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Financial portfolio performance of Belgian households: a nonparametric assessment

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Abstract

We analyze the financial portfolio performance of Belgian households, using data from the 2010, 2014 and 2017 waves of the Household Finance and Consumption Survey survey. We document the characteristics of households that participate in risky asset markets, and we examine which households achieve good financial portfolio performance. To this end, we propose a nonparametric method for performance measurement that naturally integrates the well-known Sharpe ratio. The method produces an intuitive "efficiency" measure that quantifies the evaluated household's portfolio performance relative to the observed performance of other (best performing) households. It allows us to account for cross-household variation in risk-free return rates and to mitigate the impact of outlier behavior. We report significant cross-sectional variation in portfolio efficiency. High educated, non-retired and wealthier households generally achieve higher levels of efficiency, as do households with a female head. These findings can be instrumental in developing specifically tailored financial education programs and may have implications for the evolution of (long-term) wealth inequality. Lastly, we report that households improve their performance over time, suggesting a learning-by-doing effect.

Keywords: household finance, benchmarking, mean-variance portfolios, Sharpe ratio, nonparametric method, Belgian households.

JEL Codes: D14, G11, G50

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Non-technical summary

Since the 1990s, households in Western countries have gained access to a variety of financial products. As a result, ownership of stocks, bonds and other risky assets was no longer limited to the wealthy. In addition, the past decade has been characterized by record-low interest rates, which led to a gradual decline in the return on safe bank deposits. In turn, this forced households in search of investment returns to shift their portfolio holdings toward riskier investments. While economic theory assumes that investors are rational decision makers, a large body of research reports that households hold suboptimal portfolios. This paper studies whether adjustments in household portfolio allocations reflect efficient decision making, and whether the degree of efficiency varies across socio-economic groups.

We examine the financial behavior of a panel of Belgian households using data from the first 3 waves of the HFCS survey, which contains information on household balance sheets across a wide range of asset classes. We analyze household portfolios using a non-parametric method that naturally integrates the well-known Sharpe ratio. A main distinguishing of the method is that it compares a household's portfolio performance relative to that of other households in the sample. This contrasts with the usual practice of comparing against the outcomes of optimizing economic models that do not account for biases present in financial decision-making.

We report that the participation of Belgian households in risky asset markets declines over time. Households with a male, older, employed or more educated head are more likely to hold risky assets, as are richer households. Further, only a small fraction of Belgian households performs relatively efficient, which is consistent with the presence of behavioral biases in household financial decision-making. When expressed in monetary terms, we find that suboptimal investment strategies cost the median household in the sample between 0.5% and 3.1% of annual gross income in foregone investment returns. Consistent with previous research, these losses are smaller for high educated and wealthier households, and for households with a female head. On the other hand, retired households perform significantly worse. Finally, we find preliminary evidence that households are able to increase their performance over time.

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1 Introduction

Since the 1990's product innovations in the finance industry have provided many households in Western countries with easy access to risky asset markets. For example, banks began to offer a variety of financial products and, over the years, a wide range of mutual funds were made available to retail investors. As a result, ownership of stocks, bonds and other risky assets was no longer limited to the wealthy. At the same time, despite the democratization of financial markets for the general public, many households still adhere to traditional ways of saving. In addition, the increased availability of financial products increases the risk of exposing unsophisticated households to unwanted risks. Because of these developments, how households allocate their financial portfolios has become an increasingly important issue for both economists and policymakers alike (Ameriks and Zeldes, 2004). In particular, since the financial crisis, policymakers have repeatedly stressed the importance of prudential supervision and increased transparency of financial actors to proactively assess risk profiles (see e.g. the ECB Financial Stability Review).

In addition, in response to the global financial crisis, the sovereign debt crisis and, more recently, the covid crisis, the European Central Bank (ECB) has gradually reduced interest rates to historic lows. This led to a gradual decline in the return on safe bank deposits, forcing households in search of investment returns to shift their portfolio holdings towards alternative, riskier investments. This raises the question of to what extent adjustments in household portfolio allocations reflect "efficient" decision making (i.e., maximizing investment returns for a given level of risk) and whether the degree of efficiency varies across socio-economic groups.

Indeed, previous research casts doubt on the ability of households to make optimal financial decisions. As noted by Barber and Odean (2013), the bulk of economic research assumes rational decision makers, who seek to maximize wealth while minimizing risk. However, the same authors note that empirical evidence suggests that "*the investors who inhabit the real world and those who populate academic models are distant cousins*" (Barber and Odean, 2013, p.1565). For example, they note that a large body of empirical research reports that retail investors hold suboptimal, underdiversified portfolios, which should be of concern to policymakers.

Empirical contribution. While the investment performance of institutional investors (especially mutual funds) has been studied extensively, a growing body of work examines the financial decision making of households. Many studies examine variation in (cross-country) participation rates and risky asset shares (see e.g. Gomes et al., 2021, for a review). Several papers also assess the performance of household equity portfolios (e.g. Barber and Odean, 2000; Goetzmann and Kumar, 2008; Grinblatt et al., 2011; Campbell et al., 2019). However, because high-quality micro data on the investor's entire balance sheet is often not available, most of the existing work is typically limited to studying a single asset class. With the exception of Calvet et al. (2007, 2009), very few papers examine the efficiency of comprehensive household financial portfolios.

We contribute by examining the financial behavior of a panel of Belgian households, using data from the 2010, 2014 and 2017 waves of the Household Finance and Consumption Survey (HFCS). In contrast to previous work studying heterogeneity in participation rates and risky asset shares, the HFCS survey contains information on household balance sheets across a wide range of asset classes, not limited to individual stock and mutual fund holdings.[1] Such detailed information is far from standard. As such, our analysis provides a comprehensive view of households' financial portfolios, allowing for the study of portfolio performance, on which the literature offers little guidance (the work of Calvet et al., 2007, being a notable exception). In addition, the HFCS survey provides detailed information on individuals' socio-economic and demographic characteristics as well as income and wealth levels, real estate holdings and consumption patterns.

The cited papers evaluate the performance of household portfolios by computing Sharpe ratios or (excess) returns.[2] For example, Calvet et al. (2007), computed Sharpe ratios to examine the financial portfolio holdings of a panel of Swedish households. However, we cannot readily apply Calvet et al.'s method to the HFCS data because, as explained below, we need information on index returns to calculate household portfolio return and risk, whereas Calvet et al. (2007) uses these index returns to estimate a CAPM model. Instead, this paper proposes a nonparametric method (that incorporates the Sharpe ratio) to evaluate household portfolio performance.

Methodology. A specific feature of our approach is that it is rooted in Data Envelopment Analysis (DEA, see Cooper et al. (2011), for a detailed review); as we will detail below, this has a number of distinctive advantages. Moreover, while Calvet et al. (2007) analyze Swedish households in the period 1998-2002, we study Belgian households in the period 2010-2017. Du Caju (2016) and de Sola Perea (2020) document substantial reallocation of Belgian household portfolios and financial assets over the past decade. Furthermore, whereas the period 1998-2002 was characterized by high variability of risky assets (following the dot-com crisis), the period 2010-2017 was mainly associated with decreasing risk-free returns (in addition to uncertainty due to the euro crises).

DEA is a nonparametric method to assess the relative efficiency of a group of decision making units (DMUs) that use one (or more) inputs to produce one (or more) outputs. In the finance literature, the use of such nonparametric frontier methods to study investment performance is not uncommon (see e.g. Glawischnig and Sommersguter-Reichmann, 2010; Kerstens et al., 2011; Abdelsalam et al., 2014, and the references therein). Murthi et al. (1997) were the first to use DEA to measure the performance of mutual funds. Basso and Funari (2016) provide a comprehensive overview of papers that apply DEA to study the efficiency of mutual funds, socially responsible investment funds, futures funds, pension funds, real estate funds, etc. While DEA (and its stochas-

[1]Remark that in comparison to Calvet et al. (2007, 2009), we also include individual bond and mutual fund bond holdings. While Von Gaudecker (2015) equally studies investors' total balance sheets, his analysis considers a small sample of less than 400 observations.

[2]Traditional performance measures proposed in the finance literature include the classic Sharpe, Jensen, Treynor, Sterling and Sortino ratios (all of which relate return to risk in some way or another). Another widely cited metric is Carhart's four-factor multi-performance model (Carhart, 1997). However, there is no consensus in the literature as to which of these measures is preferable.

tic counterpart Stochastic Frontier Analysis (SFA)) is well-established to measure the performance of different types of mutual funds, we are not aware of any papers using DEA methods to evaluate comprehensive household portfolios. As noted above, this is most likely due to a lack of high-quality data.

In the spirit of Markowitz (1952)'s mean-variance framework, the DEA approach constructs an empirically derived frontier that reflects observed best practice behavior. Instead of benchmarking against the predicted outcomes of a normative Capital Asset Pricing Model (CAPM) (as in Calvet et al. (2007)), our DEA-based method produces an "efficiency" score that evaluates a household's portfolio performance relative to the observed performance of other (best performing) households. This ensures that the optimal outcome is a feasible alternative for the households considered. It also allows for, unlike dimensionless Sharpe ratios, intuitively interpreting DEA-based efficiency scores as a measure of relative performance. Furthermore, by their very nature these DEA-based scores avoid the use of a normative benchmark, which may be criticized given that household financial decision making is often characterized by numerous biases (see e.g. Barber and Odean, 2001, for a review).

Next to this main motivation, our DEA approach to evaluating portfolio efficiency has some additional noteworthy advantages. Firstly, it easily allows for cross-household variation in risk-free returns to account for heterogeneity in savings account rates (as documented in Deuflhard et al., 2019). Secondly, it can directly implement a subsampling procedure to overcome the sensitivity to outlier observations. Finally, a straightforward extension of our method allows for a dynamic analysis that studies changes in portfolio performance over time.

Results. We find that the participation of Belgian households in risky asset markets declines over time. While fewer households invest through the years, those who do so gradually increase the share of risky assets in their portfolios. Over time, fewer households hold underdiversified, purely domestic stock portfolios. Participation in individual bonds declines sharply after 2014. Unsurprisingly, investment in risky asset markets is confined to relatively wealthier households, with participation rates rising sharply with the level of financial wealth. In addition, households with a male, older, employed or more educated head are more likely to participate in risky markets, as are homeowners.

Further, we report significant cross-sectional variation in household portfolio efficiency, with only a small fraction of Belgian households performing relatively efficient. When quantifying inefficiency scores in monetary terms, we find that suboptimal investment strategies cost the median household in the sample between 0.5% and 3.1% of annual gross income in foregone investment returns. Losses are found to be significantly higher for retired households. Moreover, consistent with previous research, high educated and wealthier households obtain higher efficiency scores, as do households with a female head. Finally, we find that households are able to improve their performance over time, suggesting a learning-by-doing effect.

The rest of the paper is organized as follows. Section 2 provides an overview of the HFCS data and describes both household participation rates and risky asset shares for Belgian households. We also discuss how we construct the measures of portfolio return and risk that we use in our empirical efficiency analysis. Section 3 explains the methodology underlying our efficiency estimates, describing the link between Sharpe ratios and DEA. We also show how to quantify portfolio efficiencies in monetary terms. Section 4 presents our main empirical findings, and Section 5 concludes.

2 The Belgian HFCS data

We analyze data for Belgian households that participate in the Household Finance and Consumption Survey (HFCS). The survey (coordinated by the ECB and national central banks) collects household-level data on households' financial and consumption behavior in all euro area countries, together with detailed household demographic data. As such, this unique survey makes a detailed analysis of household wealth and financial issues possible. We use the first three waves of the questionnaire, for which interviews were conducted in 2010, 2014 and 2017. After data cleaning we are left with 6480 observations. The HFCS relies on country-specific multiple imputation methods to account for item non-response. Following Waltl and Chakraborty (2022), we use the mean over the five implicates for each imputed variable.

2.1 Sample selection

Our analysis limits attention to financial assets (not including pension plans and insurance products) and does not include real assets (see infra). A key distinguishing feature of the HFCS is that it separately reports the value of financial investments held in sight and savings accounts, individual stock and bonds, various types of mutual funds (MF) and managed accounts. Such a detailed breakdown of diversification properties is far from standard in the literature. We consider a risk-free asset and distinguish seven different risky asset classes, as shown in Table 1.[3] For each household, the risky financial portfolio sums holdings over these seven assets, while the complete financial portfolio additionally includes holdings of the risk-free asset. The risky portfolio share is the weight of the risky portfolio in the complete portfolio. An investor is a household whose financial wealth includes risky assets (i.e. risky share > 0.01).[4] Section 2.3 below explains in detail how we measure return and risk for each asset class.

In order to assess household financial portfolios and investment behavior we must limit the analysis to a sample of households with the means to invest. Rather than imposing an ad hoc decision rule (e.g. a minimum threshold on household portfolio size),

[3]We make abstraction of MF "other" and MF "hedge fund" holdings (which likely require a significant minimum investment threshold and are held by very few respondents). Regarding individual stock assets, we assign the full amount of a households' individual stock holdings to either the domestic or diversified variant based on the respondent's answer to a yes-no question indicating whether they hold purely domestic stocks or also foreign stocks.

[4]In order to avoid falsely labelling observations holding very small amounts of risky assets as investors, we do not consider as investors observations with a positive risky share below 1% (around 50 observations).

Table 1: Overview of asset classes considered in the analysis

Asset	Subcategory
Risk-free asset	Sight and savings accounts + MF predominantly investing in money market instruments
MF stock	MF predominantly investing in stock
Individual stock domestic	
Individual stock diversified	
MF bonds	MF predominantly investing in bonds
Individual bonds	
MF real estate	MF predominantly investing in real estate
Mixfunds	Managed accounts + MF of various types

we implement the suggestion of Kaplan et al. (2014) and limit attention to only non-constrained households. Specifically, Kaplan et al. (2014) label households as constrained if their liquid wealth is less than half their periodic income (see their paper for more details). In our case, liquid wealth sums holdings across all assets mentioned in Table 1.

Implementing the Kaplan et al. (2014) criterion obtains a sample of 5370 observations, containing 64.5% non-investors (holding only the risk-free asset) and 35.5% investors. 77% of observations in this sample are homeowners. The investor observations represent 1445 different households, of which 361 have a panel component. As in many countries, a substantial fraction of households do not participate in risky asset markets (Vestman, 2019). Table 2 presents descriptive statistics on household portfolios and demographic variables. Average financial wealth is much higher for investors (€ 294.900) than for non-investors (€ 63.500). Second, households with a high educated head make up a more than proportional fraction of investors (61% in the investor sample versus 49% in the full sample).

Below we will study participation rates in more detail. At this point, we remark that the low risky asset participation rate (35.5% as shown in Table 2) is well-documented in earlier work analyzing various EU countries (see e.g. Guiso et al., 2008; Christelis et al., 2013; Arrondel et al., 2014; Arrondel and Coffinet, 2019), a finding commonly referred to as the "stock market participation puzzle" (Arrondel et al., 2014). The work of Calvet et al. (2007), who assess Swedish households, is an exception to this claim, attaining a risky asset participation rate of over 60%.[5]

[5]However, as noted by Guiso et al. (2003, p.128) Sweden is a bit of an outlier as it is one of the countries with the highest level of stockholding.

Table 2: Summary statistics

	FULL SAMPLE (5370 obs)			INVESTORS (1907 obs)			NON-INVESTORS (3463 obs)		
	Mean	Median	Standard Deviation	Mean	Median	Standard Deviation	Mean	Median	Standard Deviation
Portfolio characteristics									
Complete portfolio ('000 €)	-	-	-	252.2	106.5	502.8	42.0	15.0	103.8
Risky portfolio ('000 €)	-	-	-	168.9	36.0	450.2	-	-	-
Financial characteristics									
Financial wealth ('000 €)	145.7	49.3	350.6	294.9	143.0	527.5	63.5	25.8	135.6
Real estate wealth ('000 €)	364.4	268.0	515.1	504.9	357.5	624.7	287.1	221.1	424.1
Net wealth ('000 €)	477.4	311.3	689.6	769.0	524.0	915.7	316.8	226.9	450.9
Gross income ('000 € per year)	57.2	44.5	53.8	71.5	56.8	65.6	49.3	38.5	44.0
Demographic characteristics									
Female household head (dummy)	.36	.00	.48	.30	.00	.46	.40	.00	.49
Age	57.5	58	16.0	59.7	60	14.4	56.3	56	16.7
Household size	2.3	2.0	1.3	2.4	2.0	1.2	2.3	2.0	1.3
Low education dummy	.21	.00	.41	.14	.00	.34	.25	.00	.43
Mid education dummy	.30	.00	.46	.26	.00	.44	.33	.00	.47
High education dummy	.49	.00	.50	.61	1	.49	.42	.00	.49
Marital status: couple (dummy)	.59	1	.49	.70	1	.46	.53	1	.50
Marital status: single (dummy)	.16	.00	.37	.11	.00	.32	.19	.00	.39
Marital status: divorced (dummy)	.13	.00	.33	.09	.00	.28	.15	.00	.36
Marital status: widowed (dummy)	.12	.00	.33	.10	.00	.30	.13	.00	.34
Employment status: employee (dummy)	.45	.00	.50	.44	.00	.50	.45	.00	.50
Employment status: self-employed (dummy)	.06	.00	.24	.07	.00	.26	.06	.00	.24
Employment status: retired (dummy)	.41	.00	.49	.46	.00	.50	.39	.00	.49
Employment status: unemployed (dummy)	.04	.00	.19	.02	.00	.12	.05	.00	.21
Employment status: other (dummy)	.04	.00	.20	.02	.00	.12	.05	.00	.23
Homeowner (dummy)	.77	1	.42	.88	1	.32	.71	1	.45

NOTE. — Dummy variables obtain a value of 1 if the household belongs to the stated category and a value of 0 otherwise.

2.2 Financial investment behavior

As mentioned above, our analysis does not include real assets. Our motivation is fivefold. First, the data do not show a widespread trend of households starting to invest in real estate (the fraction of households owning property other than the household main residence (HMR) only increases slightly from 22.4% in 2010 to 25.7% in 2017). Roughly one out of four households invests in property other than the HMR, a fraction that seems to be rather constant over time, thus not showing a change on the extensive margin. Second, Table 12 in Appendix A.1 finds no evidence for real estate investor households acquiring additional properties (i.e. changes on the intensive margin).[6] Third, as mentioned above, the large majority of observations in the sample are homeowners. Thus, there seems limited potential for first-time home buyers to divest financial assets to purchase real-estate. Fourth, in comparison to financial investments, real estate is, in general, characterized by lower liquidity and a different tax regime. Fifth, empirical studies have not found a systematic relationship between housing and portfolios (Chetty et al., 2017).[7] In summary, we believe both kinds of investments to be sufficiently different such that they can be studied in isolation from each other.

Based on this evidence it does not seem unreasonable to maintain separability between financial and real assets, which is frequently assumed within the household economics literature. It implies that the marginal rate of substitution between investments in any two financial assets is independent from investments in the real estate asset. Moreover, separability is consistent with two-stage budgeting Deaton and Muellbauer (see 1980), which allows for a convenient representation of the investment process. Specifically, two-stage budgeting implies that, in a first stage, the investor decides how to allocate funds between different categories (i.e. real and financial assets). In a second stage the investor then makes optimal decisions within each category, given the first stage allocations. Here, separability assumes that real estate allocation decisions do not impact decision making in the financial asset category, and vice versa.

Finally, Appendix A.6 provides a robustness check that assesses only the real-estate investor households with a panel component for which the number of properties remains constant. Comfortingy, we find that the results are generally in line with those reported in the main text, although the smaller samples make it harder to establish statistical significance.

2.2.1 Participation rates

We next present some basic facts about the evolution of investment behavior of Belgian households between 2010 and 2017. We also examine households' decisions to participate in specific asset classes. Table 3 reports descriptive statistics on household participation

[6] For almost three out of four real estate investor households with a panel component (624 observations in total), the number of properties remains constant. 78 (86) observations report a drop (increase) in their number of properties. Thus, only very few observations may consider the divestment of financial assets to purchase real estate (which, of course, may be an option for first-time home buyers).

[7] Previous work examining the impact of housing on financial portfolios includes a.o. Flavin and Yamashita (2002), Cocco (2005) and Vestman (2019).

in risky asset markets. Between 2010 and 2017 household participation decreased from 39% to 32%. Thus, despite the decline in interest rates, respondents became less likely to invest in risky assets over time, with the decline being most pronounced for the individual stock and individual bond asset classes.[8]

Let us then investigate the dynamics of the risky asset share among participating households. The equal-weighted share of financial assets invested in risky assets increases from 48.9% in 2010 to 51.3% in 2017. Thus, while fewer households invest through the years, those who do so gradually allocate larger fractions of their portfolio to risky assets. These findings imply a moderate shift towards risky assets by Belgian retail investors as a whole in response to the low interest rate environment induced by central bank policy.[9]

Examining the participation rates within the investor subsample in more detail, we find that stocks and MF predominantly investing in real estate are the most and least frequently held risky assets, respectively. The participation rate of individual stock drops sharply in 2014, caused mostly by a drop in the participation rate of domestic individual stocks. From a policy point of view, it may seem positive that fewer households hold underdiversified stock portfolios. However, at the same time, the conditional weight of domestic individual stock (Table 3, Panel B) rises over the years. Thus, although fewer households hold underdiversified individual stock portfolios over time, households that do not diversify invest a larger fraction of their financial wealth in these underdiversified assets. Moreover, our unreported findings indicate that the financial portfolios of households investing only in domestic stock are generally smaller than the financial portfolios of households investing in diversified individual stock. This last result may be concerning from a policy point of view, as it implies that underdiversified households may potentially be more vulnerable to domestic shocks.

Next, an interesting pattern emerges from the participation rates and conditional weights of individual bonds. In particular, between 2010 and 2014 the participation rate of individual bonds remained stable while their conditional weight fell sharply (from 42% in 2010 to 27% in 2014), suggesting that investors reduced their exposure to individual bonds during this period without abandoning the asset class altogether. Further, we record a clear outflow from bonds in 2017, mainly due to a sharp decline in the participation rate of individual bonds (which more than halved compared to 2014). This finding suggests that households decided to monetize their investments in individual bonds. Finally, a smaller group continued to invest in these assets (as reflected by the

[8] This result may reflect survey sampling since we consider an unbalanced panel. Alternatively, some authors argue that individual priors may shape individuals' willingness to take risk (Guiso et al., 2008; Malmendier and Nagel, 2011). It could be that Belgian households became more reluctant to invest in risky assets over time due to negative experiences, such as the Fortis bailout during the global financial crisis or the Arco scandal in its aftermath. Future research may shed more light on this issue.

[9] As remarked by Calvet et al. (2009, p.310), the change in a household's risky share is partly determined by the household's active trades and partly by the returns on its risky securities. For instance, the risky share tends to increase mechanically during a bull market. Although we refrain from a detailed study of portfolio rebalancing (made difficult by the multi-year gap between waves), previous research on household stock trading reports a tendency for the bulk of the population to exhibit considerable inertia, making no active changes to their portfolio (Agnew et al., 2003; Ameriks and Zeldes, 2004; Calvet et al., 2009; Bilias et al., 2010).

larger conditional weight in 2017 compared to 2014), which could reflect inertia, a lack of financial literacy or risk-averse preferences.[10]

Table 3: Summary statistics: participation rates and portfolio weights

	Full sample			Investor sample		
A. Participation rates	2010 (1918 obs)	2014 (1723 obs)	20017 (1729 obs)	2010 (742 obs)	2014 (609 obs)	2017 (556 obs)
Fraction of households holding:						
Risk-free asset	99.6%	100%	99.8%	99.9%	100%	99.5%
Risky assets	38.7%	35.4%	32.2%			
Stock	30.5%	25.0%	24.1%	74.7%	69.8%	73.6%
Individual stock	22.2%	15.3%	14.3%	53.4%	42.2%	43.9%
Individual stock domestic	11.8%	6.4%	6.4%	27.8%	17.6%	19.4%
Individual stock diversified	10.3%	8.9%	7.9%	25.6%	24.6%	24.5%
MF stock	15.9%	15.5%	14.0%	40.7%	43.8%	42.8%
Bonds	21.7%	20.1%	13.8%	55.7%	56.3%	42.6%
Individual bonds	11.4%	10.3%	4.4%	29.3%	28.7%	13.5%
MF bonds	12.7%	12.1%	10.2%	32.8%	34.0%	31.5%
MF real estate	2.0%	1.0%	0.6%	5.0%	3.0%	2.0%
Mixfunds	1.2%	2.8%	4.3%	3.0%	8.1%	13.5%
Average risky share (equal-weighted)				48.9%	49.1%	51.3%
Average risky share (complete portfolio-weighted)				67.9%	62.1%	70.2%
B. Conditional portfolio weights						
Stock				32.6%	37.1%	39.5%
Individual stock				25.3%	27.0%	31.4%
Individual stock domestic				21.9%	20.7%	27.1%
Individual stock diversified				29.0%	31.5%	34.8%
MF stock				26.5%	33.0%	35.8%
Bonds				40.5%	34.0%	35.3%
Individual bonds				41.5%	26.9%	36.0%
MF bonds				31.7%	33.6%	32.3%
MF real estate				16.5%	19.7%	8.4%
Mixfunds				40.7%	43.2%	52.3%

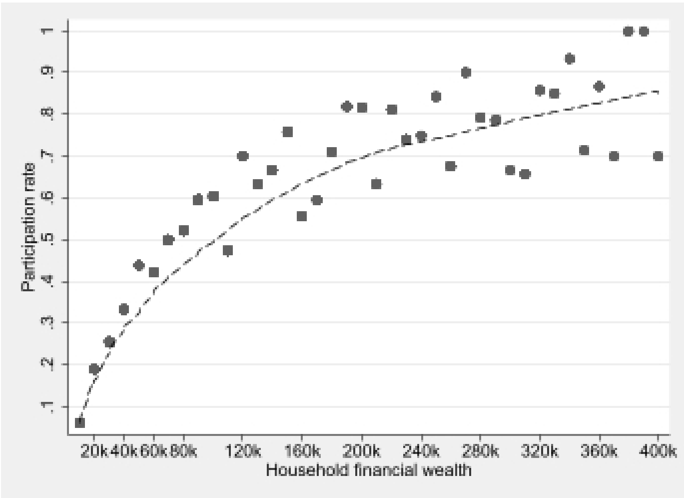
2.2.2 Which households participate in risky asset markets?

We now investigate the decision to participate in risky asset markets and how this relates to households' observable characteristics. In a following step, we will do the same for the risky asset share. As mentioned above, participation rates vary between 30% and 40% in each wave. A logical explanation for why so few households invest may simply be that a substantial fraction of households lack the financial means to invest. In this context, a rule of thumb put forward by financial advisors is to have an 'emergency fund' of six months' worth of living expenses saved up (Sabat and Gallagher, 2019), before considering investing. When applied to our sample, we find that 37% of the

[10]The sudden change in individual bond participation rates could be interpreted as a response by households to central bank policy (which has led to a sharp decline in bond interest rates over the years). At the same time, however, both the participation rates and the conditional weights of MF predominantly investing in bonds (which would be equally affected by central bank policy) remained stable. The reason for this difference is unclear. Perhaps households with individual bond holdings monitor their investments more actively than households with bond MF holdings.

household observations in our sample do not meet this rule of precautionary saving. In addition, investing may be too costly for many households (e.g., due to transaction costs or brokerage fees), as they may have little money left after building up their emergency fund. This may be particularly relevant given that the 40th and 50th percentiles of the financial portfolio distribution amount to €18.650 and €30.000, respectively. Moreover, this explanation seems consistent with the fact that the participation rate is strongly increasing in financial wealth, as is shown in Figure 1. Thus, it seems that investing remains limited to the relatively wealthier households.

Figure 1: % of investors as a function of household financial wealth (up to €400k)



Next, we observe substantial heterogeneity in the share of financial wealth invested in risky assets within the set of investors. Columns 3-4 of Table 4 report a pooled OLS regression of the investors' risky asset share on household characteristics. We find that the risky asset share increases with financial and real estate wealth and age (although the estimated coefficients are small). The risky share is also higher for households with a high educated household head. On the other hand, homeownership relates negatively to the risky asset share. Figure 2 shows in more detail how the risky portfolio share increases with financial wealth, which is consistent with decreasing relative risk aversion. As a last exercise, we investigate whether wealthier households participate in a wider range of asset categories. Appendix A.2 provides support for this hypothesis by showing that, in general, the number of different assets held by households (and thus diversification) increases with wealth levels.

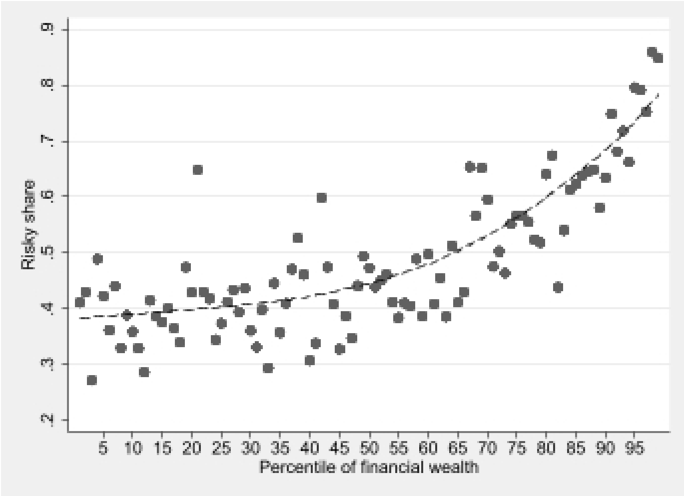
Table 4: Regression analysis

	PARTICIPATION Probit regression		RISKY SHARE Pooled OLS regression	
	Coefficient (1)	Std. Error (2)	Coefficient (3)	Std. Error (4)
Intercept	-3.279***	.308	.278***	.078
Female household head (dummy)	-.168**	.069	.022	.015
Age	.016***	.003	.004***	.001
Mid education dummy	.290***	.092	.037	.022
High education dummy	.681***	.094	.044**	.021
Marital status: couple (dummy)	.237***	.086	-.032*	.019
Marital status: single (dummy)	.052	.111	-.001	.026
Employment: self-employed (dummy)	.318	.226	.016	.060
Employment: employee (dummy)	.601***	.193	-.061	.055
Employment: unemployed (dummy)	-.128	.262	.053	.080
Employment: retired (dummy)	.334	.203	-.027	.056
Homeowner (dummy)	.438***	.088	-.049**	.020
Gross income ('0000 €)	.022***	.007	-.001	.001
Financial wealth ('0000 €)	.042***	.003	.001***	.000
Real estate wealth ('0000 €)	.002**	.001	.000***	.000
2014 (dummy)	-.169***	.064	-.004	.016
2017 (dummy)	-.352***	.068	.012	.016
(Pseudo) R^2	0.169		.139	
Number of observations	5370		1907	

NOTE. — Columns 1-2 report a random effects probit regression of the participation decision on household financial and demographic characteristics. The pseudo R^2 is computed as the loglikelihood of the model scaled by the loglikelihood of the constant-only model. Columns 3-4 report a pooled OLS regression of the investors' risky share on the same set of household characteristics.

*** denotes significance at 1%-level; ** denotes significance at 5%-level; * denotes significance at 10%-level.

Figure 2: Investors — Risky share of the financial portfolio as a function of financial wealth. We report the average risky asset share within each percentile of the financial wealth distribution, together with a trend line. Observations are pooled across HFCS waves.



2.3 Constructing portfolio return and risk measures

The remainder of our analysis focuses on the investor sample. To assess the performance of households' financial portfolios we must first estimate an expected return vector for the different asset classes, together with a variance-covariance matrix. Using information on asset allocations one may then compute a measure of household portfolio return and risk.

While the HFCS reports holdings for each of the different asset classes, it does not include return information or individual asset identifiers (i.e. ISIN-numbers). As a result, we cannot directly compute household portfolio returns. For this reason, we use index returns to approximate the return received by a respondent investing in a particular asset class. Consequently, we assume that asset returns are identical for all investors. A similar strategy was used by Grinblatt et al. (2011) to study participation and performance of mutual funds. Ideally, however, one would like to collect information on individual returns per asset class. In this respect, previous research reports that retail stock pickers tend to hold underdiversified stock portfolios that are far from the market portfolio suggested by a CAPM model (Barber and Odean, 2013). Hence, we may reasonably expect that many households will make sub-optimal investment decisions within asset classes (which would of course reduce performance relative to the current exercise, assuming common asset class returns). As such, the results presented below are likely to be upper bound estimates of household investment performance for many households.

From a conceptual viewpoint, assuming identical returns focuses attention on the first stage of a two-stage investment process, where households must first decide how to allocate funds between different asset classes before making allocation decisions within each asset class.

We compute the risk-free rate of return using data from the NBB MIR survey, which reports the average interest rate offered by Belgian banks on household deposits on a monthly basis.[11] Because the interest rates vary somewhat from month to month, we annualize the average monthly interest rate of the respective survey year.[12] Next, we calculate the annual return for risky assets as the annualized average monthly return during the survey year, using the indices shown in Table 5.[13] Appendix A.3 explains the selection of specific indices in more detail. We use the formula from Tobin (1965) (which accounts for compound interest) to annualize monthly return variances. Finally, we annualize the monthly return covariances using the formula described in Weber (2017) (which equally accounts for compound interest).

Table 5: Asset classes and respective indexes

Asset class	Index
MF stocks	MSCI ACWI Index
Individual stock domestic	BEL-20 Index
Individual stock diversified	50% MSCI ACWI Index+ 50% BEL-20 Index
MF bonds	Bloomberg Euro-Aggregate Index
Individual bonds	Bloomberg Euro-Aggregate Treasury Belgium Unhedged Index
MF real estate	GPR250 Reit Europe (EUR) Index
Mixfunds	60% MSCI ACWI Index + 40% Bloomberg Euro-Aggregate Index

Table 6 shows the annual return and standard deviation for each asset class. In general, standard deviations are highest in 2010. In all three years, standard deviations are highest for investments in MF real estate, while bonds and mix funds are generally the least risky assets. Consistent with portfolio theory, we find that investing in internationally diversified stocks reduces risk compared to investing in purely domestic stocks. Moreover, investing in individual domestic stocks and bonds in 2010 yields almost the same return, while the standard deviation is much higher for the former. Be-

[11] Previous work (e.g. Calvet et al., 2007) proxies the risk-free rate by the yield on T-bills. However, the use of T-bills seems to implicitly require a high degree of financial sophistication on the part of households, especially compared to the much simpler alternative of deposits. Moreover, the Belgian Debt Agency has stated that these products are designed for professional rather than retail investors.

[12] Remark that until July 2016 the MIR survey reported only the base interest and not the fidelity premium. This need not be a concern as the fidelity premium is likely to be very low from 2016 onward. Second, one could argue that using only base interests is preferable because the HFCS does not report how long respondents keep their money in the savings accounts.

[13] Alternatively, the expected rate of return could be calculated as the average monthly rate of return over a specified period prior to the wave in question. However, this approach can be criticized because it implies that households expect the past to repeat itself. Instead, one could compute expected returns using ARIMA-GARCH models, although these require specific assumptions to be met. Nevertheless, one could always critique the approach taken. Given that expected asset returns are notoriously difficult to estimate (Calvet et al., 2007, p. 725) and that their estimation is not the core of the current paper, we choose to keep this as simple as possible.

Table 6: Annual returns (std. dev.s) of the various asset classes

	2010	2014	2017
Risk-free asset	1.12%	.48%	.11%
	(-)	(-)	(-)
MF stock	21.65%	19.39%	9.66%
	(12.37%)	(6.32%)	(6.94%)
Individual stock domestic	3.64%	12.80%	16.77%
	(14.94%)	(10.48%)	(10.68%)
Individual stock diversified	12.32%	16.05%	10.21%
	(11.63%)	(7.56%)	(7.20%)
MF bonds	2.26%	11.11%	.71%
	(4.06%)	(1.82%)	(2.65%)
Individual bonds	2.23%	14.20%	.31%
	(6.14%)	(2.77%)	(4.81%)
MF real estate	14.39%	31.26%	11.60%
	(22.21%)	(14.45%)	(12.29%)
Mixfunds	13.52%	16.01%	6.00%
	(6.61%)	(3.69%)	(4.52%)

cause households investing in individual domestic stocks in 2010 were not compensated for the increased risk, they are likely to be identified as inefficient in the analysis below.

Using the wave-specific return vector and variance-covariance matrix we compute a measure of portfolio return and risk for each household. Table 7 shows mean and median portfolio standard deviations for each wave. We find that investors' risk taking is most pronounced in 2010 but falls sharply in 2014. As mentioned above, this may be related to Belgian households becoming more reluctant to invest over time. Thereafter, investors seem to increase their risk exposure in 2017, although risk taking remains well below 2010 levels. Kruskal-Wallis tests indicate that the wave-specific distributions of portfolio standard deviation are statistically different (p=0.000). Consistent with the U-shaped pattern mentioned above, Kolmogorov-Smirnov tests indicate that standard deviations in 2010 are significantly larger than those in both 2014 and 2017, and that the standard deviations in 2014 are significantly smaller than those reported in 2017 (all p-values=0.000). Finally, Appendix A.4 shows scatterplots of the portfolio return and standard deviation for each wave.

Table 7: Investor sample — Summary statistics of households' portfolio standard deviation

	2010 (742 obs)	2014 (609 obs)	2017 (556 obs)
Mean	4.15%	2.45%	2.99%
Median	3.45%	1.78%	2.61%

3 Measuring portfolio efficiency: methodology

This section presents the nonparametric methodology that we will use to measure the portfolio efficiency of Belgian households, which is rooted in Data Envelopment Analysis (DEA). We begin by describing the link between the Sharpe ratio, portfolio efficiency and DEA. Subsequently, we show how the DEA-based efficiency scores can be expressed in monetary terms through the construction of so-called "return loss" measures. Finally, we introduce the Malmquist index that we use in our dynamic efficiency analysis.

3.1 Sharpe ratio, portfolio efficiency and DEA

Our efficiency measure builds on the well-known Sharpe ratio that is widely used for evaluating the performance of financial investments. For a financial portfolio $i \in I_t$ that is observed in period/wave t, let us denote the portfolio return by Y_{it}, the risk by X_{it} and the risk-free return by RF_t. The observation's Sharpe ratio is then computed as:

$$\text{Sharpe}_{it} = \frac{Y_{it} - RF_t}{X_{it}}, \tag{1}$$

which divides the portfolio's excess return ($Y_{it} - RF_t$) by the portfolio's risk (X_{it}).

Now assume that we want to evaluate some household portfolio $0 \in I_t$ that corresponds to the risk-return combination (X_{0t}, Y_{0t}). We will quantify this portfolio's efficiency (denoted by PE_{0t}) by comparing its Sharpe ratio to that of the other observed portfolios $i \in I_t$. More specifically, we calculate portfolio efficiency as the foregone increase in the household's Sharpe ratio as it can be inferred from the observed portfolio performance of the other households that operate in the same economic environment:

$$\text{PE}_{0t} = \frac{\text{Sharpe}_{0t}}{\text{maximum Sharpe}_{it} \text{ in wave } t}, \tag{2}$$

which obtains a portfolio efficiency measure that takes values of at most one, with larger values indicating higher efficiency (i.e. less potential for improvement). Intuitively, it sets out the evaluated portfolio performance (measured as Sharpe_{it}) against the best observed performance in wave t (measured as the maximum Sharpe_{it} in period t).

In view of our following exposition, we reformulate the portfolio efficiency measure in (2) as the outcome of a programming problem that takes the form of a DEA problem for measuring the relative efficiency of Decision Making Units (DMUs, which correspond to households' financial portfolios in our application setting). To obtain this equivalent formulation, we assign a weight w to the numerator and a weight v to the denominator of the Sharpe ratio in (1). Then, it is easy to verify that portfolio 0's efficiency can be computed by solving the following fractional programming problem:

$$\text{PE}_{0t} = \max_{w,v} \quad \frac{w * Y_{0t} - w * RF_t}{v * X_{0t}}$$

subject to

$$\tfrac{w*Y_{it}-w*RF_t}{v*X_{it}} \leq 1 \qquad (\forall i \in I_t)$$

$$w, v \geq 0,$$

where the inequality constraints ensure that the weights w and v are chosen such that no portfolio obtains an efficiency score that exceeds unity (or 100%). This formally presents our portfolio efficiency measure as a DEA efficiency measure of the type originally introduced by Charnes et al. (1978). As shown by these authors, the fractional programming problem can readily be converted into a linear programming problem, which is obviously attractive for practical applications.[14]

At this point, it is interesting to indicate that our proposed portfolio efficiency measure closely resembles the Relative Sharpe Ratio Loss (RSRL) measure that was used by Calvet et al. (2007). These authors similarly computed Sharpe ratios to obtain a measure of suboptimal investment. However, they calculate portfolio return and risk by using a Capital Asset Pricing Model (CAPM), hereby assuming a (currency-hedged) world index as an exogenous benchmark. Whether this is a viable alternative for households or too strict is unclear.[15] In our methodology, we refrain from imposing exogenous benchmarks and instead estimate efficiency relative to an endogenous benchmark (i.e. the best observed performance in wave t). As a result, we can be sure that the efficient household portfolio is feasible.

Attractively, the above DEA-type representation of our portfolio efficiency measure is directly instrumental to overcome several shortcomings of the Sharpe ratio. Firstly, prior analyses (such as Calvet et al., 2007) typically assume a common risk-free rate for all households. However, previous research established heterogeneity in savings account returns across households (Deuflhard et al., 2019). Conveniently, the above model easily allows us to impose various assumptions regarding this risk-free rate. Specifically, one extreme treats the risk-free rate as fixed for all households (as in our above formulation). Replacing the term $w * RF_t$ with a sign-free variable C_t leads to the other extreme, allowing complete freedom in the risk-free rate that is used for evaluating the portfolio 0. In what follows, we will take an intermediate stance by allowing for limited flexibility in the risk-free rate, through lower and upper bounds on the variable C_t. Particularly,

[14]Specifically, we obtain this linear programming formulation by (1) normalizing the denominator in the objective function to unity (i.e. $v * X_0 = 1$) and (2) linearizing the inequality constraints as $w * Y_{it} - w * RF_t - v * X_{it} \leq 0$ $(\forall i \in I_t)$.

[15]For example, in Figure 2B of their paper, no household is positioned on the capital market line (formed by the optimal currency-hedged world-index).

for $C_t = w * RF_t$ we can define a lower bound as $C_t \geq \alpha * w * RF_t$ and an upper bound as $C_t \leq \beta * w * RF_t$. In our application, we set $\alpha = 0.8$ and $\beta = 1.2$, thus obtaining the following problem:

$$\text{PE}_{0t} = \max_{w,v,C_t} \quad \frac{w * Y_{0t} - C_t}{v * X_{0t}}$$

subject to

$$\frac{w*Y_{it}-C_t}{v*X_{it}} \leq 1 \qquad (\forall i \in I_t)$$

$$C_t \geq 0.8 * w * RF_t$$

$$C_t \leq 1.2 * w * RF_t$$

$$w, v, c \geq 0$$

Notably, this programming problem effectively chooses the value of C_t that maximizes the efficiency of the evaluated portfolio 0, so assessing the household's portfolio performance in the best possible light. This reflects the "benefit-of-the-doubt" interpretation that is specific to DEA-based efficiency evaluation (see e.g. Cherchye et al., 2007, for more discussion).

Secondly, we use a subsampling procedure to robustify the estimated portfolio efficiency scores to the presence of outlier observations. The implemented subsampling procedure is similar in spirit to the order-m approach introduced by Cazals et al. (2002) and Daraio and Simar (2005) in a DEA-context.[16] Particularly, in line with Cherchye et al. (2013), we construct 200 random subsamples by drawing 80% of the observations in our original sample (for each wave separately). The robust portfolio efficiency score is then calculated by taking the average over all 200 iterations.

Lastly, we can build on our DEA-representation of PE_{0t} to analyze changes in portfolio efficiency over time (here, across waves), which can be further decomposed in catching up and environmental change components. We explain this in more detail in Section 3.3.

3.2 Expressing efficiency in monetary terms

Because our portfolio efficiency measure (only) quantifies the performance of a household's risky portfolio, it arguably provides only partial information. For example, portfolio inefficiency may not be economically meaningful for households with very low risky shares. To account for this caveat, our empirical application will also have a main focus on three measures of "return loss". The construction of these measures follows Calvet

[16]Specifically, instead of comparing a portfolio to all observed portfolios in the sample (which may include outliers), the order-m approach benchmarks the portfolio against a subsample of $m \geq 1$ comparison partners that are drawn from the original sample. This method is readily implemented through subsampling. The robust portfolio efficiency score is then calculated by taking the average over all iterations.

et al. (2007), with the only difference that we make use of our DEA-based efficiency measure PE_{0t}.

The first return loss (RL) measure quantifies the foregone return that a household loses by holding the chosen household portfolio instead of the optimal portfolio combined with cash to obtain the same level of risk. It places greater weight on low Sharpe ratios that coincide with aggressive investment strategies, and is defined as follows:

$$\mathrm{RL}_{0t} = \left(\frac{1}{\mathrm{PE}_{0t}} - 1\right) * (Y_{0t} - RF_t). \tag{3}$$

This measure RL_{0t} quantifies underperformance in terms of return units, i.e. per euro that is invested in financial assets. Evidently, the economic impact of return loss will be different for household financial portfolios of different sizes; e.g. it will be negligible for households with small portfolios. Our second measure corrects for this by multiplying the return loss by the household's risky portfolio, thus providing an intuitive estimate of the additional yield (in monetary terms) that the household could have earned if it had invested efficiently:

$$\mathrm{RL}_{i0}^{€} = \mathrm{RL}_{i0} * \text{Risky Portfolio} \tag{4}$$

Finally, our third measure expresses $\mathrm{RL}_{i0}^{€}$ as a fraction of the household's annual gross income:

$$\mathrm{RL}_{i0}^{€,\text{ GROSS}} = \frac{\mathrm{RL}_{i0}^{€}}{\text{Annual gross income}}, \tag{5}$$

which incorporates the possibility that investment returns are a form of household income, which is particularly relevant for retired households.

3.3 Dynamic efficiency analysis

To study intertemporal changes in portfolio performance, we can implement the "Malmquist productivity change index" (see Caves et al., 1982; Tone, 2004; Färe et al., 1992, 2011) to our particular application setting. Specifically, the Malmquist index examines performance in periods t and $t+1$, where $T(t)$ and $T(t+1)$ indicate the "technology sets" (representing the economic environment) of the two periods. We may then compute the Sharpe ratio and portfolio efficiency of a household observation 0 in period $t+1$ when compared to the portfolio technology of period t as, respectively:

$$\mathrm{Sharpe}_{T(t)(x_{0,t+1};y_{0,t+1})} = \frac{Y_{0,t+1} - RF_t}{X_{0,t+1}}, \text{ and} \tag{6}$$

$$\mathrm{PE}_{T(t)(x_{0,t+1};y_{0,t+1})} = \frac{\mathrm{Sharpe}_{T(t)(x_{0,t+1};y_{0,t+1})}}{\text{maximum Sharpe}_{it} \text{ in wave } t}. \tag{7}$$

Analogously, we construct $\mathrm{Sharpe}_{T(t+1)(x_{0,t};y_{0,t})}$ and $\mathrm{PE}_{T(t+1)(x_{0,t};y_{0,t})}$ to represent the household's Sharpe ratio and portfolio efficiency in period t when compared to the portfolio technology of period $t+1$.

Using these concepts, the change in portfolio performance between t and $t+1$ can be measured by the Malmquist index (omitting the subscript "0" to simplify notation):

$$M^i(x_t, y_t, x_{t+1}, y_{t+1}) = \left[\frac{\mathrm{PE}_{T(t)(x_t,y_t)}}{\mathrm{PE}_{T(t)(x_{t+1},y_{t+1})}} * \frac{\mathrm{PE}_{T(t+1)(x_t,y_t)}}{\mathrm{PE}_{T(t+1)(x_{t+1},y_{t+1})}}\right]^{1/2}, \tag{8}$$

where we take a geometric mean between periods t and $t+1$ to avoid an arbitrary choice of base year to define the portfolio technology. Index values below unity indicate progress of portfolio performance, while index values above unity signal performance regress.

An attractive feature of this Malmquist index is that it can be rewritten as:

$$M^i(x_t, y_t, x_{t+1}, y_{t+1}) = \frac{\mathrm{PE}_{T(t)(x_t,y_t)}}{\mathrm{PE}_{T(t+1)(x_{t+1},y_{t+1})}} * \sqrt{\frac{\mathrm{PE}_{T(t+1)(x_t,y_t)}}{\mathrm{PE}_{T(t)(x_t,y_t)}} * \frac{\mathrm{PE}_{T(t+1)(x_{t+1},y_{t+1})}}{\mathrm{PE}_{T(t)(x_{t+1},y_{t+1})}}}, \tag{9}$$

which effectively decomposes the portfolio performance change as the product of two components. The first component,

$$\frac{\mathrm{PE}_{T(t)(x_t,y_t)}}{\mathrm{PE}_{T(t+1)(x_{t+1},y_{t+1})}}, \tag{10}$$

measures performance change that can be attributed to "catching up" with best practice between periods t and $t+1$ (with values below (above) unity indicating improvement (decline)). This catch-up component measures whether households have increased their portfolio efficiency through reallocation decisions, thus measuring the "endogenous" part of portfolio performance change. The second component,

$$\sqrt{\frac{\mathrm{PE}_{T(t+1)(x_t,y_t)}}{\mathrm{PE}_{T(t)(x_t,y_t)}} * \frac{\mathrm{PE}_{T(t+1)(x_{t+1},y_{t+1})}}{\mathrm{PE}_{T(t)(x_{t+1},y_{t+1})}}}, \tag{11}$$

measures performance change that can be attributed to changes in the economic environment (or "portfolio technology") between periods t and $t+1$ (with, again, values below (above) unity signalling progress (regress)). It captures changes in the feasible set of risk-return combinations that are due to variations in asset returns, thus quantifying the "exogenous" part of portfolio performance change.

4 Efficiency results for Belgian households

The great level of detail available in the HFCS data allows for an informative analysis of the portfolio performance of Belgian households. In what follows, we first describe the portfolio efficiency and return loss results for each HFCS wave that we study. Subsequently, we examine how our portfolio efficiency measure correlates with households' socio-economic and demographic characteristics. Finally, we report the results of a dynamic analysis that examines efficiency changes over time.

4.1 Portfolio efficiency and return loss

Table 8 reports descriptive statistics of the cross-sectional distributions of the robust portfolio efficiency scores in each of the three HFCS waves. As explained in Section 3, our portfolio efficiency measure quantifies the performance of a household's financial investments relative to the other (best performing) households in the sample.

First, mean and median scores indicate that households were able to increase the efficiency of their investments over time. While the average household in 2010 could about double its Sharpe ratio when compared to the best performing benchmark, the average household's Sharpe ratio in 2017 is about 70% of the best performing household. Interestingly, we find almost no correlation between portfolio efficiency scores and the risky share or risky portfolio size. However, because the results for each wave were calculated in isolation from each other, we should be cautious in making direct comparisons across waves; we will conduct a more refined dynamic efficiency analysis in Section 4.3. Second, the figures indicate considerable heterogeneity in household performance, with only a small fraction of households performing nearly efficient. This widespread evidence of poor performance is consistent with the reported evidence on behavioral biases in household financial decision making (see e.g. Barber and Odean, 2013).

Table 8: Descriptive statistics of robust portfolio efficiency scores (PE)

	Mean PE	Median PE	St. Dev. PE	5th perc. PE	95th perc. PE
2010 (742 obs)	.47	.51	.34	.09	.98
2014 (609 obs)	.56	.55	.23	.18	.88
2017 (556 obs)	.71	.86	.30	.04	.96

The figures in Table 8 indicate widespread heterogeneity in household portfolio efficiency. To assess the economic significance of our estimates, we quantify portfolio efficiency in monetary terms. Table 9 shows descriptive statistics for the three measures of return loss that we introduced in Section 3.2. Panel A shows that the median return loss, expressed in return units, amounts to 2.3%, 4.6% and 0.6% for the 2010, 2014 and 2017 waves, respectively. Thus, the median household in 2010 could have increased its risky portfolio return by over 2%, which –in our opinion– does represent a sizeable improvement. In general, return losses are highest in 2014 and lowest in 2017, reflecting the fact that return losses tend to increase with asset returns.[17] Just like for the portfolio efficiency scores in Table 8, our results reveal substantial heterogeneity in return losses, with a non-negligible fraction of households severely underperforming. For example, the 75th percentile return loss equals almost three times the median loss in both 2010 and 2014. Moreover, for all three waves we find a significant and positive correlation (of around 0.25) between return loss and risky portfolio size.

Next, to correct for the size of a household's risky portfolio, Panels B and C of Table 9 report return losses expressed in euros and as a fraction of the household's annual gross

[17] More specifically, higher asset returns make that the feasible set of risk-return combinations expands, leading to greater potential for foregone returns (and thus greater return losses).

Table 9: Descriptive statistics of return loss measures

	10th Percentile	25th Percentile	Median	75th Percentile	90th Percentile	Mean
			A. Return loss (RL)			
2010	.002	.007	.023	.061	.097	.040
2014	.005	.014	.046	.124	.222	.091
2017	.001	.003	.006	.010	.030	.011
			B. Return loss in € ($RL^{€}$)			
2010	13	85	617	4369	19495	12706
2014	36	245	1840	10910	39772	22732
2017	4	38	277	1607	4491	3761
			C. Return loss as a fraction of income ($RL^{€,\text{ GROSS}}$)			
2010	.000	.002	.013	.099	.463	.323
2014	.001	.005	.031	.204	.821	.609
2017	.000	.001	.005	.031	.109	.048

income. The median cost of inefficient investing amounts to € 617, € 1840 and € 277 for the 2010, 2014 and 2017 waves, respectively. Similar to before, these average numbers conceal strong variation in household-level outcomes. While the lower percentile values reflect that some households hold small portfolios, the distribution has a fat right tail due to large portfolios that are underperforming.

Lastly, the results in Panel C may be particularly relevant in view of the many participating households in our sample that are retired or approaching retirement (as the median age in our sample equals 60 years; see Table 2) and, therefore, may begin to use investment gains to supplement pension income. In this respect, Kolmogorov-Smirnov tests show that the figures in Panel C are significantly higher for retired households (p-values=0.000 for all three waves). More specifically, for all three waves we find that the median return losses reported in Panel C are five to nine times larger for retired households than for non-retired households. Whether this reveals that retired households make larger optimization errors or that they do not fit within a rational agent model remains to be explored; we do provide some further exploratory analysis of the determinants of portfolio inefficiency in Section 4.2. Next, although median return loss amounts to only 1.3%, 3.1% and 0.5% of gross income (in 2010, 2014 and 2017, respectively), it increases to less than 10% for the 90th percentile in all three waves. Again, the distribution is characterized by a fat right tail due to sizeable portfolios that are associated with low annual gross income.

4.2 Who is inefficient?

In this subsection we examine whether portfolio efficiency scores can be explained by observable characteristics. As argued by Simar and Wilson (2007, 2011), standard approaches to inference (e.g. regression analysis) are invalid when applied to efficiency estimates, unless very specific assumptions are made about the data generating process. In this respect, the results of a Shapiro-Wilk test indicate that the portfolio efficiencies are not normally distributed (p=.0000). Therefore, we also refrain from using standard t-tests and instead conduct nonparametric Kolmogorov-Smirnov (K-S) tests to assess the equality of distributions between subsamples based on observable characteristics.

Specifically, we divide the investor sample into two non-overlapping subsamples based on a specific observable characteristic and then test for the equality of the portfolio efficiency distributions of the two subsamples. For simplicity we pool observations across waves. Table 10 reports p-values of one-tailed and two-tailed K-S tests examining different observable household characteristics. One-tailed tests always place observations with the characteristic that is studied in the second group.

We find that households with high educated, employed and female heads achieve significantly higher portfolio efficiency scores, as do households with higher gross income, net wealth and larger complete portfolios. Our results are consistent with those of Calvet et al. (2007), who find that households with standard predictors of financial sophistication (such as education, income and wealth levels) have higher Sharpe ratios. In addition, previous research has also found that women achieve better investment performance, which may be explained by the fact that men are generally more overconfident than women (Barber and Odean, 2001). Furthermore, the third column of Table 10 shows that portfolio efficiency is significantly smaller for retired households than for non-retired households, which confirms our results in the previous subsection. If richer or more highly educated households systematically invest more efficiently, our findings may also have important repercussions for the evolution of wealth inequality (Campbell, 2016).[18] For completeness, Appendix A.5 documents the outcomes of wave-specific K-S tests and K-S tests for quartiles. In general, our above conclusions turn out to be largely robust, albeit that the wave-specific effects are not always significant (due to smaller sample sizes).

While the outcomes of the K-S tests reveal significant differences in the distribution of portfolio efficiency scores across subsamples, they do not reveal how much higher performance is in the best performing subsample. To obtain a more general overview of performance difference, we implement a shift function, after Doksum (1974, 1977). In general, the shift function indicates by how much one distribution must be shifted to match the other one, at various deciles. This allows for a more detailed analysis of differences in household performance and can also help to assess whether the differences are located in the bulk of the observations or more towards the tails.

More specifically, Figure 3 and Figure 4 show the shift functions for the various observable characteristics considered in Table 10. For example, the y-axis in Panel

[18] See also Fagereng et al. (2020, 2022), who assess persistence in household investment returns.

Table 10: Two-sample K-S tests for equality of portfolio efficiency distributions: p-values

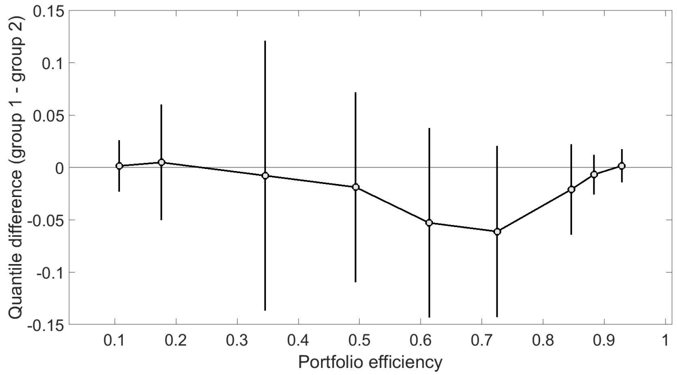
	Two-sided test (1): P-value	One-sided test (2): P-value	One-sided test (3): P-value
Female household head (dummy)	.073*	.036**	.780
Marital status: couple (dummy)	.191	.095*	.292
Employment status: retired (dummy)	.063*	.972	.031**
Employment status: employee or self-employed (dummy)	.058*	.029**	.866
High education (dummy)	.003***	.001***	.971
Gross income above median (dummy)	.001***	.000***	.713
Net wealth above median (dummy)	.004***	.002***	.843
Complete portfolio above median (dummy)	.000***	.000***	.325
HMR value above median (dummy)	.148	.074*	.301

NOTE. — Column 1 reports the p-values of a two-tailed K-S test. The second (third) column reports the p-values of a one-tailed K-S test, with the alternative hypothesis that the portfolio efficiency scores for the second group are greater (smaller) than those for the first group. One-tailed tests always place observations with the characteristic in question in the second group. Observations are pooled across waves.
*** denotes significance at 1%-level; ** denotes significance at 5%-level; * denotes significance at 10%-level.

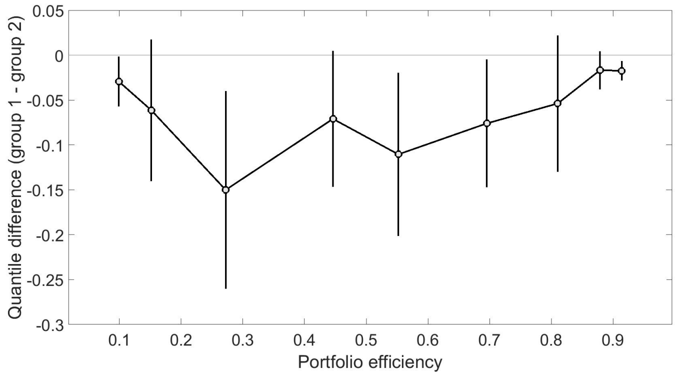
A plots the difference between the deciles of portfolio efficiency for households with and without a female head. Specifically, the leftmost (rightmost) dot is obtained by subtracting the 10th (90th) percentile portfolio efficiency score for households with a female head from the 10th (90th) percentile portfolio efficiency score for households without a female head. Thus, the middle dot measures the difference in medians and negative values indicate higher portfolio efficiency for households with a female head. The location of the dots on the x-axis is determined by the portfolio efficiency deciles for households without a female head. For each decile difference, the vertical line indicates the 95% bootstrap confidence interval.

Some interesting patterns emerge from these figures. For example, we find that the reported underperformance of households without a highly educated head (see panel B in Figure 3) is a general finding that holds across the different deciles. However, the degree of underperformance varies. While the third decile of the households without a highly educated head needs to increase by almost 15 percentage points to match the third decile of the households with a highly educated head, the effect size becomes progressively weaker from the median onwards. A similar finding is obtained for retired households, which underperform the non-retired households at all deciles. By contrast, regarding gender of the household head, performance is more or less equal for the lowest and highest deciles for households split based on gender, with larger differences in the bulk of the distribution. Regarding marital status we obtain mixed evidence, establishing over- and underperformance of married households at the lower and higher percentiles of the portfolio efficiency distribution, respectively.

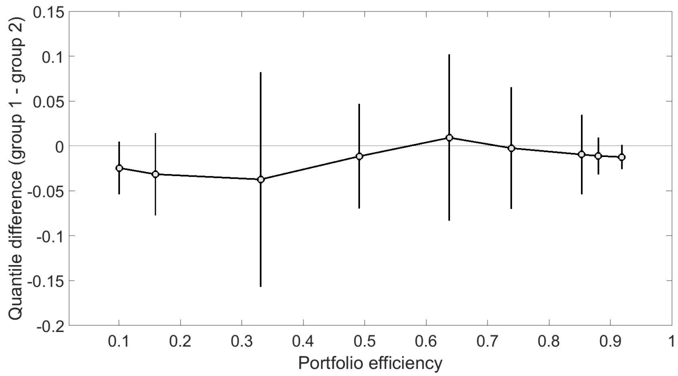
Figure 3: Shift functions for various household characteristics



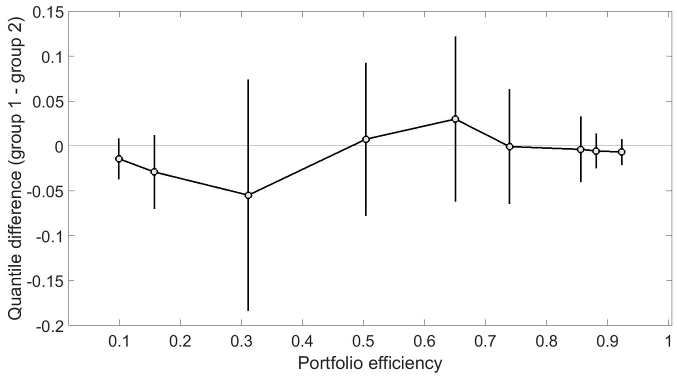
(a) Female household head



(b) Highly educated household head



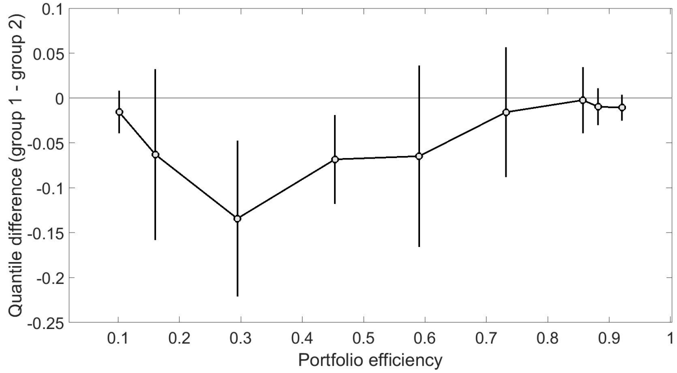
(c) Employed household head



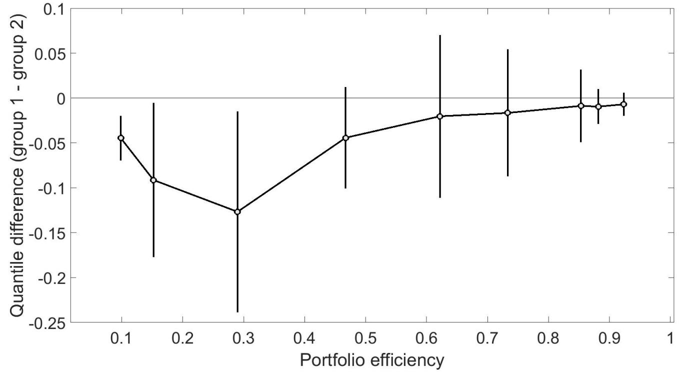
(d) Marital status: couple

Each panel plots the shift function for a different observable characteristic. The y-axis shows the difference between the deciles of portfolio efficiency for households with (group 2) and without (group 1) the characteristic in question. The leftmost (rightmost) dot, representing the 10th (90th) percentile, is obtained by subtracting the decile portfolio efficiency for households with the characteristic (group 2) from the decile portfolio efficiency of the households without the characteristic (group 1). The x-axis shows the decile values of the households without the characteristic (group 1).

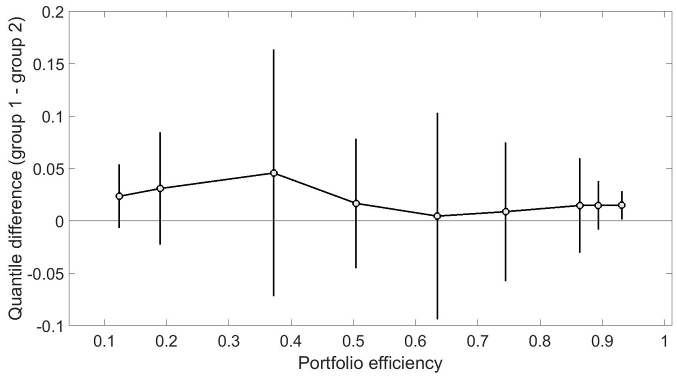
Figure 4: Shift functions for various household characteristics – continued



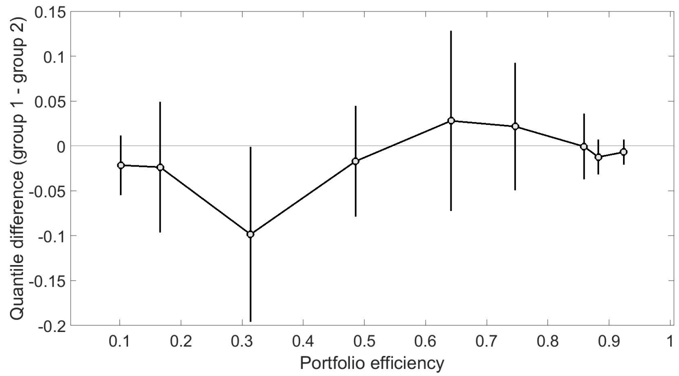
(a) Net wealth above median



(b) Gross income above media



(c) Employment status: retired



(d) HMR value above median

Each panel plots the shift function for a different observable characteristic. The y-axis shows the difference between the deciles of portfolio efficiency for households with (group 2) and without (group 1) the characteristic in question. The leftmost (rightmost) dot, representing the 10th (90th) percentile, is obtained by subtracting the decile portfolio efficiency for households with the characteristic (group 2) from the decile portfolio efficiency of the households without the characteristic (group 1). The x-axis shows the decile values of the households without the characteristic (group 1).

4.3 Dynamic efficiency analysis: do households become better investors over time?

So far, we have documented findings for portfolio efficiency scores that are calculated separately for each wave. These wave-specific efficiency estimates are not directly comparable across waves and, thus, do not readily allow for dynamic efficiency analysis. As a final exercise, we move beyond these wave-specific analyses and examine the extent to which intertemporal changes in portfolio performance may reflect variation in asset returns between waves and/or investors' reallocation decisions. To do so, we restrict our analysis to the subset of participating households with a panel component (obtaining a data set with 823 observations for 361 different households).

Table 11 reports descriptive statistics of the Malmquist index values and its components for the three waves (2010, 2014 and 2017) that we consider in our empirical study.[19] Panel A reveals that over 90% of the households experienced progress in portfolio performance between 2010 and 2014 (i.e. Malmquist index values are below unity). The decomposition shows that almost all households experienced a better economic environment in 2014 than in 2010. This is not surprising given that asset returns in 2014 generally exceed those in 2010 (see Table 6), thus expanding the set of feasible portfolio return-risk combinations. By contrast, only one out of two households reports positive catch-up (i.e. improved portfolio returns for the chosen risk level, relative to the best performing households). These results suggest that much of the performance progress between 2010 and 2014 was made possible by external factors beyond the control of retail investors. Moreover, while the median household improved its performance by 2% as a result of catch-up, changes in the economic environment allowed for almost a tripling of performance.

Almost all households experienced a decline in portfolio performance between 2014 and 2017, mostly due to a less favorable economic environment. Interestingly, compared to the period between 2010 and 2014, a larger share of households experienced positive catch-up between between 2014 and 2017. Moreover, households were able to increase their portfolio returns to a greater extent than in the period between 2010 and 2014. Although these results must be cautiously interpreted as preliminary and exploratory, they do suggest a learning-by-doing effect, with households becoming more able to optimize portfolio performance as they become more experienced over time. This would be consistent with the (sparse) previous research providing evidence that individual investors may learn from their stock trading experience; see e.g. Nicolosi et al. (2009) and Seru et al. (2010). Learning effects may also relate to our previous finding of declining participation rates for the underdiversified individual domestic stock asset class.

[19] For some observations the Malmquist index and the economic environment component may be undefined. In particular, if an observation in period $t+1$ has a portfolio return below the risk-free rate of period t it will have a negative intertemporal Sharpe ratio ($\text{Sharpe}_{T(t)(x_{i,t+1};y_{i,t+1})}$) and consequently a negative intertemporal portfolio efficiency ($\text{PE}_{T(t)(x_{t+1},y_{t+1})}$). Because the formulas for the Malmquist index and the economic environment component (see Equations 8 and 9) require taking a square root, their values will be undefined. Note, however, that this problem does not affect the calculation of the catch-up component.

Table 11: Descriptive statistics of Malmquist index and component values

	10th Percentile	25th Percentile	Median	75th Percentile	90th Percentile	Mean	% obs. showing progress
A. 2010 vs 2014 – 238 obs.							
Malmquist	.067	.168	.346	.557	.858	.435	92.9%
Catch-up	.149	.294	.979	1.661	2.456	1.161	50.8%
Econ. Env.	.299	.312	.348	.458	.573	.410	98.7%
B. 2014 vs 2017 – 196 obs							
Malmquist	1.450	2.080	3.155	4.749	10.045	6.779	4.1%
Catch-up	.318	.449	.706	1.119	4.765	1.975	71.4%
Econ. Env.	4.646	4.691	4.849	5.344	6.850	5.471	-
C. 2010 vs 2017 – 129 obs							
Malmquist	.278	.669	1.191	1.583	2.739	1.335	43.2%
Catch-up	.136	.490	.771	1.004	2.596	1.282	73.6%
Econ. Env.	1.430	1.495	1.748	2.298	3.205	2.031	-

Lastly, we also directly assess the change in portfolio efficiency between 2010 and 2017. Although the external environment negatively impacted the performance of all households, more than 40% of households experienced performance progress and more than 70% reported positive catch-up.

5 Conclusion

The effects of ECB policy in response to the global financial and euro crises have been well-documented. Much less well-understood is how household portfolios have been affected by the lowering of interest rates. From a policy perspective, increased awareness about financial actors and their behavior is important for monitoring risks that are related to financial vulnerability. If households increase their investment in risky assets in search of investment returns while lacking the financial capability to make informed financial decisions, they risk reducing their own welfare and distort capital markets.

Because the HFCS data (which does not contain return information) does not allow implementation of Calvet et al. (2007)'s method, we alternatively propose a nonparametric DEA-based method to quantify households' portfolio efficiency (that naturally integrates the Sharpe ratio). Interestingly, our proposed method also combines several advantages compared to the one used by Calvet et al.. For example, it does not rely on normative benchmarks of optimal investment behavior, but instead measures a household's portfolio performance relative to the observed performance of other (best performing) households. Moreover, the DEA-based measure allows us to account for cross-household variation in risk-free return rates and to mitigate the impact of outlier behavior. We also show how the method can be used to study efficiency change over time.

We have analyzed household portfolios of a panel of Belgian households that we obtained from the HFCS survey. While the HFCS reports investor-level data on the aggregate value held in various financial asset classes (which is far from standard) together with detailed socio-economic and demographic characteristics, it does not contain return information at the individual asset level. Therefore, we proxy portfolio return and risk by using index returns.

We find declining participation rates over time. Participation levels rise sharply with wealth and education levels and with homeownership. Consumption data reveal that almost 40% of the households in our sample hold less than six months' expenses in the form of savings, suggesting that participation remains primarily a privilege for the relatively wealthy, with many households simply lacking the means to invest. Next, participating households increased their risky portfolio share by only a few percentage points, averaging just over 51% in 2017. Risky portfolio shares are generally higher for wealthier and high educated households but lower for homeowners. Further, most households seem to be increasingly aware of the benefits of diversification (as evidenced by the considerable decline over time in the proportion of households holding underdiversified purely domestic stock portfolios). Moreover, diversification appears to increase with wealth levels, suggesting that those most at risk of being unable to withstand financial pressure are poorer households with smaller portfolios.

Only a small fraction of households manage their finances efficiently. We report significant cross-sectional variation in portfolio efficiency in all three waves, with many households performing poorly. This contrasts with the findings of Calvet et al. (2007), who report that many Swedish households are well-diversified in the period 1998-2002. High educated and wealthier households show better performance, as do households with a female head. Retired households perform significantly worse than non-retired households. When expressing efficiency scores in monetary terms, we find that efficient investing could generate additional investment returns of between 0.5% to 3.1% of annual gross income for the median household. In all years, over 10% of the households adopt investment strategies that incur return losses of more than 10% of their annual gross income.

Finally, the panel component of the HFCS allows for a dynamic analysis studying efficiency change over time. We report that households are able to increase performance over time, suggesting the possibility of a learning-by-doing effect. Specifically, over 70% of the households in our sample could increase their portfolio efficiency between 2010 and 2017.

The reported results imply several important takeaways for policymakers. First, the finding that wealthier and more educated households have higher participation rates, hold more diversified portfolios and show better performance, combined with the equity premium (i.e. the phenomenon that risky assets earn higher expected returns than risk-free assets), may lead financially sophisticated households to (systematically) incur higher investment returns. Combined with the recent evidence on persistence in investment returns (Fagereng et al., 2020) and assortative matching (Fagereng et al., 2022), our results may have far-reaching implications for the debate on wealth inequality. Specifically, less financially sophisticated households hold smaller financial portfolios and are less likely to participate; and if they do participate, they are likely to experience lower investment returns (caused either by underdiversification or lower performance), which may lead to an increase in wealth inequality over time.

Second, when examining the evolution of risky shares over time, we find no evidence of a widespread increase in risk taking behavior in response to lower interest rates. While risk taking does follow a U-shaped pattern over time, risk levels in 2017 remain lower than in 2010. From this perspective, given the recent evidence that innovations in fintech may increase risk taking (Hong et al., 2022), it seems particularly interesting to study how these risk taking patterns have evolved after the period that we studied in the current paper.

Third, the substantial cross-sectional variation in portfolio efficiency, with many households performing poorly, suggests a clear need for financial literacy initiatives. In this respect, Van Rooij et al. (2011) establish a link between financial literacy and risky asset participation. Next, the literature also shows the importance of facilitating financial advise and information sharing within social networks (see, for example, Gomes et al., 2021). Unfortunately, we cannot examine the financial education levels of Belgian households as they do not respond to the HFCS module containing questions on financial literacy. While we find that households may improve their performance over time, aggregate performance remains subpar even in 2017. In this respect, the higher return losses for retired households are particularly concerning, as these households have fewer opportunities to supplement pensions with other sources of income. These findings also point to the importance of developing financial education programs that are specifically tailored to retirees.

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Table 12: # and % of households owning a certain number of properties other than the HMR

	2010 (429 obs - 22.4%)	2014 (419 obs - 24.3%)	2017 (444 obs - 25.7%)
1	285 (66.4%)	275 (65.6%)	300 (67.6%)
2	80 (18.7%)	84 (20.1%)	96 (21.6%)
3	34 (7.9%)	29 (6.9%)	25 (5.6%)
4	10 (2.3%)	18 (4.3%)	10 (2.3%)
4+	20 (4.7%)	13 (3.1%)	13 (2.9%)

A Appendix

A.1 Real estate investments

Table 12 shows that around two thirds of the households owning properties other than the HMR own a single additional property, a fraction that remains stable across waves. For all three waves, over 92% of households own three or fewer additional properties. Thus, within the subsample of real estate investor households, we do not find evidence of a boom in real estate investing.

A.2 Wealthier households own multiple assets

Table 13 shows that wealthier households tend to participate in a wider range of asset classes. Specifically, the table shows, for different subsamples, the proportion of households investing in a given number of the eight different assets (shown in Table 1). Focusing on the investor sample, the share of households holding only two assets decreases with the size of the financial portfolio, while the share of households with four or more assets increases.

Table 13: Proportion of households owning a given number of different assets, by wealth level

# assets	Full sample (5370 obs)	Investor sample (1907 obs)	Investor sample, fin. port. ≤ €20k (223 obs)	Investor sample, €20k <fin. port. ≤ €50k (327 obs)	Investor sample, €50k <fin. port. ≤ €150k (609 obs)	Investor sample, €150k <fin.port. ≤ €500k (535 obs)	Investor sample, fin. port. >€500k (213 obs)
1	63.5%	0.2%	0.9%	0.3%	0.2%	-	-
2	22.5%	60.7%	85.2%	76.7%	63.9%	46.0%	38.0%
3	8.8%	24.7%	11.2%	19.0%	26.6%	30.3%	27.7%
4	3.9%	10.9%	2.7%	4.0%	7.9%	18.0%	20.7%
5	1.1%	3.1%			1.3%	5.2%	10.8%
6	0.2%	0.5%			0.2%	0.6%	2.8%

A.3 Estimating risky asset returns using index returns

As mentioned in Section 2.3 we calculate annual risky asset returns as the annualized average monthly return during the survey year, using specific indices. This section motivates the selection of indices in more detail:

Asset class: individual stock (domestic and diversified). We use the returns of the BEL-20 index for the domestic individual stock asset class. Next, previous work has found that retail investors prefer local and familiar stocks over investing in foreign stock (Barber and Odean, 2013). A home bias in equity holdings occurs when the proportion of foreign assets held by domestic investors is too small relative to the predictions of portfolio theory (see e.g. Lewis, 1999; Coval and Moskowitz, 1999). Of course we should take this into account when computing returns for diversified individual stock portfolios. Estimates for Belgium indicate that the proportion of foreign stocks in equity portfolios amounts to almost 45%-50% in 2003 (Sørensen et al., 2007) and 2005 (Sercu and Vanpée, 2007). Therefore, we calculate returns for the diversified individual stock asset class as an equal-weighted combination of the MSCI ACWI index (representing foreign stocks) and the BEL-20 index (representing domestic stocks).

Asset class: MF stocks. We assume that investments held in mutual funds (which are managed by professionals) are optimally diversified and thus do not suffer from a home bias. Therefore, we calculate returns using the MSCI ACWI index (a global equity index).

Asset class: MF bonds. We use monthly return data from the Bloomberg Euro-Aggregate index, which is a benchmark index measuring the investment grade, euro-denominated, fixed-rate bond market, including treasuries, government-related, corporate and securitized issues. As such our estimation accounts for both government and corporate bond returns.

Asset class: individual bonds. Similar to the stock asset classes we assume that assets held by individuals suffer from a home bias. Because the HFCS does not ask whether households hold domestic/foreign bonds we cannot infer a home bias for bonds. We calculate returns for the individual bonds asset class using the annualized monthly return of the Bloomberg Euro-Aggregate Treasury Belgium Unhedged Index. This index measures both government and corporate bond returns.

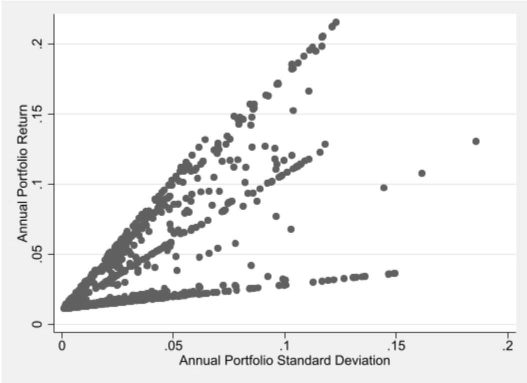
Asset class: MF real estate. We calculate returns using the GPR250 REIT EUROPE (EUR) Index.

Asset class: mix funds. This asset class combines both the MF of various types and managed accounts (see Table 1). The name "MF of various types" indicates a mix of funds. In addition, managed accounts often consist of multiple assets.Therefore, we combine both products into a single multi-asset class, for which we calculate returns using a 60-40 portfolio (consisting of 60% stocks and 40% bonds) as index. For decades, the 60-40 portfolio has been considered a rule of thumb for portfolio allocation (see e.g. Chaves et al., 2011).

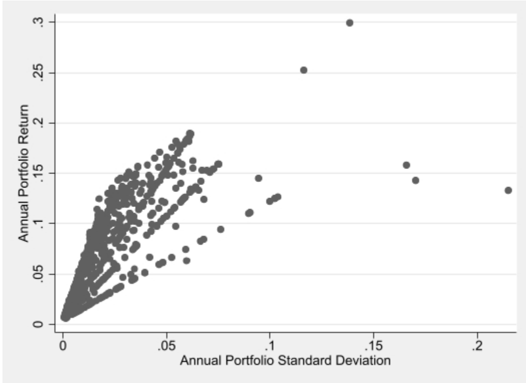
A.4 Scatterplots of household portfolio return and standard deviation

Figure 5 shows scatterplots of the portfolio return and standard deviation for each wave. The scatters for 2010 and 2014 indicate observations to be positioned between an upper and a lower line. The lower line is formed by households investing mostly in individual domestic stocks (which obtain a return barely above that of bonds but require substan-

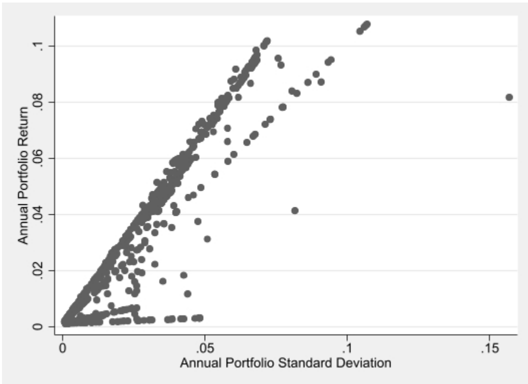
Figure 5: Scatterplots of household portfolio return and standard deviation



(a) Wave 1 — 2010



(b) Wave 2 — 2014



(c) Wave 3 — 2017

tially higher risk, see Table 5). The upper line is formed by households investing in various assets. For 2014, the lower line again contains households investing predominantly in individual domestic stocks. Most households positioned on the upper line hold some bonds (which attain a relatively high return in 2014 in combination with a low risk).

A.5 Who is inefficient? Additional Kolmogorov-Smirnov tests

We replicate the analysis of Section 4.2 for each wave separately (instead of pooling observations). As before, we aim to assess the equality of distributions between two non-overlapping subsamples based on observable characteristics. Table 14 reports p-values of one-tailed and two-tailed K-S tests assessing the equality of the portfolio distributions for different subsamples.

In general, the wave-specific results more or less confirm the pooled effects described in the main text. Note, however, that not all effects described in the main text are significant for all years, due to smaller sample sizes. We find that households with high educated or employed heads achieve significantly higher portfolio efficiency scores, as do households with higher gross income, net wealth and larger complete portfolios. Conversely, the finding that portfolio efficiency is higher for households with a female head is less robust. Again, retired households have lower portfolio efficiency than non-retired households. Lastly, portfolio efficiency does not seem to be strongly related to the value of the household's main residence.

Surprisingly, the effects for the 2014 wave are often opposite to those for the 2010 and 2017 waves. It is unclear why this is the case; this may form the subject of follow-up research.

Table 14: One-tailed and two-tailed, two-sample K-S tests: p-values (wave-specific)

	2010			2014		
	Two-sided test (1): P-value	One-sided test (2): P-value	One-sided test (3): P-value	Two-sided test (1): P-value	One-sided test (2): P-value	One-sided t (3): P-value
Female household head (dummy)	.430	.504	.217	.303	.152	.828
Marital status: couple (dummy)	.136	.068*	.851	.055*	.471	.028**
Employment status: retired (dummy)	.001***	.774	.001***	.006***	.003***	.993
Employment status: employee or self-employed (dummy)	.002***	.001***	.757	.001***	.987	.000***
High education (dummy)	.000***	.000***	.912	.137	.872	.068*
Gross income above median (dummy)	.000***	.000***	.313	.119	.433	.060*
Net wealth above median (dummy)	.007***	.003***	.255	.633	.328	.388
Complete portfolio above median (dummy)	.014*	.007***	.181	.150	.075*	.643
HMR value above median (dummy)	.598	.343	.308	.017**	.604	.009***

NOTE. — Column 1 reports the p-values of a two-tailed K-S test. The second (third) column reports the p-values of a one-tailed K-S test, with the alterna second group are greater (smaller) than those for the first group. One-tailed tests always place observations with the characteristic in question in the second g
*** denotes significance at 1%-level; ** denotes significance at 5%-level; * denotes significance at 10%-level.

Column 1 reports the p-values of a two-tailed K-S test. The second (third) column reports the p-values of a one-tailed K-S test, with the alternative hypothesis that the portfolio efficiency scores for the second group are greater (smaller) than those for the first group. One-tailed tests always place observations with the characteristic in question in the second group. Observations are pooled across waves.

Finally, we examine the relationship between financial variables and portfolio efficiency in more detail. Specifically, we search for significant differences in the distribution of portfolio efficiency scores across subsamples defined by gross income, net wealth and complete portfolio quartiles. Of course, the creation of additional subsamples further reduces the sample size of each group, making it more difficult to obtain significance at the 5% and 1% levels. Therefore we pool observations across waves. Table 15 reports p-values of one-tailed and two-tailed K-S tests assessing equality of the portfolio distributions for pairwise comparisons of subsamples. With regard to gross income, we observe that portfolio efficiencies of the fourth quartile are significantly higher than those of the remaining quartiles. Next, for both net wealth and complete portfolio size fourth quartile portfolio efficiencies are significantly higher than those of the first and second quartiles, but not the third quartile. In general, although the null hypothesis of equal distributions is not always rejected, the results confirm the evidence presented in Section 4.2 that there is a positive relationship between portfolio efficiency and wealth measures.

Table 15: Two-sample K-S tests for equality of portfolio distributions: p-values (quartiles)

	A. Gross income			B. Net wealth			C. Complete portfolio		
	Second quartile	Third quartile	Fourth quartile	Second quartile	Third quartile	Fourth quartile	Second quartile	Third quartile	Fourth quartile
First quartile	.070*	.002***	.000***	.029**	.341	.085*	.195	.045**	.001***
	[.035]**	[.001]***	[.000]***	[.702]	[.172]	[.043]**	[097]*	[.022]**	[.000]***
Second quartile		.886	.072*		.000***	.005***		.270	.012**
		[.507]	[.036]**		[.000]***	[.002***		[.135]	[.006]***
Third quartile			.061*			.143			.656
			[.031]**			[.632]			[.341]

NOTE. — The first row reports the p-values of a two-tailed K-S test. The second row reports p-values of a one-tailed K-S test, with the alternative hypothesis that the portfolio efficiency scores for the higher quartile group are greater than those for the smaller quartile group.
*** denotes significance at 1%-level; ** denotes significance at 5%-level; * denotes significance at 10%-level.

A.6 Robustness check: no change in real estate holdings

We report results for the subsample of real estate investor households with a panel component for which the number of properties remain constant across waves. This obtains a total of 448 observations, 251 from 2014 and 197 from 2017. Note that the condition 'the number of properties remains constant' deletes observations from 2010 as these cannot be compared to a previous wave.

Table 16 shows descriptive statistics of robust portfolio efficiency scores. The scores are similar to those shown in Table 8 for the full sample. Specifically, mean and median scores increase over time and there is considerable heterogeneity in household performance, with many households performing poorly. In Table 17 we also quantify portfolio efficiency in monetary terms. These results can be compared against Table 9 showing full sample results. In general, our findings are again comparable. However, for panel B and panel C results are mostly a bit smaller than those reported in the main text. This is an obvious consequence of the smaller samples we here consider: the sample in the main text is larger and thus is a stricter benchmark. Kolmogorov-Smirnov tests again confirm that the figures in Panel C are significantly higher for retired households (p=0.000 for both waves).

Table 16: Descriptive statistics of robust portfolio efficiency scores (PE) - no change RE subsample

	Mean PE	Median PE	St. Dev. PE	5th perc. PE	95th perc. PE
2014 (251 obs)	.57	.49	.24	.19	.92
2017 (197 obs)	.71	.87	.31	.05	.97

Table 17: Descriptive statistics of return loss measures - no change RE subsample

	10th Percentile	25th Percentile	Median	75th Percentile	90th Percentile	Mean
A. Return loss (RL)						
2014	.004	.011	.046	.126	.198	.087
2017	.001	.002	.006	.010	.028	.010
B. Return loss in € ($RL^{€}$)						
2014	26	214	1607	9592	39474	14223
2017	5	42	311	1668	4037	2737
C. Return loss as a fraction of income ($RL^{€,\ GROSS}$)						
2014	.001	.004	.029	.182	.714	.427
2017	.000	.000	.005	.027	.103	.038

Next, we study whether portfolio efficiency scores can be explained by observable characteristics. In Table 18 we replicate the results shown in Table 10 in subsection 4.2. As before, one-tailed tests always place observations with the characteristic that is studied in the second group. Because the sample is now much smaller we establish less significance in general. We still report that households with high-educated heads achieve significantly higher portfolio efficiency scores, as do households with larger complete portfolios. Contrary to previous results, homeowners with a main residence value exceeding the median obtain lower efficiency scores.

Table 18: Two-sample K-S tests for equality of portfolio efficiency distributions: p-values (no change RE subsample)

	Two-sided test (1): P-value	One-sided test (2): P-value	One-sided test (3): P-value
Female household head (dummy)	.645	.335	.925
Marital status: couple (dummy)	.657	.342	.865
Employment status: retired (dummy)	.294	.167	.148
Employment status: employee or self-employed (dummy)	.199	.158	.100
High education (dummy)	.096*	.048**	.818
Gross income above median (dummy)	.465	.235	.319
Net wealth above median (dummy)	.230	.115	.931
Complete portfolio above median (dummy)	.077*	.039**	.319
HMR value above median (dummy)	.185	.745	.092*

NOTE. — Column 1 reports the p-values of a two-tailed K-S test. The second (third) column reports the p-values of a one-tailed K-S test, with the alternative hypothesis that the portfolio efficiency scores for the second group are greater (smaller) than those for the first group. One-tailed tests always place observations with the characteristic in question in the second group. Observations are pooled across waves.
*** denotes significance at 1%-level; ** denotes significance at 5%-level; * denotes significance at 10%-level.

Lastly, we study dynamic changes in efficiency using Malmquist indices. Table 19 is the counterpart to Table 11 in the main text, showing descriptive statistics of the Malmquist index values and its components. Note however that the sample under consideration becomes very samll (containing only 78 obs). In general, Malmquist index scores are somewhat lower than in the main text, with 5.9% of obs making progress between 2014 and 2017, compared to 4.1% before. A similar picture emerges for the catch-up component, where now 74.4% of respondents shows progress (vs. 71.4% before). Results for the economic environment component are also comparable.

Table 19: Descriptive statistics of Malmquist index and component values (no change RE subsample)

	10th Percentile	25th Percentile	Median	75th Percentile	90th Percentile	Mean	% obs. showing progress
			B. 2014 vs 2017 – 78 obs				
Malmquist	1.289	1.636	2.401	4.726	6.953	5.202	5.9%
Catch-up	.288	.347	.540	1.040	4.883	2.111	74.4%
Econ. Env.	4.467	4.524	4.699	5.257	6.804	5.089	-

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