, \theta_i, \eta_t$). Standard errors are clustered at the country-household pair level.

Table 1 reports the coefficient estimates, for each valuation type. Education is strongly associated with higher returns. This complements the findings from the pre-

[16]For this specification, we only report results for return and not for risk because the latter is a second-moment measure, requiring the use of standard deviation controls. This prevents us from exploiting the time dimension as we do for return, making comparisons difficult and reducing the number of observations significantly in the regressions themselves.

[17]Rather than the NEER, it would be ideal to use debt-weighted exchange rate indices for our context. However, these are not available for our period of interest.

vious section and generalises them to euro area countries. While the previous result was about the entire distribution, the coefficient here is the point estimate of the average effect. Households with higher education benefit from a total return that is 31.4% higher compared to households without tertiary education (column 1). Confirming the descriptive evidence from the previous sections, total valuations mainly arise from market price valuation (column 2) as no significant effect of education appears when looking at valuation due to exchange rates (column 3).

TABLE 1: Regression results – Return

	(1)	(2)	(3)
Return:	Total	Market Prices	Exchange Rates
Education	**0.314****	**0.314****	**-0.001**
	(0.147)	**(0.138)**	**(0.010)**
Market Capitalisation	0.019***	0.014***	0.008***
	(0.005)	(0.005)	(0.001)
Credit to GDP	-0.016***	-0.013***	-0.005***
	(0.005)	(0.005)	(0.001)
Deposits to GDP	-0.041***	-0.048***	-0.003***
	(0.004)	(0.004)	(0.000)
NEER	0.583***	0.675***	0.159***
	(0.069)	(0.077)	(0.009)
10Y Government bond yield	0.011	-0.095	0.055***
	(0.073)	(0.075)	(0.010)
Inflation	0.121***	0.188***	-0.028***
	(0.031)	(0.033)	(0.005)
GDP growth	-0.044***	-0.056***	-0.012***
	(0.011)	(0.011)	(0.001)
Observations	84,256	84,256	84,256
R^2	0.924	0.932	0.983
Country FE	YES	YES	YES
Household FE	YES	YES	YES
Quarter FE	YES	YES	YES

Notes: Clustered standard errors in parenthesis. *, **, *** represent significance at 10%, 5%, and 1%, respectively.

Market capitalisation is positively associated with returns that households receive in their (mostly) cross-border positions, in line with the fact that stock markets co-move across countries. The coefficient for credit suggests that the more developed the domestic financial system, the more households invest locally. Moreover, in countries were credit is more developed, households invest less, while the opposite is true for market based economies. Given that our valuation sample from SHS has a large component of cross-border investments, this explains why credit is negatively associated with returns. A similar interpretation applies to deposits, for higher levels of household deposits one would expect less that less money is available for investments. We also find that an appreciation of the Nominal Effective Exchange Rate is positively associated with total returns. This could reflect that the appreciation of the domestic currency correlates with better performance of the assets (coefficient of market price return) held and/or that households with higher exposure to foreign financial markets benefit from currency appreciation (coefficient of exchange rate return). Although not significant, the higher the yield on government bonds the higher the return. This follows from the fact that debt securities are themselves part of the portfolio and this indicates that they contribute positively to the performance of the entire portfolio. Finally, we find that higher prices (inflation) increase total and market-based returns but reduce exchange rate returns.

To summarise, the non-parametric approach shows a robust association between education and portfolio returns. This result is confirmed by the parametric specification, showing robustness to the addition of country-specific conditioning factors. The two approaches deliver the same finding, i.e., that these differences emerge in market-based valuations rather than in exchange rates. As we mentioned above, exchange rate returns are generally harder to predict than market price returns, independent of education levels. Moreover, most of the variation in total returns arises from market price changes.

5 Conclusion

In this paper, we contribute to the literature on households and international finance by building a dataset combining the Security Holding Statistics (SHS) database with the Household Finance and Consumption Survey (HFCS) data. This novel dataset allows us to better understand the links between households and international finance and their implications for financial stability.

First, focusing on the role of education as a conditioning factor for Irish households, we find that households with higher levels of education exhibit a distinct investment behaviour that significantly impacts their portfolios. More educated Irish households not only display a greater likelihood of positive returns but also a higher risk tolerance. This underlines the pivotal role of education (and potentially financial literacy) in shaping investment strategies and risk management among households.

Beyond its immediate implications for understanding households' financial decisions in Ireland, our research carries broader significance. Could similar patterns be observed in other European countries? As such, we extend our analysis to a panel of euro area countries, and we find that these results can be generalised.

Overall, this preliminary analysis encourages further exploration of the conditioning factors beyond education, such as employment status, age, gender, income, and wealth, in the context of household finance. While this work could be the basis for valuable academic contributions, it could also be used as an input for policymakers. Understanding household finances is relevant, considering its implications for many economic behaviours including consumption, labour supply, macro-financial linkages, and more. Therefore, the insights derived from our novel dataset can serve as a valuable resource for policymakers seeking to assess the implications of households' decisions and enhance financial stability. For example, informing policy decisions that mitigate household exposure to risk and promote responsible financial behaviour are well within reach.

References

BACH, L., L. E. CALVET, AND P. SODINI (2020): "Rich pickings? Risk, return, and skill in household wealth," *American Economic Review*, 110(9), 2703–2747. 1

BOERMANS, M., ET AL. (2022): "A literature review of securities holdings statistics research and a practitioner's guide," *DNB Working Papers*, (757). 5, 8

BOERMANS, M. A., AND R. VERMEULEN (2020): "International investment positions revisited: Investor heterogeneity and individual security characteristics," *Review of International Economics*, 28(2), 466–496. 1

DEATON, A. (2017): *Consumer Expenditure*. Palgrave Macmillan UK, London. 1

ECB-HFCN (2020): "The household finance and consumption survey: Results from the 2017 wave," Discussion paper, ECB Statistics Paper. 13

——— (2021a): "HFCS User Database Documentation," Available here. 6

——— (2021b): "The Household Finance and Consumption Survey: Methodological report for the 2017 wave," Available here. 6

——— (2023): "Household Finance and Consumption Survey: Results from the 2021 wave," Discussion paper, ECB Statistics Paper. 1

FAN, J., AND Q. YAO (2017): *The elements of financial econometrics*. Cambridge University Press. 10

GALSTYAN, V., P. R. LANE, C. MEHIGAN, AND R. MERCADO (2016): "The holders and issuers of international portfolio securities," *Journal of the Japanese and International Economies*, 42, 100–108. 1

GALSTYAN, V., AND A. VELIC (2018): "International investment patterns: the case of german sectors," *Open Economies Review*, 29, 665–685. 1

GIOFRÉ, M. (2013): "International diversification: Households versus institutional investors," *The North American Journal of Economics and Finance*, 26, 145–176. 1

KAISER, T., AND L. MENKHOFF (2017): "Does financial education impact financial literacy and financial behavior, and if so, when?," *The World Bank Economic Review*, 31(3), 611–630. 19

KIM, Y. K., M. SETTERFIELD, AND Y. MEI (2015): "Aggregate consumption and debt accumulation: an empirical examination of US household behaviour," *Cambridge Journal of Economics*, 39(1), 93–112. 1

LANE, P. (2019): "Households and the transmission of monetary policy," in *Speech at the Central Bank of Ireland/ECB Conference on Household Finance and Consumption, Dublin, December*, vol. 16. 1

MIAN, A., AND A. SUFI (2018): "Finance and business cycles: The credit-driven household demand channel," *Journal of Economic Perspectives*, 32(3), 31–58. 1

MUELLBAUER, J. (1994): "The assesment: consumer expenditure," *Oxford Review of Economic Policy*, 10(2), 1–41. 1

ROQUE, V., AND M. C. CORTEZ (2014): "The determinants of international equity investment: Do they differ between institutional and noninstitutional investors?," *Journal of Banking & Finance*, 49, 469–482. 1

SANTOSO, W., M. SUKADA, ET AL. (2009): "Risk profile of households and the impact on financial stability," *BIS Papers*, 46, 58–74. 1

A Appendix

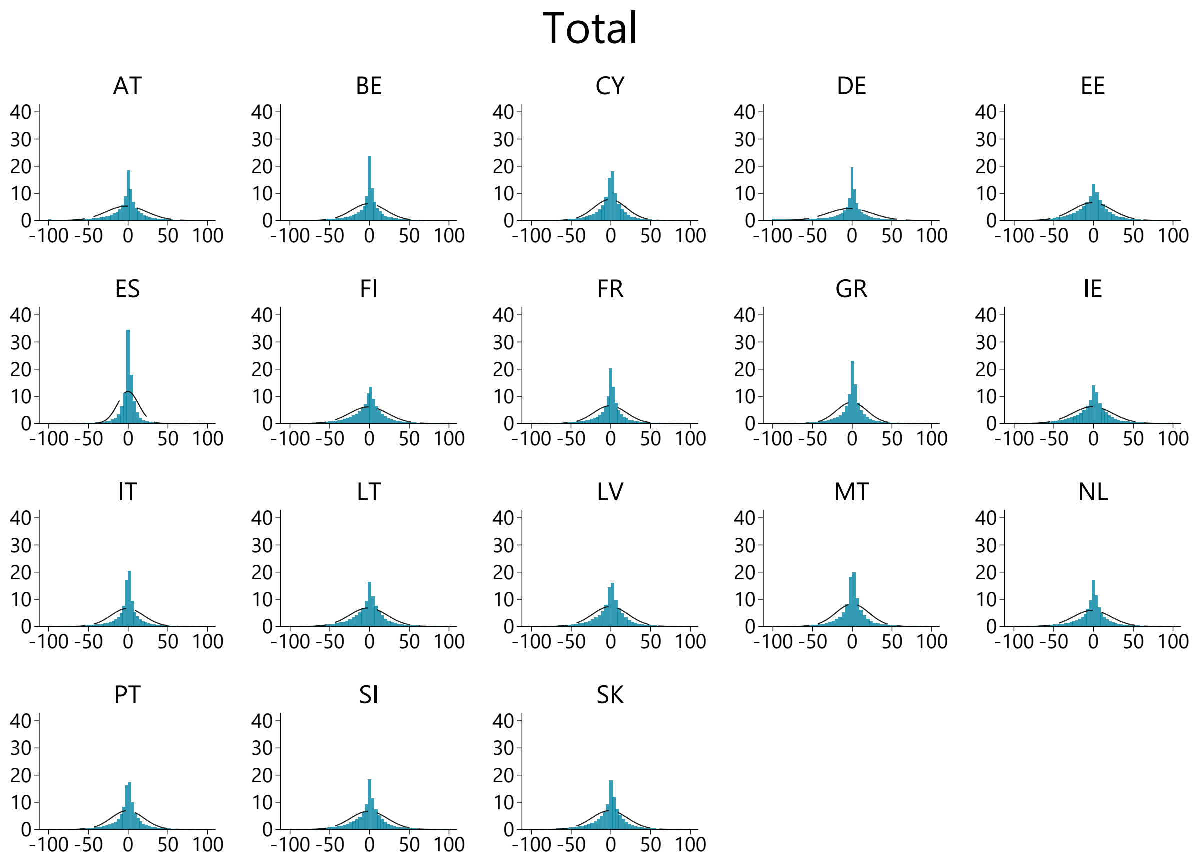

FIGURE A1: Distributions of total valuation rates (SHS)

Source: SHS and authors' calculations.
Notes: Percent on the y-axis, valuation rates in percent on the x-axis. Quarter-on-quarter valuation rates computed over the period 2019Q4-2022Q4 using all securities. The black dashed line is a standard normal distribution.

FIGURE A2: Distributions of market prices valuation rates (SHS)

Source: SHS and authors' calculations.
Notes: Percent on the y-axis, valuation rates in percent on the x-axis. Quarter-on-quarter valuation rates computed over the period 2019Q4-2022Q4 using all securities. The black dashed line is a standard normal distribution.

FIGURE A3: Distributions of exchange rates valuation rates (SHS)

Source: SHS and authors' calculations.
Notes: Percent on the y-axis, valuation rates in percent on the x-axis. Quarter-on-quarter valuation rates computed over the period 2019Q4-2022Q4 using all securities. The black dashed line is a standard normal distribution.

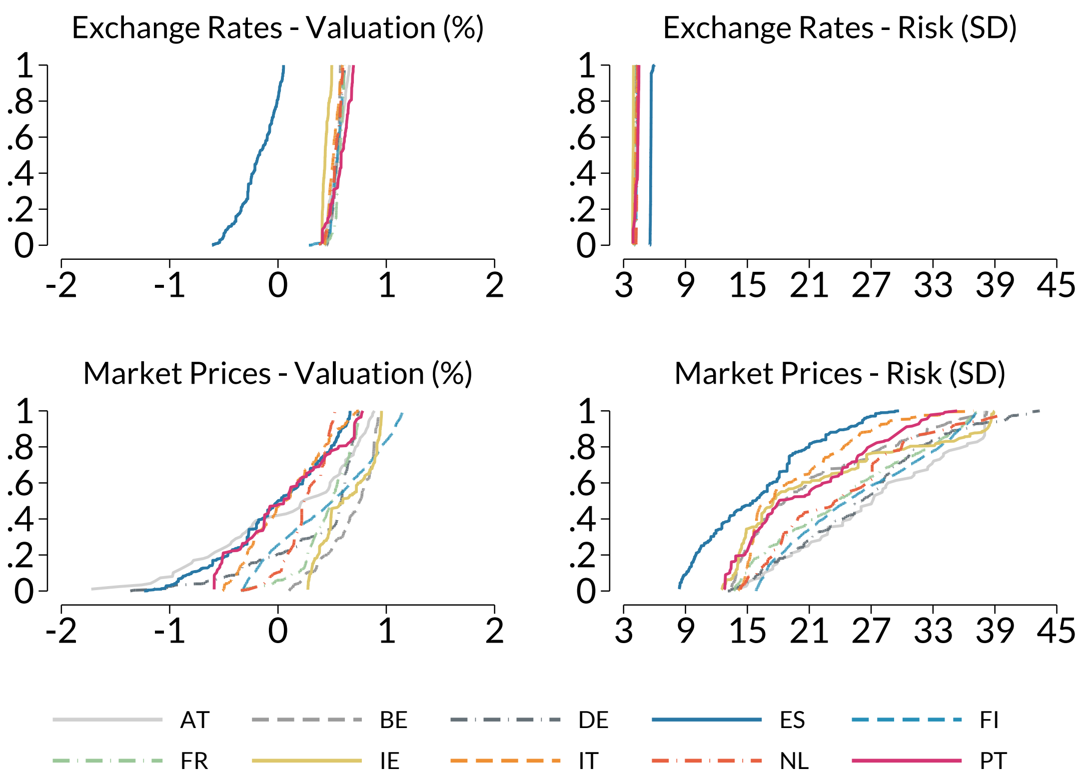

FIGURE A4: CDF of total valuation (left) and risk (right), by valuation type

Source: SHS, HFCS, and authors' calculations.
Notes: Cumulative share of households on the y-axis. CDFs of total valuation are computed using average valuations of each instrument type.

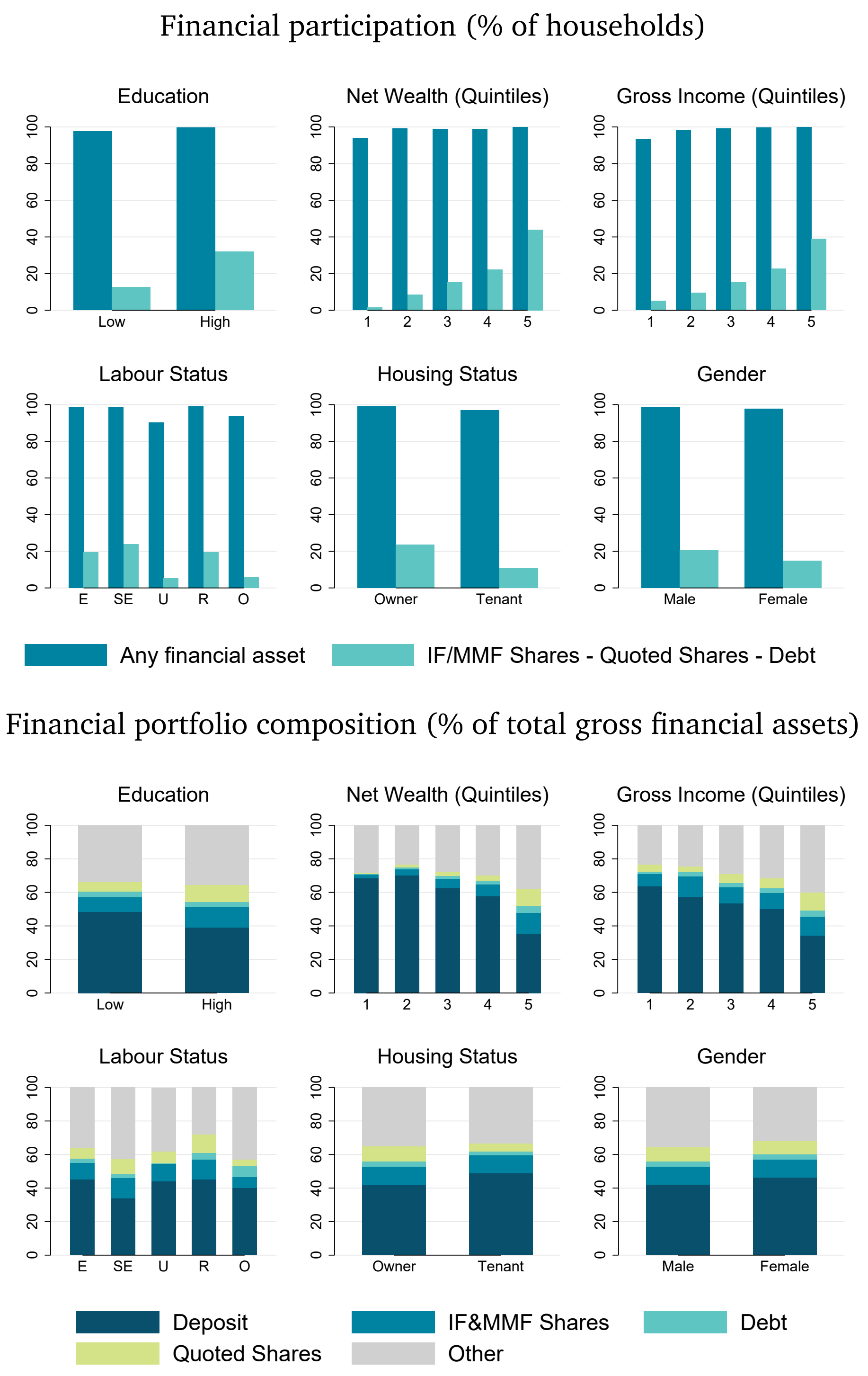

FIGURE A5: Financial holdings by households' characteristics, euro area

Source: HFCS (Wave 3 – 2017/18).
Notes: The upper panel illustrates household participation in financial assets, by instrument type. The lower panel shows the composition of financial portfolio, using the total by instrument type over the total of gross financial assets. "Other" includes non self-employment private business, managed accounts, money owed to households, voluntary pension/whole life insurance, and other financial assets. Labour status: E = employed, SE = self-employed, U = unemployed, R = retired, O = other. For housing status, "owner" includes both households with and without mortgage. Countries included are those considered in the main analysis, i.e., Austria, Belgium, Germany, Spain, Finland, France, Ireland, Italy, Netherlands, Portugal.

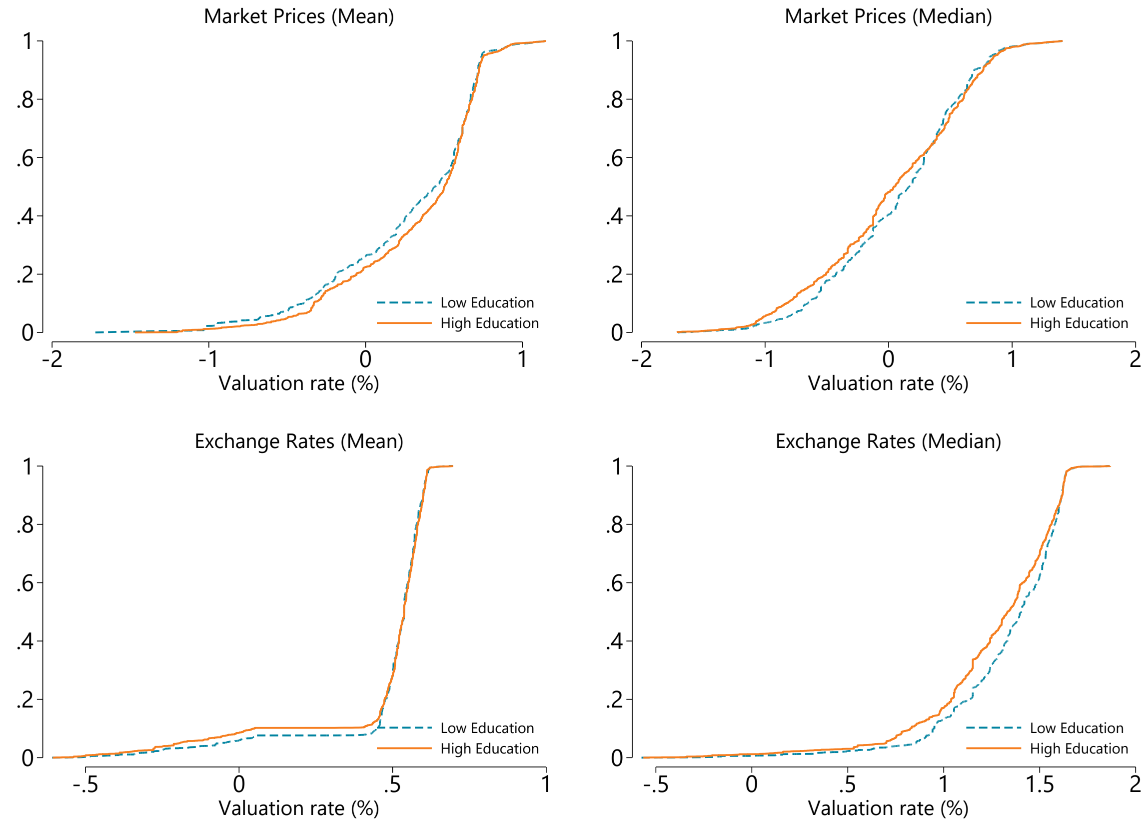

FIGURE A6: CDFs of return, market prices and exchange rates (euro area)

Source: HFCS and authors' calculations.
Notes: Cumulative share of households on the y-axis. Education level of the reference person in the household. Low Education is defined as no education/early childhood, primary, lower secondary, upper secondary, or post-secondary non-tertiary education. High Education is defined as short-cycle tertiary education, Bachelor, Master, or Doctoral. Countries included are Austria, Belgium, Germany, Spain, Finland, France, Ireland, Italy, Netherlands, Portugal. We use country-level household weights as representative of the euro area aggregate.

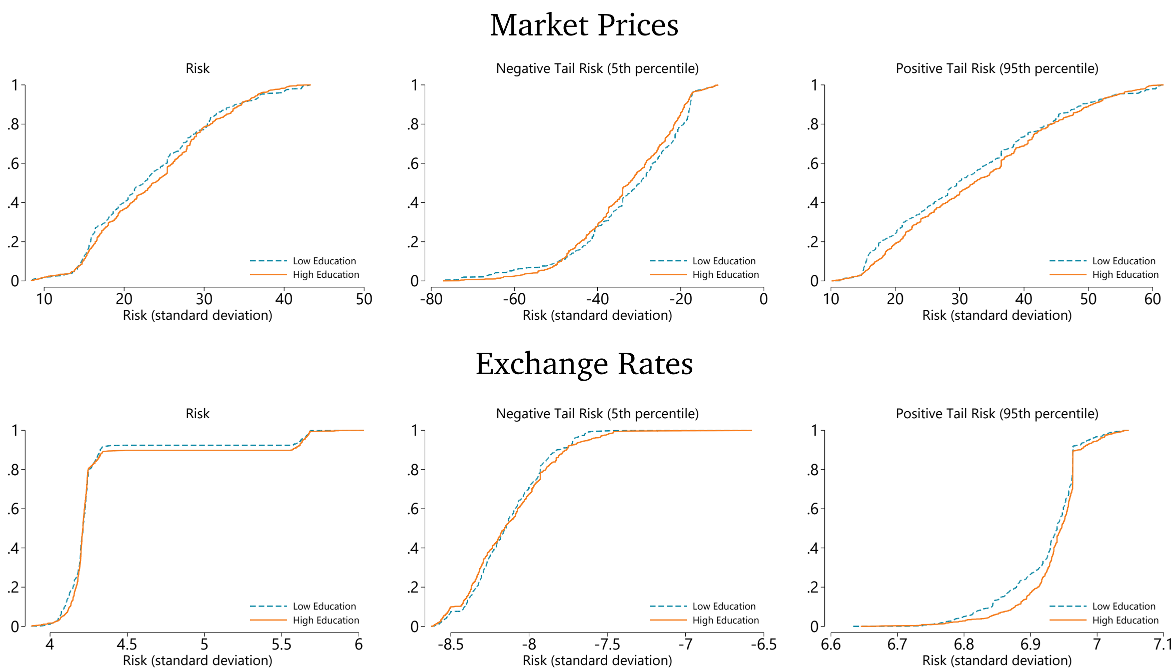

FIGURE A7: CDFs of return, market prices and exchange rates (euro area)

Source: HFCS and authors' calculations.
Notes: Cumulative share of households on the y-axis. Education level of the reference person in the household. Low Education is defined as no education/early childhood, primary, lower secondary, upper secondary, or post-secondary non-tertiary education. High Education is defined as short-cycle tertiary education, Bachelor, Master, or Doctoral. Countries included are Austria, Belgium, Germany, Spain, Finland, France, Ireland, Italy, Netherlands, Portugal. We use country-level household weights as representative of the euro area aggregate.

TABLE A1: Data sources and description

Variable	*Description*	*Source*
Stock market capitalisation	Total capitalisation of domestic market index, Quarterly, End of Period, EUR Million	Bloomberg
Credit	Total Credit to Households and Non-Profit Institutions Serving Households, Adjusted for Breaks, Quarterly, End of Period, LCU (Billions of Euros)	BIS (via FRED)
Deposits	Stock of deposits held in bank accounts by households, Euro Quarterly, End of Period	ECB
NEER	Broad Effective Exchange Rate (2020=100), Quarterly	BIS (via FRED)
10-year government yields	Long term bond yields, Quarterly, Basis points	Datastream
Inflation	Year on year growth rate of CPI, Quarterly	OECD
Real GDP	Quarterly real GDP, Millions of Chained 2010 Euros, Seasonally Adjusted	Eurostat (via FRED)