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

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

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Financial wealth is important for many decisions, for example in relation to spending, labour supply, saving and retirement. To help inform policy in these areas, we combine survey and administrative data to study the financial assets held by Irish households, and the characteristics of the households who hold them. Looking across education groups, we find that higher educated households tend to hold assets with higher returns, but also riskier assets that are more susceptible to losses. Whilst this suggests that higher educated households exhibit distinct investment behaviour that significantly impacts returns, this is not a causal analysis. For example, it could also be related to income differences, which is positively correlated with education.

Introduction

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). 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 households' 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).

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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 held 20.1% of their gross wealth as financial assets in 2021 (ECB, 2023).

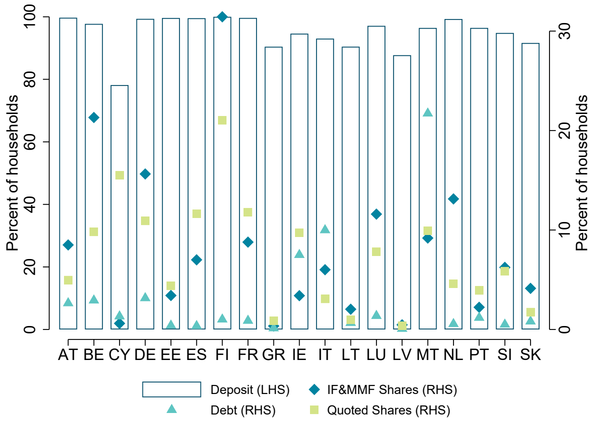
In an effort to bridge this gap, this *Letter* introduces novel data linking detailed attributes of the financial assets owned by Irish households with comprehensive information about the households themselves. We use this augmented dataset to illustrate the potential research and policy applications 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 association between education and 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 Irish households not only display a greater likelihood of positive returns but also a higher risk tolerance. This underlines the pivotal role of education, among other factors, in shaping investment strategies and risk management among households.

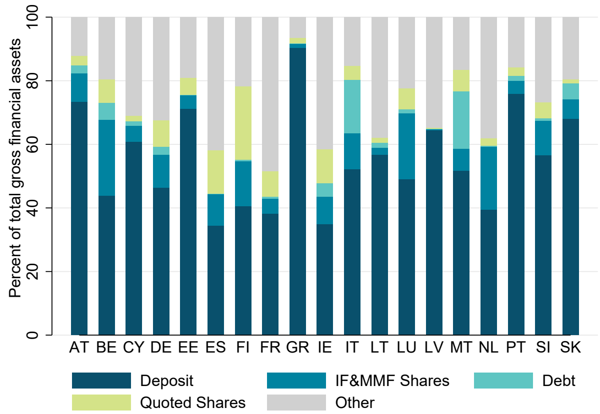
Disaggregated information on the financial asset holdings of households will be useful on a number of dimensions. For example, facilitating the identification of risks and imbalances within the sector concerning financial assets. Moreover, it enables a comprehensive examination of the impact of shocks 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 different 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, both in Ireland and the euro area more generally. To align the instrument coverage in the security database (SHS) with the household survey (HFCS), this *Letter* focuses on Investment Funds (IF) and Money Market Funds (MMF) shares, Quoted Shares, and Debt Securities. These assets collectively represent 24% of the total gross financial assets held by Irish households, with almost one in five Irish households owning at least one of these investment assets. Deposits, not included in the financial assets explored in this *Economic Letter*, account for 35% of total gross financial wealth in Ireland.[2]

[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.

Figure 1 | Financial participation (left) and financial portfolio composition (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.

Data

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, this *Letter* focuses on the Household sector.[3] Data at the security level are grouped into the following instrument types:

- *Investment Funds (IF) & Money Market Funds (MMF) Shares:* shares and units issued by investment funds and trust funds, respectively, and shares issued by MMF (i.e. collective investment schemes).
- *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] The households sector consists of individuals or groups of individuals as 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.

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

These are available at quarterly frequency starting from 2013Q4. For the purpose of this *Letter* we will focus on Ireland.[4] However, the SHS sample covers the 19 euro area countries and 4 participating non-euro area countries (Bulgaria, Czech Republic, Denmark, and Romania).

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 *Letter*, 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 a number of national statistical institutes.[5]

The set of questions asked in the HFCS survey are harmonised across euro area countries and the household sample is representative of the population (for more details see the HFCS Methodological Report). 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*.[6] Households are asked to report both domestic and international investments in these instruments.

[4] We build on work by Coates et al (2007).

[5] So far, four waves of the survey have been completed. The fieldwork for the first HFCS survey (2010 wave) was conducted 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. In this *Letter* we use data for the third wave.

[6] 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).

Combining SHS and HFCS to assess valuation effects and associated risk in Ireland

In order to combine the SHS data with the HFCS data, we proceed in four steps. First, we compute quarter-on-quarter valuation rates at the security level using SHS data over the period 2019Q1–2022Q4 as follows:[7]

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

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 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. Figure 2 shows the distribution of valuation rates for each valuation type. We can see that valuation changes due to market prices are larger than valuation changes due to exchange rates.[8] The distributions of total and market prices valuation changes are more volatile than that of valuation changes due to 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.[9] 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&P 500 lost around 20% in the first quarter of 2020, while the EUR/USD exchange rate only fell by 1.9%.[10]

Turning to distributions of the valuation rate themselves, none of them is normally distributed. This is in line with stylised facts of financial returns (see Fan and Yao, 2015 for a summary). 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

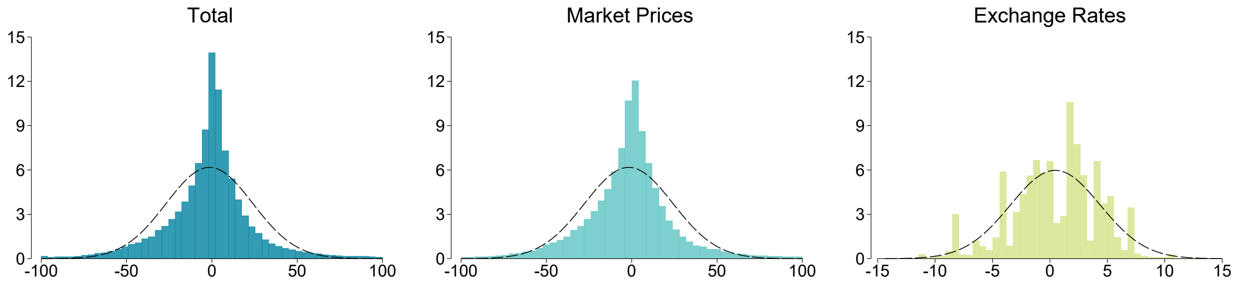
[7] Valuation rates/returns, as used in this context, encompass any capital gains or losses arising from fluctuations in market prices and exchange rates. The selected time frame for computing returns corresponds to the aftermath of the HFCS fieldwork for Wave 3 in Ireland, conducted between April 2018 and January 2019.

[8] Although we only show the distribution for Ireland here, this stylised fact applies to the entire sample of countries as well.

[9] For example, using data over the same horizon of interest, the coefficient of variation ($\frac{\text{Standard Deviation}}{\text{Mean}} \times 100$) 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.

[10] We take the United States as an example because 42% of the observations in our sample for total valuation are denominated in USD, and 37% of observations are issued by the United States. Note that 90% of observations are cross-border investments.

Figure 2 | Distribution of valuation rates from 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. For summary statistics see the Appendix.

around the mean.[11] For summary statistics on the distributions for each valuation type by instrument class see the Appendix section.

Second, we compute summary statistics of these valuation rates, namely the mean, median, standard deviation, 5th and 95th percentiles (See the Appendix section for details). 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 increases with net wealth but their share in total financial assets remains relatively constant (see Figure 6 in Appendix). This suggests that the household risk profile does not vary substantially with the wealth distribution, making it plausible to assume that households invest in the same pool of securities within these assets, but with different intensities.

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

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

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

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 (quoted shares, debt, IF & MMF shares). The mean return will be our baseline measure of return. Note that there is no time subscript in the return metrics,

[11] One has to 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 a period of high inflation.

as we compute them at the time of the HFCS fieldwork for wave 3, i.e. in 2018, using ex-post valuation rates.[12]

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.

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

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

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

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 household investment diversification, we focus only on households that report holding at least two of the three instrument types. Following this rationale, our sample includes 239 households only.[13].

Fourth, we generate cumulative distribution functions (CDF), to highlight how valuation rates and the risk associated with them evolve alongside the household distribution.[14] 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).[15] Figure 3 shows the cumulative distributions of total valuation effects and risk across households. 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

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

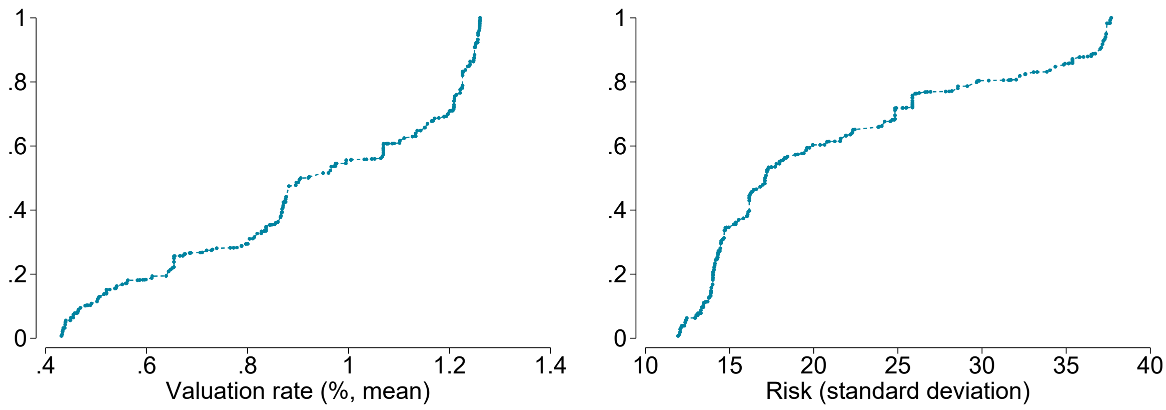
[13]This is around 5% of the full sample consisting of 4,793 Irish households. While financial participation from the survey is generally high in Ireland, most of the households either have all their savings in bank accounts or they invest in only one of the three assets we are considering for our exercise (see Figure 1).

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

[15]Looking at Figure 3, when taking for example 0.2 as a value from the y-axis, this will tell us that 20% of households experience an average valuation rate of around 0.6% (left panel) and a risk of around 15 (right panel).

the right side of the CDF suggests a higher likelihood of observing valuation rates that are higher than the average. Instead, the CDF of risk suggests 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 3 | Cumulative distributions of total valuation effects (left) and risk (right)



Source: HFCS and authors' calculations.
Notes: Cumulative share of households on the y-axis.

An illustrative example: education as conditioning factor

Given that the goal of our exercise is to complement the HFCS granularity at the household level with returns based on security level information from SHS, we now use these augmented data to produce cumulative distribution functions conditional on household characteristics. In this *Letter* we show an application with 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 straight forward to implement on several other dimensions, e.g., labour status, age, housing tenure status, income, and so on.[16] In our case, we focus on education because it allows us to explore the connection between financial literacy and investment decisions. According to the latest data from the Eurobarometer, Ireland demonstrates a relatively high level of financial literacy compared to the EU27 average.

We split our sample between households with high and low levels of education, exploiting the education level of the reference person in the household.[17] *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 ed-

[16] For illustration purposes on the potential of our methodology, Figure 7 in Appendix shows the heterogeneity of financial participation and the composition of financial portfolios across various household characteristics.

[17] The reference person in HFCS is designated as the most financially knowledgeable person within the responding household.

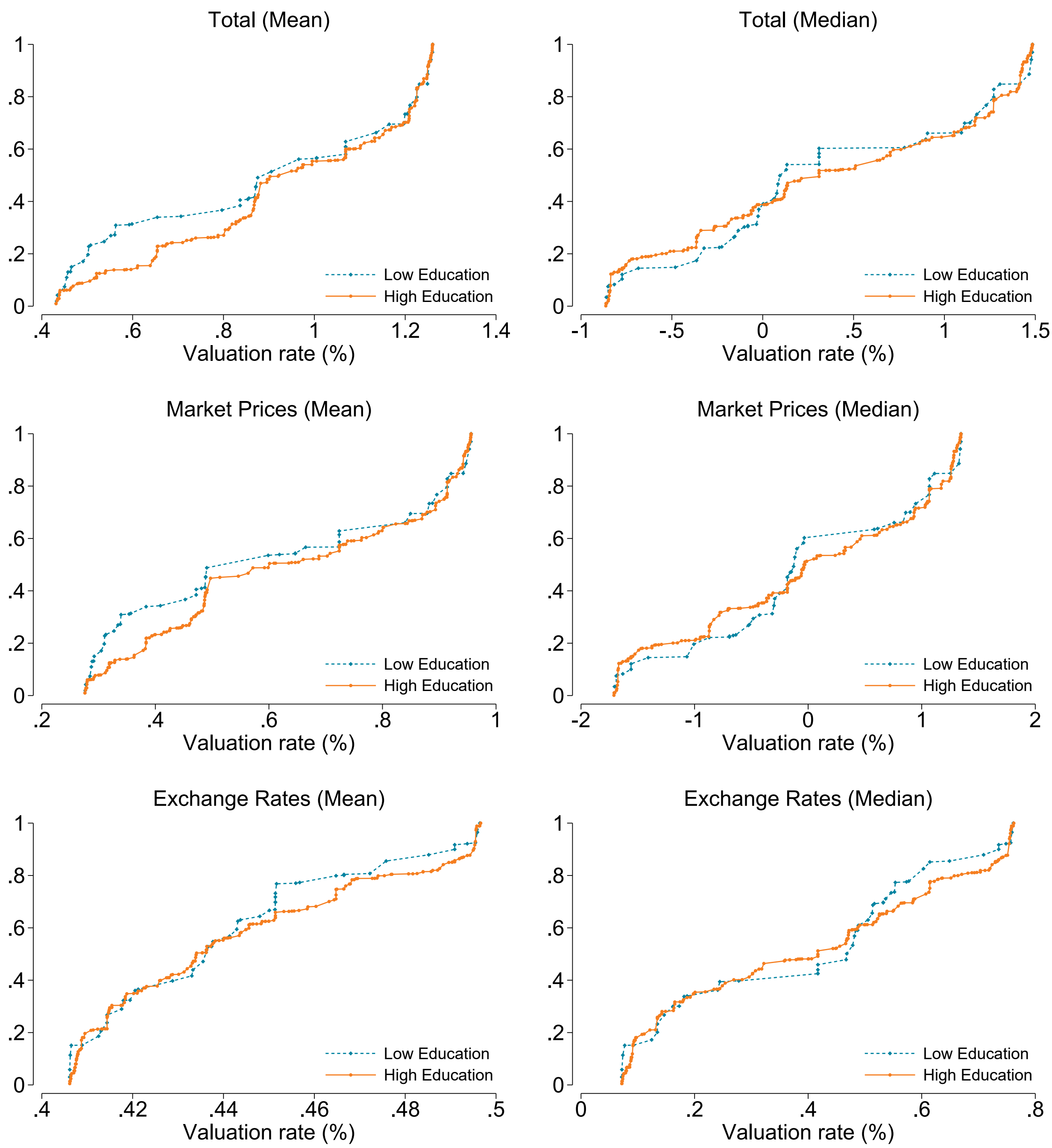
ucation, Bachelor, Master, or Doctoral.[18] While the goal of this note is to illustrate what can be done with these augmented data taking education as an example, we acknowledge that education might be correlated with other factors which in turn are associated with portfolio performance.Thus, results should not be interpreted as evidence of a causal relationship.

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 cumulative distribution functions (CDF) 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 than the other for all possible outcomes. We opted for 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 his approach helps in mitigating estimation uncertainty and bias more effectively than a narrow focus on a specific point within the distribution.

Figure 4 reports the CDF of mean and median returns conditional on household education level being low or high. 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 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 balance 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

[18] Given the limited sample size, we refrain from considering the results as representative of all Irish households. 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 4 | Return, by valuation type



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.

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 5 visually depicts the dimension of risk, with each row in the panel offering insights into 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.

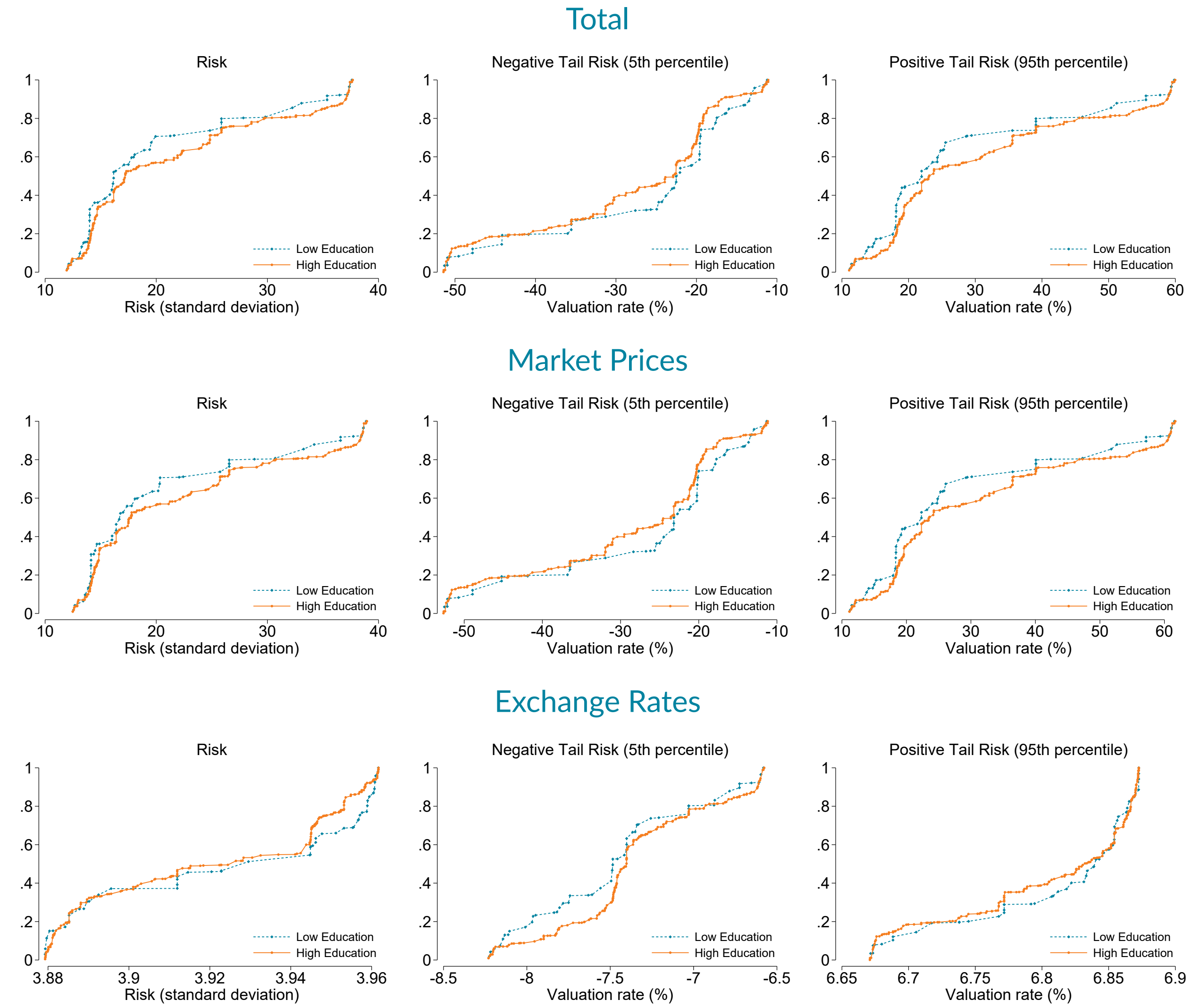
When examining total valuation, three messages emerge. First, households with higher levels of education exhibit higher exposure to risk across the entire distribution (top-left panel). This relates to the concept of risk tolerance. As education and financial literacy are correlated (Kaiser and Menkhoff, 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 low-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 return findings, 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 rates valuation the story of tail risks seems to be reversed. This might be explained by the fact that hedging exchange rates possibly requires less knowledge than hedging market prices or that exchange rates only explaining a minor part of the variance in total valuation. To summarise, while it is expected that higher returns come with higher risk – where markets are priced rationally – we find that this result derives from market price changes rather than exchange rate fluctuations.

Conclusion

In this *Letter*, 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.

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

Figure 5 | Risk, by valuation type



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.

suggests that higher educated households exhibit distinct investment behaviour that significantly impacts returns. However, this is not a causal analysis. For example, it could also be related to income differences, which is positively correlated with education. This underlines the role of education (and potentially financial literacy and income) in shaping investment strategies and risk management among households.

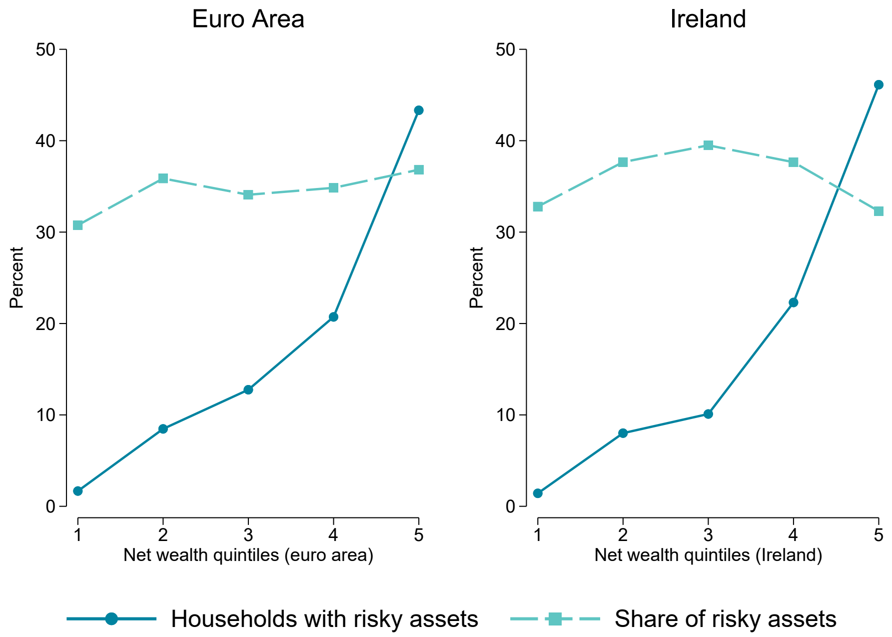
Beyond its immediate implications for understanding households' financial decisions in Ireland, our research carries broader significance. Could similar patterns be observed in other European countries? This opens the door to cross-country comparisons and policy considerations. In addition, our analysis encourages further exploration of the conditioning factors beyond education, such as labour status, age, income, and wealth, in the context of household finance. Moreover, the dataset we have constructed can also be used to implement a cross-country panel data analysis of European countries, allowing for the incorporation of macro-financial factors into the analysis.

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 unique 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.

Appendix

Financial holdings in HFCS

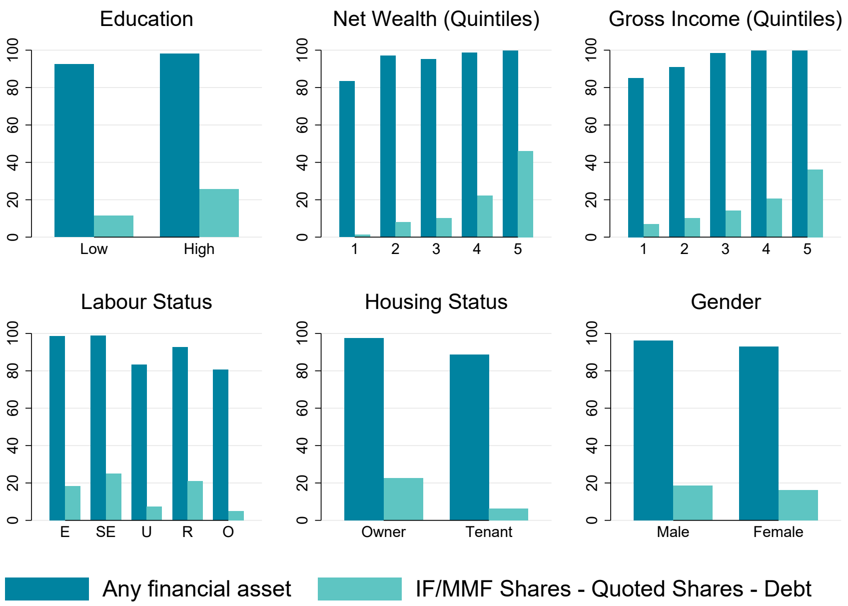
Figure 6 | Risky assets alongside the net wealth distribution



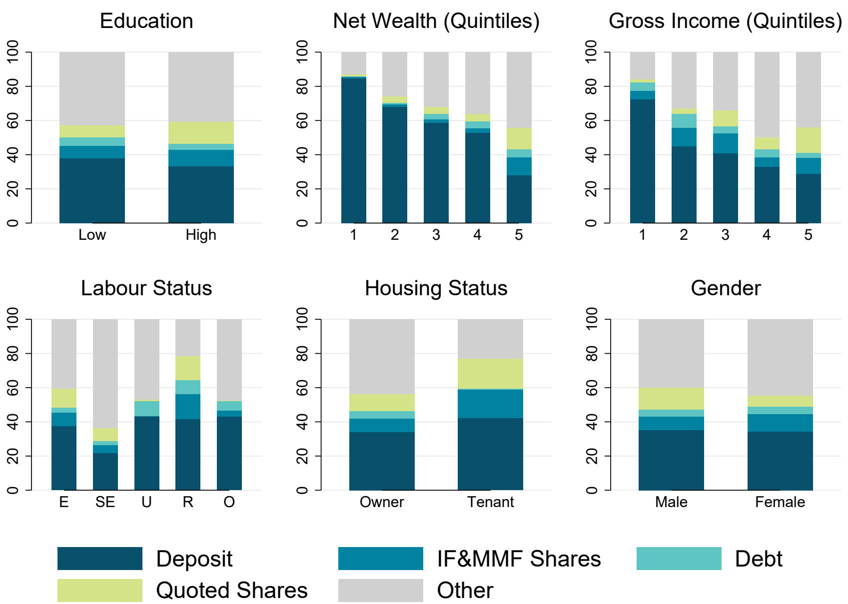
Source: HFCS (Wave 3) and authors' calculations.
Notes: Risky assets include quoted shares, mutual funds, and debt securities. The solid line indicates the proportion of households holding risky assets, while the dashed line represents the conditional average share of risky assets in gross financial wealth. The left panel is based on all euro area countries surveyed in wave 3.

Figure 7 | Financial holdings by households' characteristics, Ireland

Financial participation (% of households)



Financial portfolio composition (% of total gross financial assets)



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.

Data cleaning in SHS

Before computing valuation rates, we perform a set of data-cleaning procedures on the full SHS dataset. 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 haven, unallocated or unknown issuer country, issued by institutions, issued by Luxembourg or with Luxembourg as a reference area.[19]

As mentioned in the main text, we restrict the time sample to 2019Q1-2022Q4 to have measures of return and risk which follow the fieldwork period of HFCS Wave 3.

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 all countries, not just Ireland).

Table 1 presents the number of observations on which our analysis for SHS is based on, by valuation and instrument types.

Table 1 | SHS final sample for Ireland, by valuation and instrument types

	Total	Market Prices	Exchange Rates
All securities	129,251	122,639	106,950
Quoted Shares	94,968	88,996	84,444
Debt	6,739	6,243	2,354
IF & MMF Shares	27,544	27,400	20,152

Source: SHS.
Notes: These are observations, not single securities. The pool of securities might differs across groups.

[19] 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.

Summary statistics on returns in SHS

Table 2 summarises the statistics related to the distributions of valuation returns in SHS, by asset class and valuation type.

Table 2 | Summary statistics

	Total	Market Prices	Exchange Rates
▷ All Securities			
Mean	0.94	0.58	0.48
Median (P50)	0.24	-0.10	0.70
Standard Deviation (SD)	33.08	34.00	3.93
5th Percentile (P5)	-46.25	-47.17	-6.60
95th Percentile (P95)	49.25	50.41	6.72
▷ Quoted Shares			
Mean	0.88	0.49	0.50
Median (P50)	-0.86	-1.71	0.76
Standard Deviation (SD)	37.72	38.99	3.94
5th Percentile (P5)	-51.48	-52.70	-6.57
95th Percentile (P95)	60.04	61.76	6.67
▷ Debt			
Mean	0.43	0.28	0.43
Median (P50)	0.14	-0.03	0.47
Standard Deviation (SD)	11.94	12.49	3.96
5th Percentile (P5)	-11.08	-11.18	-8.23
95th Percentile (P95)	11.08	11.17	6.86
▷ IF & MMF Shares			
Mean	1.26	0.96	0.41
Median (P50)	1.48	1.34	0.07
Standard Deviation (SD)	14.01	14.14	3.88
5th Percentile (P5)	-19.62	-20.23	-7.48
95th Percentile (P95)	18.14	18.39	6.87

Source: SHS and authors' calculations.

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