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Unravelling household financial assets and demographic characteristics: a novel data perspective[1]

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[1] This contribution was prepared for the conference. The views expressed are those of the authors and do not necessarily reflect the views of the European Central Bank, the Bank of Spain, the BIS, the IFC or the other central banks and institutions represented at the event.

Unravelling household financial assets and demographic characteristics: a novel data perspective

Simone Arrigoni, Agustín Bénétrix, Tara McIndoe-Calder, Davide Romelli[1]

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 high 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.

Contents

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1. Introduction and related literature

International financial integration measured through cross-border positions varies across 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, has been extensively documented in the relevant literature. However, most of those 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, only few papers have studied the sectoral heterogeneity in asset holdings (see Giofré, 2013; Roque and Céu 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. For example, household income determines aggregate private spending (Deaton, 2008; Muellbauer, 1994). Moreover, 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 value of their assets as well as their debts, 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 in 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 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 debts, labour income and/or ownership of small firms. Instead, the role of households in the macroeconomy via their holdings of financial assets is less well understood (Santoso and Sukada, 2006). This is despite the substantial holdings of financial assets by this sector. In the euro area households hold 20.1% of their gross wealth as financial assets in 2021 (ECB, 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 provide a methodology to combine two key sources for the analysis: financial information data on domestic and cross-border investments from the Security Holdings Statistics (SHS) and household-level data from the Household Finance and Consumption Survey (HFCS). The Security Holding Statistics (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 Household Finance and Consumption Survey (HFCS) collects cross-sectional household-level data on wealth (real and financial assets, liabilities, and credit constraints), income, consumption, saving and other household characteristics.

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.

Graph 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 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.[2]

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 to create an augmented dataset. Section 4 provides two applications to showcase the usage of the augmented dataset. Section 5 concludes.

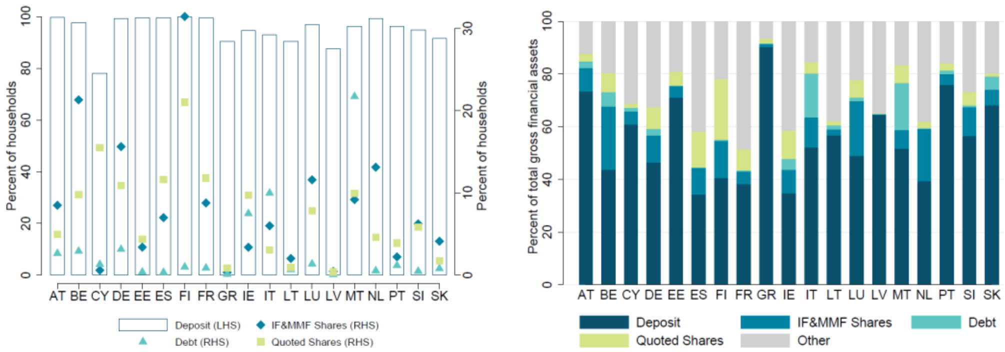
2. Data

This Section describes in detail the two datasets used in our analysis.

[2] 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.

Households' portfolios in the euro area[1]

Financial participation (left) and financial portfolio composition (right) Graph 1



[1] 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.

Sources: HFCS (Wave 3 – 2017/18).

2.1 Security Holdings Statistics (SHS)

The Security Holding Statistics (SHS) dataset is a Eurosystem database which 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, the *Centralised Securities DataBase (CSDB)* and the *Securities Holdings Statistics by Sector (SHS-S)*, that provide information about the issuer and the holder of securities, respectively. We link them using the unique common International Securities Identification Number (ISIN) identifier of each instrument.

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

1. *Investment Funds (IF) & Money Market Funds (MMF) Shares*: shares and units issued by investment funds and trust funds, and shares issued by MMF (i.e. collective investment schemes), respectively.

[3] 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. It also includes the non-profit institutions serving households, which are separate legal entities that serve households under voluntary contributions.

2. *Debt Securities*: short-term (original maturity of at most one year or repayable on demand of the creditor) and long-term (original maturity of more than one year or with no stated maturity).

3. *Quoted Shares*: shares listed either on a recognised stock exchange or any other form of organised secondary market.

Data are available at quarterly frequency starting from 2013Q4. The SHS sample covers the euro area countries and four additional participating non-euro area countries (Bulgaria, Czech Republic, Denmark, and Romania).

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 (Boermans, 2022), we include both observation types. This choice is in line with the guidelines provided in the ECB's 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, consumption and saving. 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 and 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 HFCS Methodological Report). 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 the security types in SHS: *Mutual Funds* (equivalent to IF & MMF Shares in SHS), *Debt*, and *Quoted Shares*.[4] Note that households are asked to report both domestic and international investments in these instruments.

3. Combining SHS and HFCS information to assess valuation effects and risk

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 compared 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. Graph 2 illustrates the comparison. From this exercise it emerges that for the vast majority of the countries households' portfolio on aggregate are similar in 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 to explore within country heterogeneity as well. This will be one relevant dimension of our contribution.

3.1 Data cleaning

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

We exclude securities that fall in 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 heaven, unallocated or unknown issuer country, issued by institutions, issued by Luxembourg or with Luxembourg as a reference area.[5]

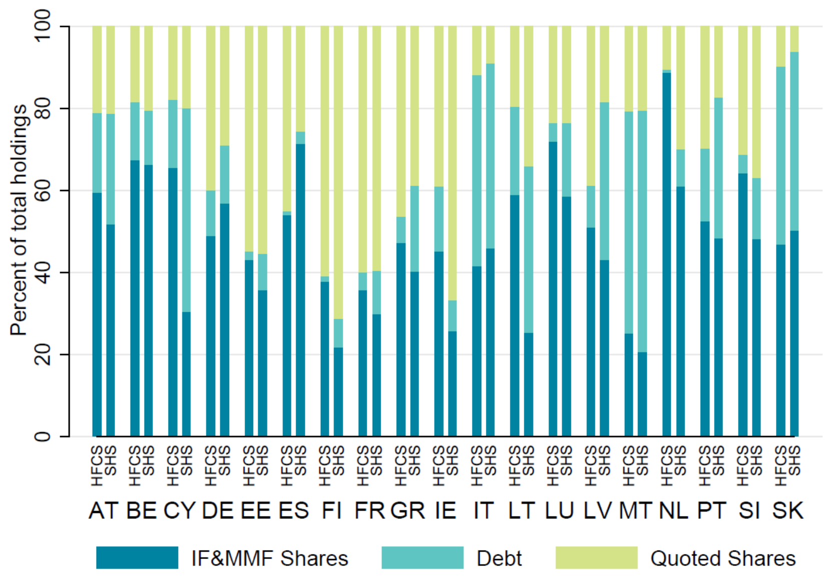
4 Differently from SHS, HFCS does not disaggregate mutual funds into investment funds and money market funds shares nor debt into short- and long-term. HFCS identifiers are DA2102, DA2103, and DA2105 for quoted shares, debt, and mutual funds, respectively (see HFCS User Database Documentation for details.)

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.

Instrument shares, HFCS vs SHS[1]

Wave 3, portfolio shares of total in percent

Graph 2



[1] 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.

Sources: HFCS, SHS, and authors' calculations.

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

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

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*

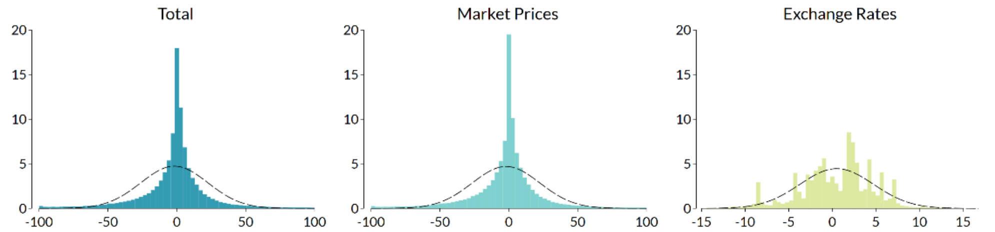
[6] Valuation rates/returns, as used in this context, encompass any capital gains or losses arising from fluctuations in market prices and exchange rates. The selected time frame for computing returns corresponds to the aftermath of the HFCS fieldwork, considering the last country in the sample. Separately, 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.

valuation is due to movements in the exchange rates of the currency of denomination of the security against the euro. We define *total* valuation as the sum of the two.

Graph 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 distributions of total and market prices valuation changes are more volatile than that of valuation changes due to exchange rates. On average, the standard deviation for total and market prices valuation is three times higher than the one for exchange rates. 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.[7] 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%.

Distribution of valuation rates from SHS[1]

Euro area countries, 2019Q4-2022Q4, percent — Graph 3



[1] 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.

Sources: SHS and authors' calculations.

It is important to note that 70% of the observations in our sample for total valuation are not issued by the holder country, which means they are cross-border (including other euro area countries). 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, 2015 for a summary). In particular, financial returns tend to display heavier tails compared to normal distributions, with asymmetry, i.e., returns are often

[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.

negatively skewed, and a larger mass concentrated around the mean.[8] It is worth noting that these stylised facts apply to all the countries in the sample (see Graphs A1, A2, A3 in Appendix).

Second, we compute summary statistics of these valuation rates, namely the mean, median, standard deviation, 5th and 95th percentiles. Then, we merge them with the HFCS data. 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. We take this information from the HFCS dataset.

Third, we compute household-level valuation rates for each country as a weighted average of the SHS summary statistics using household-specific portfolio shares (w_i^c) as weights:

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

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

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.[9]

Alongside returns, in a similar way, we compute two types of risk. One is based on realised volatility (the 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. Precisely, we designate the 5th percentile (P5) to represent significant valuation losses and the 95th percentile (P95) for substantial valuation gains.

$$Risk_{i,v} = \frac{1}{\sum_c w_i^c = 1} \sum_c \underbrace{w_i^c}_{HFCS} \underbrace{SD(Valuation\ Rate_{v,s,t}^c)}_{SHS}$$

$$Negative\ Tail\ Risk_{i,v} = \frac{1}{\sum_c w_i^c = 1} \sum_c \underbrace{w_i^c}_{HFCS} \underbrace{P5(Valuation\ Rate_{v,s,t}^c)}_{SHS}$$

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.

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

$$Positive\ Tail\ Risk_{i,v} = \frac{1}{\sum_c w_i^c = 1} \sum_c \underbrace{w_i^c}_{HFCS} \underbrace{P95(Valuation\ Rate_{v,s,t}^c)}_{SHS}$$

We exclude from our analysis households that do not have any investment in the three asset classes we consider. Moreover, given that our goal is to investigate investment diversification, we focus only on households that report holding at least two of the three instrument types. While financial participation from the survey is generally high, most of the households either have all their savings in bank accounts or they invest in only one of the three assets we are considering for our exercise. On average in the euro area, 10.2%, 3.2%, and 8.6% of households holds mutual funds, bonds, and shares respectively (ECB, 2020). These holdings account for an average of around 5% of the aggregate household net wealth and are mostly owned by wealthier households. Therefore, our sample includes a restricted number of households only (5,266 households) and we focus on countries with at least 50 households, i.e., Austria, Belgium, Germany, Spain, Finland, France, Ireland, Italy, Netherlands, Portugal.[10]

Before using the augmented dataset for our empirical analysis, we provide a visualisation of the dataset. We generate Cumulative Distribution Functions (CDFs), to highlight how valuation rates and the risk associated with them evolve alongside the household distribution.[11] 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). Graph 4 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 CDFs reflects a higher likelihood of lower-risk outcomes.

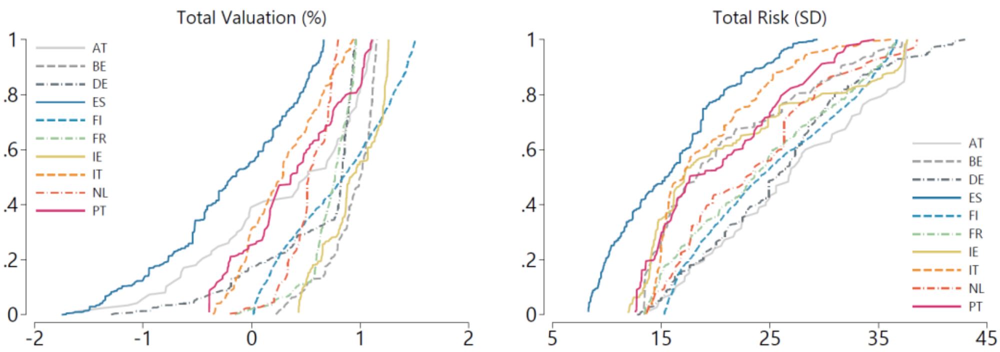
Visual comparison reveals substantial heterogeneity both *between* and *within* countries. Heterogeneity between countries is highlighted by the fact that countries have different return and risk profiles. Spanish households for example have the lowest return and risk. In contrast, countries like Ireland and Finland have the highest return and risk. Other countries show a mixed profile. Austrian households for example don’t 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.

[10] 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.

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

Cumulative distributions of total valuation (left) and risk (right)[1]

Percent (left), Standard Deviation (right) Graph 4



[1] Cumulative share of households on the y-axis.

Sources: SHS, HFCS, and authors' calculations.

4. Empirical analysis: the role of education

In this Section, we provide two empirical exercises that showcase how the augmented dataset constructed as above can be implemented 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. However, 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. 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* is defined as no education/early childhood, primary, lower secondary, upper secondary, or post-secondary non-tertiary education, while *high education* includes short-cycle tertiary education, Bachelor, Master, or Doctoral. While the goal of this paper is to illustrate 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.[12]

We comment on the results on two dimensions, i.e., return and risk. In each case, we will 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 dataset 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 within the distribution.

Graph 5 reports the CDFs of mean and median returns conditional on household education level being low or high.[13] A compelling narrative emerges. The CDF for households with high education levels *first-order* stochastically dominates the CDF for 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 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 return 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

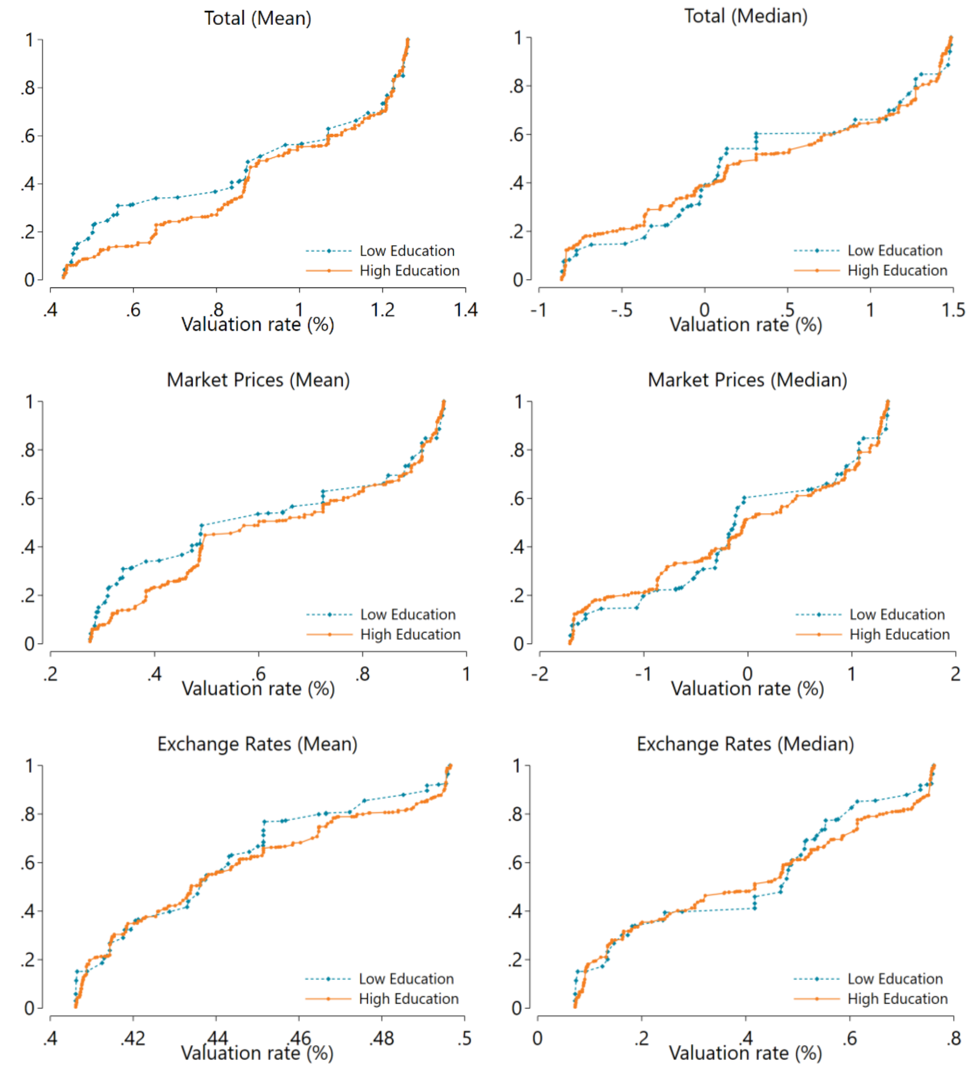
12 A detailed report of the results from the Eurobarometer is available here.

13 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.

diversification, impacting the distribution and composition of returns across different asset classes.

Return, by valuation type[1]

Ireland, Cumulative Distribution Functions (CDFs) Graph 5



[1] 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.

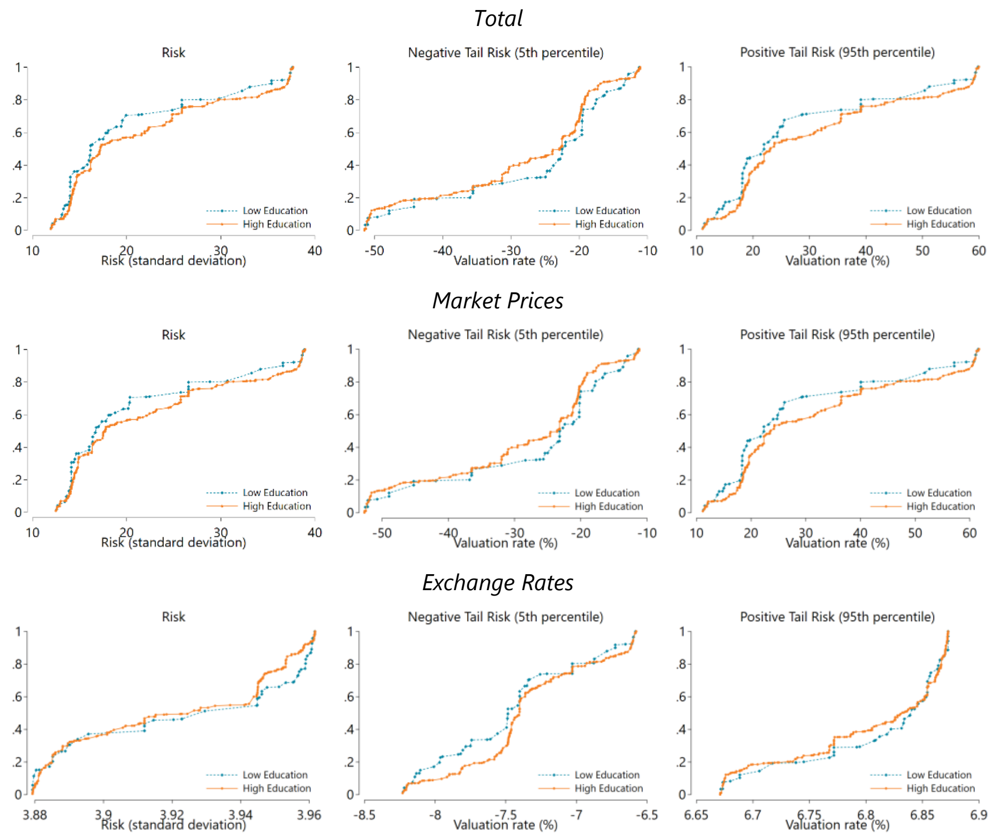
Sources: HFCS and authors' calculations.

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.

Graph 6 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 understanding of risk. Meanwhile, the middle and right sides delve into negative and positive tail risks, respectively. While comprehending standard deviation is relatively straightforward, we aim to offer a more detailed interpretation 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 rationalise our findings.

Risk, by valuation type [1]

Ireland, Cumulative Distribution Functions (CDFs) Graph 6



[1] Cumulative share of households on the y-axis. See Graph 4 for a description of education groups.

Sources: HFCS and authors' calculations.

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, however, higher-educated households realise greater returns in situations of elevated positive risk (top-right panel).

Delving into sub-components, similar to what we had for returns, the magnitude of risk primarily stems from market price valuation rather than changes in exchange rates. Notably, in the context of high-low education comparisons, market 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 chose to discuss the results for 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 following one, Graph 7 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 in the Irish examples. Compared to their lower-educated peer, higher-educated euro area households display greater returns and exhibit higher risk tolerance. Graphs A4 and A5 in Appendix, show the disaggregation into market prices and exchange rates.

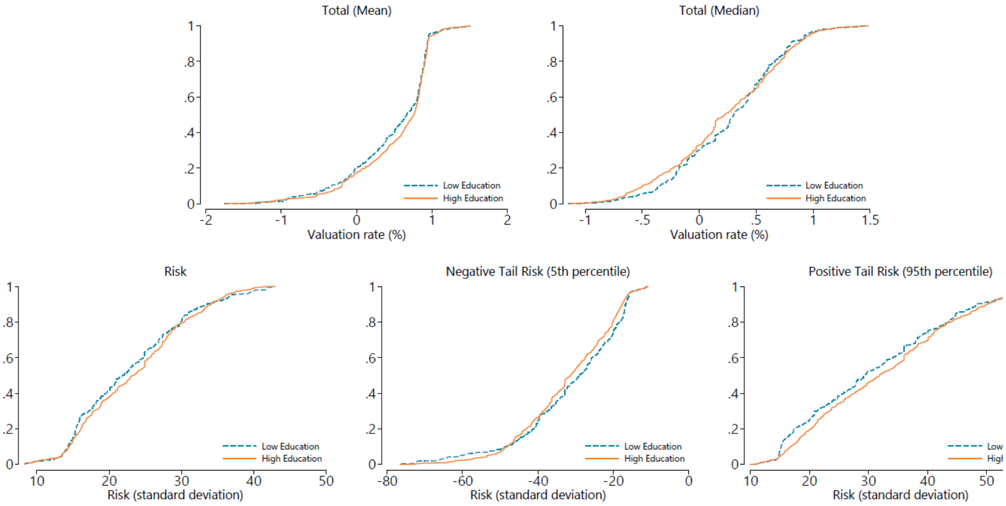
4.2 A parametric analysis through panel regressions

The empirical exercise discussed in the previous section allowed us to look at the link between education and portfolio return 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 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. As for the data, we use the same data methodology as implemented above when explaining the SHS-HFCS merge. The only difference here is that, alongside the country and household dimension, we exploit the time dimension as well. This means that return and risk measures are computed at the 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 by 10 countries, 5,266 households, and 16 quarters (2019Q1-2022Q4). The model we estimate using OLS is defined by the following equation:

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

Total return (top panel) and risk (bottom panel)[1]

Euro area, Cumulative Distribution Functions (CDFs) Graph 7



[1] Cumulative share of households on the y-axis. Countries included are Austria, Belgium, Germany, Spain, Finland, France, Ireland, Italy, Netherlands, Portugal. Education level of the reference person in the household. See Graph 4 for a description of education groups. We use country-level household weights as representative of the euro area aggregate.

Sources: HFCS and authors' calculations.

$Return_{c,i,t}$ 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* is the level of education of the household's reference person as described in the previous section (1=high education, 0=low education). X is a set of macro-financial controls at the country level.[14]

We have two sets of controls. The first group captures the dynamics of local financial systems. 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 condition and features the Nominal Effective Exchange Rate (NEER), 10-year government bond yields, quarterly GDP growth, and the inflation rate.[15] Time fixed effects account for global factors that change over time but are common to the country sample. See Table A1 in Appendix for details on data sources and descriptions.

[14] 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. In future versions of this paper, we plan to extend the analysis to risk as well in a complementary manner.

[15] 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. Thus, we proxy them with the NEER. However, we plan to construct our own measure of currency-weighted exchange rates using SHS data.

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 previous 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 tertiary education benefit from a total return that is 34% higher compared to households without tertiary education (column 1). Confirming descriptive evidence from the previous sections, total valuations mainly arise from market price valuation as no significant effect of education appears when looking at valuation due to exchange rates (columns 2 and 3).

Regression results[1]

Dependent variable: Return (percent) Table 1

	(1) *Total*	*(2)* *Market Prices*	*(3)* *Exchange Rates*
Education	0.343**	0.314**	-0.001
	(0.147)	(0.138)	(0.010)
Market Cap	0.019***	0.014***	0.008***
	(0.005)	(0.005)	(0.001)
Credit	-0.016***	-0.013***	-0.005***
	(0.005)	(0.005)	(0.001)
Deposits	-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)
Gov 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

[1] Clustered standard errors in parenthesis. * p<0.1, ** p<0.05, *** p<0.01.

Market capitalisation is positively associated with returns that household receive in their (mostly) cross-border positions, in line with the fact that stock markets comove across countries. The coefficient for credit suggests that the more developed the domestic financial system, the more households are incentivised to invest locally. 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 NEER is positively associated with total returns. Given that the majority of holdings in SHS for our sample of valuations are cross-border, this is due to the fact that these investments would be issued in foreign currency and then converted into euro. Thus, when the domestic currency appreciates, we households will experience an increase in the performance of their portfolio. 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. Higher prices (inflation) increase the total and market-based returns but reduce the exchange rates based one.

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

5. Conclusion

In this paper we contribute to the literature on households and international finance by building a dataset obtained by combining the Security Holding Statistics (SHS) with Household Finance and Consumption Survey (HFCS) data. This comprehensive 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, our study reveals 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 various economic behaviours such as consumption, labour supply, macro-financial linkages, and more. Therefore, the insights derived from our unique dataset can serve as a valuable resource for policymakers seeking to assess the implications of households' decisions and enhance financial stability. For example, informed policy decisions that mitigate household exposure to risk and promote responsible financial behaviour are well within reach.

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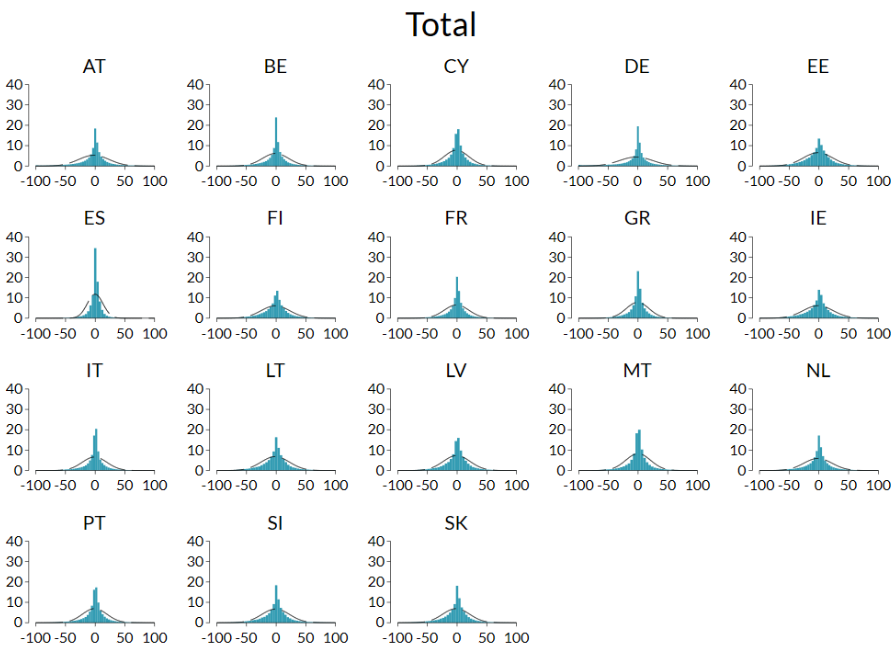
Appendix

Data description and sources: macro controls — Table A1

- *Market capitalisation*. Total capitalisation of the domestic market index, end of the period, Euro. Quarter on quarter growth rate.
  - Source: Bloomberg.
- *Credit to GDP*. Total credit to households and non-profit institutions serving households, adjusted for breaks, end of the period, Euro.
  - Source: BIS (via FRED).
- *Deposits to GDP*. Stock of deposits held in bank accounts by households, Euro.
  - Source: ECB.
- *NEER*. Broad nominal effective exchange rate (2020=100).
  - Source: BIS (via FRED).
- *10-year government yields*. Long term yields on government bonds.
  - Source: Refinitiv Datastream.
- *Inflation*. Year on year growth rate of CPI index.
  - Source: OECD.
- *GDP growth*. Real GDP (2010 chained Euro), seasonally adjusted. Quarter on quarter growth rate.
  - Source: Eurostat (via FRED).

Distribution of total valuation rates from SHS (%)[1]

2019Q4-2022Q4, percent — Graph A1



[1] 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.

Sources: SHS and authors' calculations.

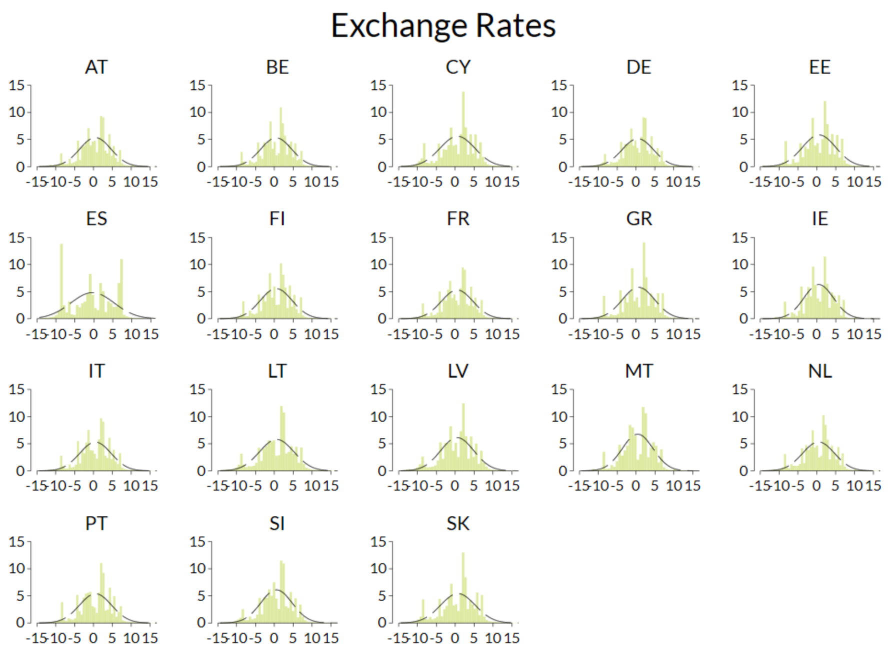
Distribution of market prices valuation rates from SHS (%)[1]

2019Q4-2022Q4, percent | Graph A2

[1] See Graph A1 for details and description.

Distribution of exchange rates valuation rates from SHS (%)[1]

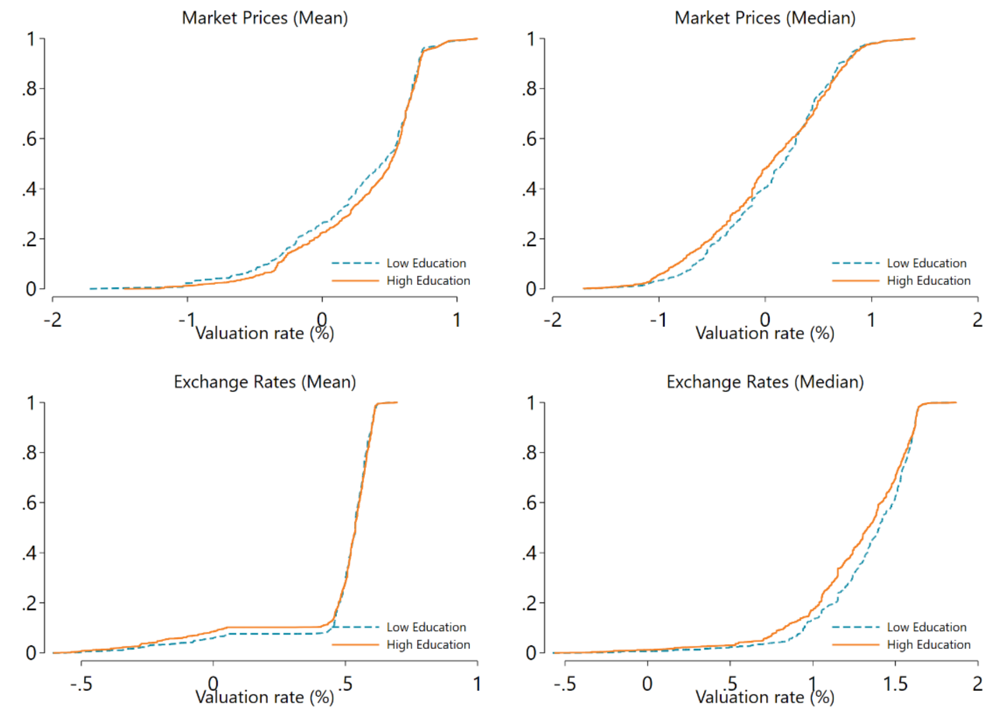
2019Q4-2022Q4, percent | Graph A3



[1] See Graph A1 for details and description.

Return, market prices and exchange rates[1]

Euro area, Cumulative Distribution Functions (CDFs) Graph A4

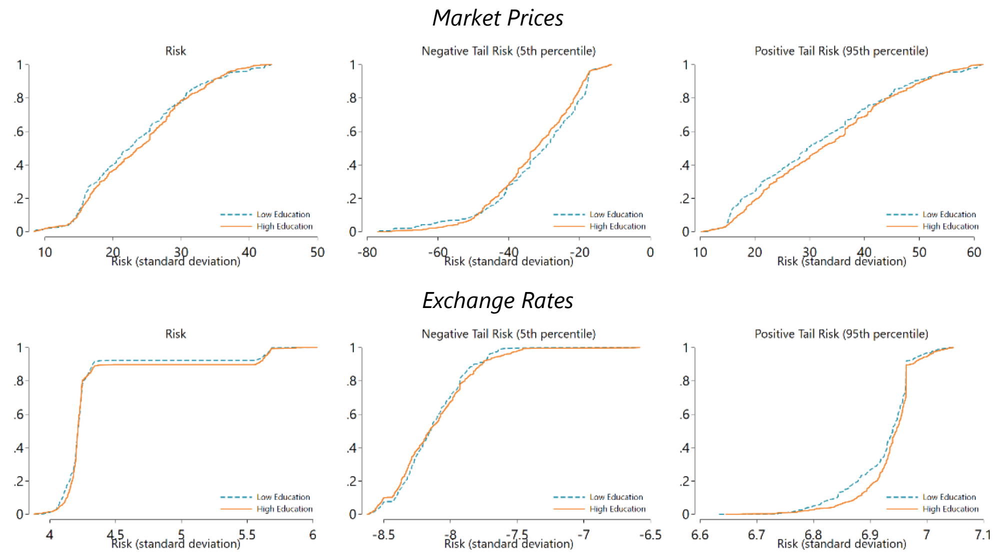


[1] Cumulative share of households on the y-axis. Countries included are Austria, Belgium, Germany, Spain, Finland, France, Ireland, Italy, Netherlands, Portugal. Education level of the reference person in the household. Low Education is defined as no education/early childhood, primary, lower secondary,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

Sources: HFCS and authors' calculations.

Risk, market prices and exchange rates[1]

Euro area, Cumulative Distribution Functions (CDFs) Graph A5



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Sources: HFCS and authors' calculations.

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Household portfolios in the spotlight: what can augmented data tell us?

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BdE-IFC-ECB 'External statistics after the pandemic'

Banco de España 12th February 2024

The views expressed are those of the authors and do not necessarily reflect those of the Central Bank of Ireland or the Eurosystem. The data have been cleared by the Eurosystem for non-disclosure of confidential data.

Introduction

Motivation

- International financial integration varies across countries and over time.
  - However, most of the literature take an aggregate perspective.
  - Little is known about sectoral characteristics, in particular for the household sector.
    Giofré (2013); Roque and Cortez (2014); Galstyan et al. (2016); Galstyan and Velic (2018); Boermans and Vermeulen (2020)
  - How do households' portfolios differ? What explains these differences?

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    Giofré (2013); Roque and Cortez (2014); Galstyan et al. (2016); Galstyan and Velic (2018); Boermans and Vermeulen (2020)
  - How do households' portfolios differ? What explains these differences?
- Why relevant? Household finances are important in assessing the macroeconomy, as decisions taken by households affect aggregate outcomes.
  Muellbauer (1994); Kim et al. (2015); Deaton (2017); Mian and Sufi (2018); Lane (2019); Bach et al. (2020)
  - However, the role of households via their holdings of financial assets is less well understood, despite substantial holdings (20% of gross wealth, euro area).
    Santoso et al. (2009); ECB-HFCN (2023)

This paper

- We study the link between international financial integration and household sector heterogeneity, *between* and *within* countries.
- We provide a methodology to **combine** two key data sources:
  - Financial information on investments from the Security Holdings Statistics (SHS).
  - Household level data from Household Finance and Consumption Survey (HFCS).
- We use this **augmented dataset** to illustrate research and policy applications arising from the combined information.

Data

1. Security Holdings Statistics (SHS)

- Eurosystem database which collects security-by-security information for euro area countries by holding sector. We focus on the household sector.
- Two sources of information:
  - Securities Holdings Statistics by Sector (SHS-S): **holder** view.
  - Centralised Securities Database (CSDB): **issuer** view.
- Information:
  - Stock-flow-**valuation(prices & exchange rates)**, **asset type**, issuer, currency.
  - Market value (€). euro area + BG, CZ, DK, RO. 2013Q4 onward.
- Investment Funds & MMF shares (IFMMF), Debt Securities (D), Quoted Shares (QS).

Holder Area vs Reference Area

2. Household Finance and Consumption Survey (HFCS)

- Cross-sectional household-level Eurosystem survey.
- Information: wealth (real and **financial assets**, liabilities, credit constraints), income, consumption and saving, household characteristics.
- Mutual Funds (=IFMMF), Debt Securities (D), Quoted Shares (QS).
- Survey design:
  - Waves: 2009/10 (W1), 2013/14 (W2), **2017/18 (W3)**, 2020/21 (W4). Fieldwork (W3)
  - Ex-ante harmonised across euro area countries.
  - Population representative sample and probabilistic sample design.
  - Oversampling of wealthy households.

Augmented Dataset

Combining SHS and HFCS

- In **SHS** we have detailed disaggregated information on **security holdings** at the sectoral level (household)
  ... **but** no demographic information on who holds them.

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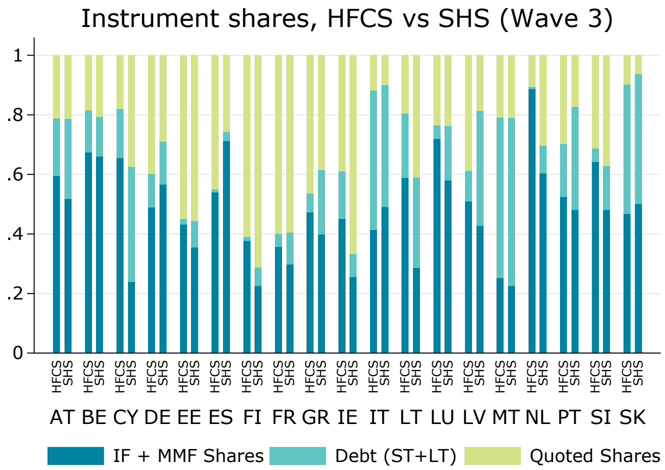
  ... **but** no information on valuation and risk.

Combining SHS and HFCS

- In **SHS** we have detailed disaggregated information on **security holdings** at the sectoral level (household)
  … **but** no demographic information on who holds them.
- In **HFCS** we have detailed disaggregated information on **household characteristics**
  … **but** no information on valuation and risk.
- The goal of the **augmented dataset** is to complement the missing information in a comparable manner for a panel of euro area countries

$$\underbrace{\underbrace{\text{Asset characteristics}}_{\text{SHS}} \Leftrightarrow \underbrace{\text{Household characteristics}}_{\text{HFCS}}}_{\text{Augmented Dataset}}$$

Rationale for merging: level differences, but shares are consistent



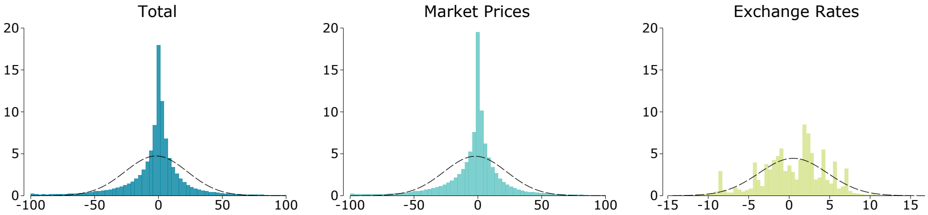
Notes: We match SHS with HFCS using the average of the quarters in which HFCS fieldwork was conducted in each country. *Source:* SHS, HFCS.

Step 1

- We compute quarter-on-quarter valuation rates at the security level using SHS data over the period 2019Q1-2022Q4:

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

  - v is the valuation type: total, market prices, exchange rates.
  - s is the unique security as identified by the ISIN.
  - t is the quarter.



Step 2

- We compute summary statistics of valuation rates: Mean, P50, SD, P5, P95.
- Then, we merge these information with HFCS data (W3).
    - *Assumption: every household in a country invests in the same pool of securities* ***within*** *each asset class (equity, debt, IF shares).*
    - **Heterogeneity** arises from the portfolio allocations across instruments for each household (in HFCS).

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  - **Heterogeneity** arises from the portfolio allocations across instruments for each household (in HFCS).
- Sample:
  - We focus on households that holds *at least two* of the asset classes.
  - We consider countries with at least 50 households.
  - $\Rightarrow$ 10 countries, 5266 households.

Step 3: Return

- We compute household-level returns for each country as a weighted average of the SHS summary statistics using HFCS household-specific portfolio shares (w_i^c) as weights:

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

$$Return_{i,v}^{median} = \frac{1}{\sum_c w_i^c = 1} \sum_c \underbrace{w_i^c}_{HFCS} \underbrace{P50(Valuation\ Rate_{v,s,t}^c)}_{SHS}$$

Step 3: Risk

- Capacity of households to diversify risk on an **ongoing basis**:

$$Risk_{i,v} = \frac{1}{\sum_c w_i^c = 1} \sum_c \underbrace{w_i^c}_{HFCS} \underbrace{SD(Valuation\ Rate_{v,s,t}^c)}_{SHS}$$

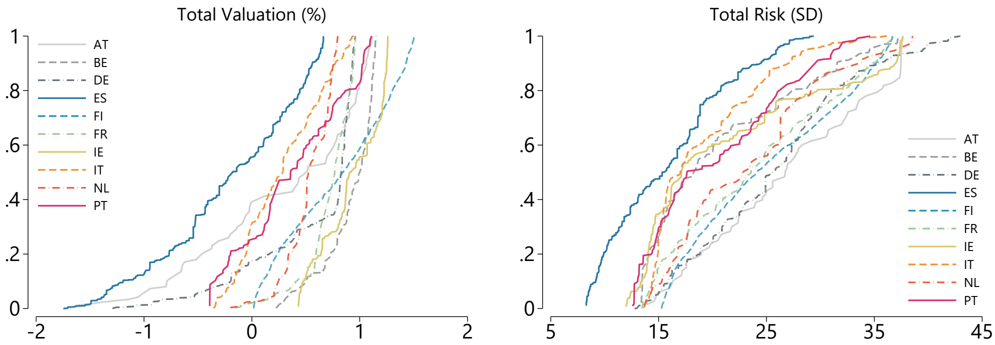
- **Tail risk** associated with big shocks (VaR):

$$Negative\ Tail\ Risk_{i,v} = \frac{1}{\sum_c w_i^c = 1} \sum_c \underbrace{w_i^c}_{HFCS} \underbrace{P5(Valuation\ Rate_{v,s,t}^c)}_{SHS}$$

$$Positive\ Tail\ Risk_{i,v} = \frac{1}{\sum_c w_i^c = 1} \sum_c \underbrace{w_i^c}_{HFCS} \underbrace{P95(Valuation\ Rate_{v,s,t}^c)}_{SHS}$$

Visualisation

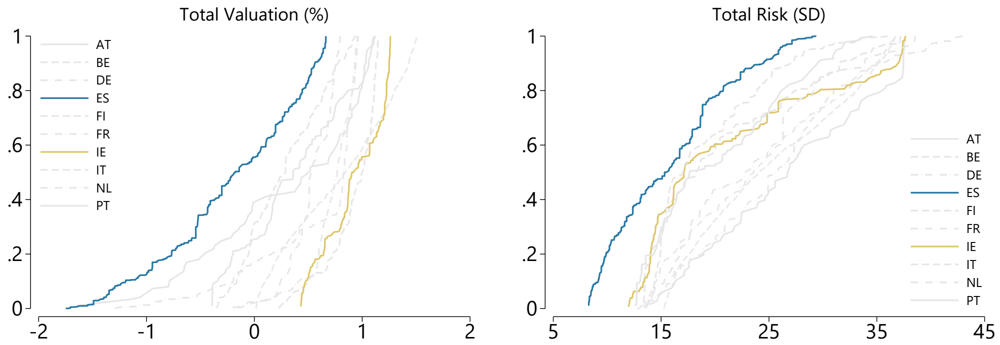
- **Cumulative Distribution Functions (CDF)**: how valuation rates and the risk associated with them compares *between* and *within* countries.



Notes: Cumulative share of households on the y-axis.

Visualisation

- **Cumulative Distribution Functions (CDF)**: how valuation rates and the risk associated with them compares *between* and *within* countries.



Notes: Cumulative share of households on the y-axis.

Applications

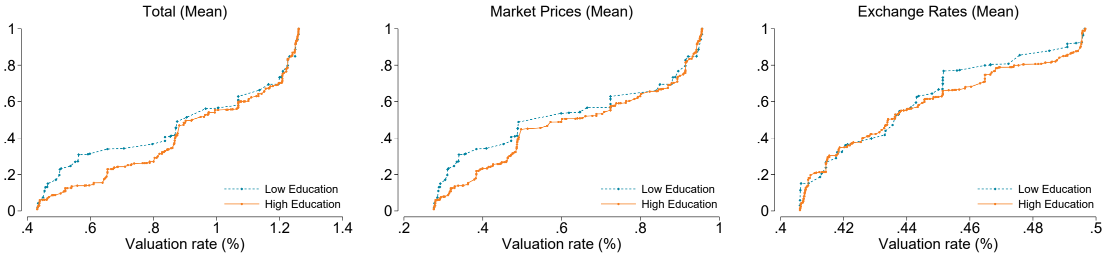
Why useful?

- The augmented dataset allows us to condition portfolio performances to **household characteristics** (of the reference person).
- We take **education** as an *illustrative example*, as it is a crucial dimension of portfolio choices (education → financial literacy → investment choices).
  Finke and Huston (2014)
  However, HFCS allows to extend to a wide range of dimensions, e.g., *labour status, age, housing tenure status, income.*
- **Low Education**: non-tertiary, **High Education**: tertiary.[1]
- We propose two **applications:**
  - 1. *Non-parametric*: conditional distributions (CDF) of returns/risk.
  - 2. *Parametric*: point estimates using regressions.

[1] Low: none/early, primary, secondary, post-secondary non-tertiary. High: short-cycle tertiary, Bachelor, Master, Doctoral

1. Conditional CDFs, Ireland – Return

Return

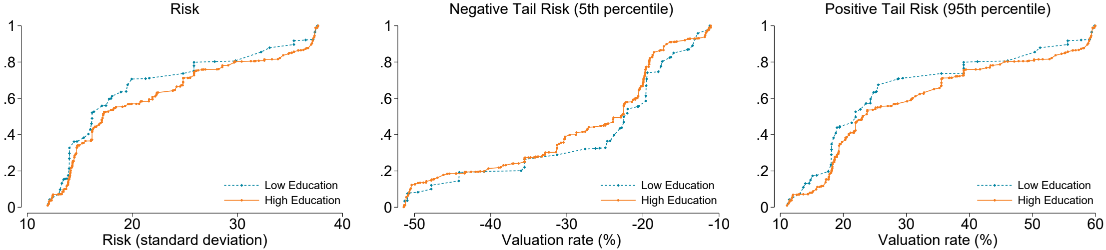


Notes: Cumulative share of households on the y-axis.

- The message is consistent with *median* CDFs too. CDFs (Median)

1. Conditional CDFs, Ireland – Risk

Risk (Total)



Notes: Cumulative share of households on the y-axis.

- Similar for market prices, reversed for exchange rates. CDFs

1. Conditional CDFs, Ireland – Summary

- Robust link between high education levels and returns.
- This link is consistent for both market prices and exchange rates.
- More educated households exhibit higher risk tolerance.
- Is Ireland an outlier? CDFs - Euro Area

2. Panel regressions, euro area

- CDF methodology is more powerful than parametric approaches, *but* it might not be the best approach for a panel of countries and once considering additional conditioning factors.
- To generalise the analysis, we turn to point estimates.

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- CDF methodology is more powerful than parametric approaches, *but* it might not be the best approach for a panel of countries and once considering additional conditioning factors.
- To generalise the analysis, we turn to point estimates.

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

  - c, i, t country, household identifier, and quarter.
  - $Return_{c,i,t}$ is the **quarterly** return measure computed using the augmented dataset.
  - $Education_{c,i,t}$ is a dummy: 1 = high education, 0 = low education.
  - $X_{c,t}$ is a set of macroeconomics controls at the country level. Sources and decription
  - 10 countries, 5266 household, 16 quarters (2019Q1-2022Q4)

2. Panel regressions, euro area

	(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

Notes: Country, households, and quarter fixed effects. Clustered standard errors in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

- Results are in line with those of the non-parametric approach.
  - Strong link education–return.
  - Market prices driving total returns.
  - Exchange rates not significant (High and Low CDFs crossing each other).

Conclusion

Conclusion

- We contribute to the literature on **households and international finance** by building an augmented dataset obtained by combining SHS and HFCS data.
- This **comprehensive dataset** allows us to better understand the links between households and international finance and their implications for policy.
- As an illustrative example, using two different methodological applications, we find a **positive link** between household education and portfolio performance.
- Our analysis encourages **further exploration** of conditioning factors and serves as input for **academic** contributions and **policymaking**. E.g., mitigate household risk exposure and promote responsible financial behaviour.

Thank you!

Any feedback is gratefully appreciated.

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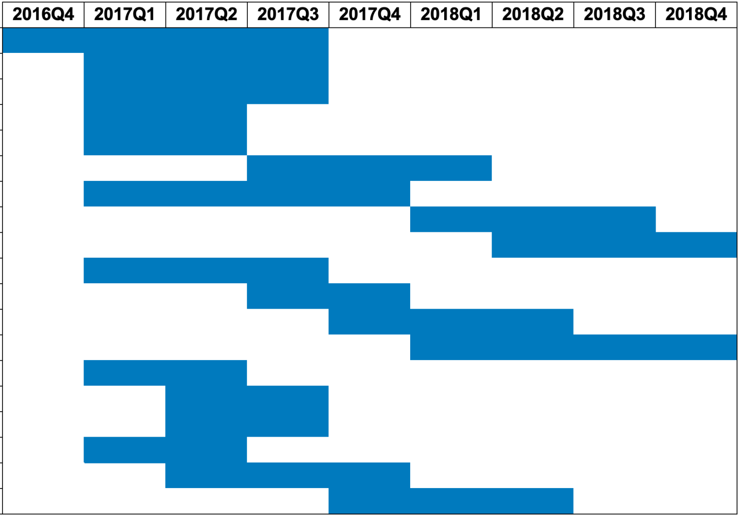
Appendix

Holdings by currency of issue Back

- Two concepts:
  - **Holder Area** = residency of the investor.
  - **Reporting Area** = country of the custodian.
- Example:
  - US assets (US issuer country) held by Irish Household sector via a German custodian.
  - $\rightarrow$ Holder Area is IE, Reference Area is DE, Issuer Area is US.
- For all sectors *except Households* - where double counting cannot occur.
- In our case, for the household sector, we include all information (i.e., both when Holder Area is equal and different than Reference Area)

HFCS fieldwork period (wave 3)

Back



	# Households
Austria	3,072
Belgium	2,329
Cyprus	1,303
Estonia	2,679
Finland	10,210
France	13,685
Germany	4,942
Greece	3,007
Ireland	4,793
Italy	7,420
Latvia	1,249
Lithuania	1,664
Luxembourg	1,616
Malta	1,004
Netherlands	2,556
Portugal	5,924
Slovakia	2,179
Slovenia	2,014
Spain	6,413
	78,059

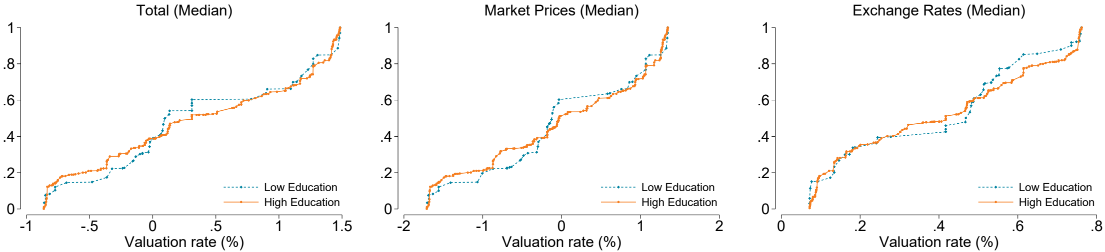
SHS data cleaning Back

- Reference: Boermans et al. (2022) + tailored adjustments for our analysis.
- We *exclude* securities that fall in one or more of these categories: unknown type, short positions, missing stock amount, issued by tax heavens / ISIN related to a tax haven, unallocated/unknown issuer country, issued by institutions, issued by LU / LU as a reference area.[2]
- We *restrict* the time sample to 2019Q1-2022Q4 (following HFCS W3).
- 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 all countries).

[2] 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.

1. Conditional CDFs, Ireland – Return

Back

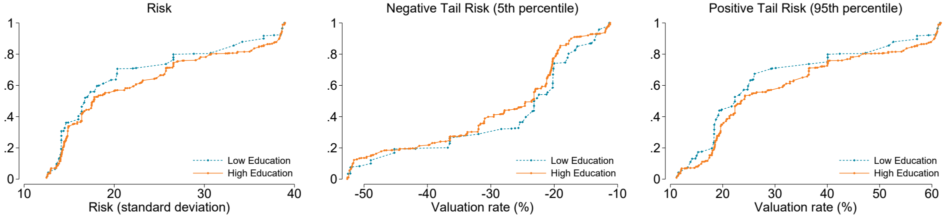


Notes: Cumulative share of households on the y-axis.

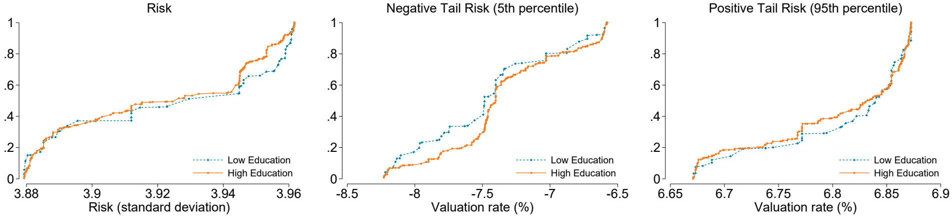
Conditional CDFs, Risk – Ireland

Back

Market Prices

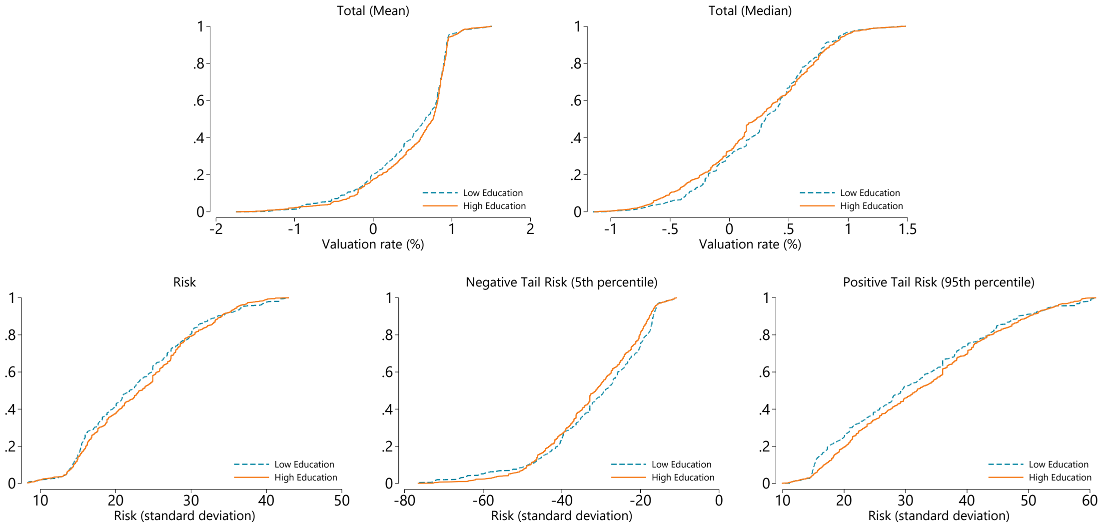


Exchange Rates



1. Conditional CDFs, euro area

Back



Data sources Back

- **Market capitalisation.** Total capitalisation of the domestic market index, end of the period, Euro. Quarter on quarter growth rate. *Source: Bloomberg.*
- **Credit to GDP.** Total credit to households and non-profit institutions serving households, adjusted for breaks, end of the period, Euro. *Source: BIS (via FRED).*
- **Deposits to GDP.** Stock of deposits held in bank accounts by households, Euro. *Source: ECB.*
- **NEER.** Broad nominal effective exchange rate (2020=100). *Source: BIS (via FRED).*
- **10-year government yields.** Long term yields on government bonds. *Source: Refinitiv Datastream.*
- **Inflation.** Year on year growth rate of CPI index. *Source: OECD.*
- **GDP growth.** Real GDP (2010 chained Euro), seasonally adjusted. Quarter on quarter growth rate. *Source: Eurostat (via FRED).*