Why is investors' mutual fund market allocation far from the optimum?

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Abstract

We analyse the differences between the optimal portfolio of funds that a fully informed investor might select and the current structure of the mutual fund markets as characterized by the funds' risk profile (conservative or aggressive) and target investor type (retail or wholesale). We find that the relationship between fund age, market share and change in total net assets – but not fees – and the optimal portfolio of funds depends on the structure of the mutual fund market.

Keywords: Optimal portfolio of funds, fund characteristics, risk profile, retail, frictions.

JEL Classification: G11, G19..

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1. Introduction

The collective investment industry, particularly mutual funds, is an important area of the Spanish financial economy. As well as providing one of the major channels through which savings are invested to enhance economic growth, the supply of mutual funds constitutes an important investment opportunity for investors. Mutual funds offer several advantages over direct investment in individual securities, including increased diversification, daily liquidity and professional investment management. In exchange, investors have to pay fees, mainly to the investment management companies that administer the funds.

However, there are a number of frictions in mutual fund markets, as shown by Gavazza (2011) for the U.S. market and Cambón and Losada (2014) for the Spanish market. In particular, the switching, search and informational costs that investors face, especially retail investors, deter them from finding the fund that offers the highest utility and allow management companies to enjoy market power irrespective of financial performance. An important consequence is that management companies can set fees that are higher than they would be in a more competitive environment and continue to enjoy market power (Losada, 2016). Therefore, it is plausible to assume that the current investors' optimal portfolio of funds differs from the optimum.

This paper investigates the difference between the optimal portfolio of funds that fully informed investors might select and the current structure of the mutual fund markets by exploring the main drivers of this difference. To do this, we explore the information embedded in the cross-section of fund characteristics to explain the optimal deviation from a value-weighted diversified portfolio of funds depending on the market structure. The market structure is explained by two dimensions: the type of investor at which a fund is aimed, retail vs. wholesale, and the fund's risk profile, conservative vs. more aggressive. Accordingly, we analyse the determinants of the optimal deviation from the current fund market structure in four different segments that seek to represent the heterogeneity of the Spanish mutual fund market: retail/conservative, retail/more aggressive, wholesale/conservative and wholesale/more aggressive.

Although this optimal mutual fund allocation is not necessarily achievable in practice due to frictions present in the market, especially search costs and short-selling restrictions, it could help clarify how suboptimal the current mutual fund market is and the main determinants.

In our framework we assume that an aggregate investor who holds a diversified portfolio of funds representing the mutual fund market tries to optimize his/her portfolio by maximizing the expected utility of their final wealth conditional on the information conveyed by the cross-section of funds' characteristics. Our aim is to compare this optimal portfolio attainable in a frictionless world, which obviously depends on the standard assumptions made about the investor's preferences and his/her information set, with the aggregated portfolio of funds that is actually observed. We can then go on to estimate the optimal deviation from the value-weighted portfolio of funds that depends on different characteristics across funds: momentum, flows, fees, market share, age, volatility and the asset under management of the funds.

However, rather than focusing exclusively on the portfolio implications per se – which would in itself be an interesting exercise – we seek to identify an economic interpretation that explains the factors driving the optimal portfolio. Our analysis highlights the importance of considering funds' characteristics and the structure of the mutual fund market in order to optimize a portfolio of funds. This complements a strand of the literature that emphasises considering different assumptions about the funds' return distribution or the investor's objective function (see Morton et al., 2006; Giamouridis and Vrontos, 2007; Harris and Mazibas, 2013). Our main hypothesis is validated and the type of investor at which a fund is aimed, retail vs. wholesale, and the fund's risk profile are confirmed as factors that influence the varying degrees of competition in mutual fund market segments. We therefore conclude that these same features also influence the fund characteristics that explain the difference between the optimal portfolio in a frictionless world and the actual allocation of funds. Retail and institutional investors belong to two differentiated segments whose demands may exhibit different characteristics that would lead to a different relationship between the cross section of fund characteristics and the optimal portfolio of funds. Retail investors, who can be classified as an unsophisticated type of disadvantaged investor (Del Guercio and Tkac, 2002), usually invest in funds from one single fund manager as a search for the most suitable fund would usually be too costly for this type of investor. In contrast, wholesale investors in mutual funds, who are classified as sophisticated investors, exhibit another pattern of demand and are better informed than retail investors. These investors have greater financial knowledge which allows them to compare the existing funds in the market and check which best suits their investment profile. They also more frequently incur the cost of searching for the funds with the highest returns and/or the lowest fees, and they do not normally exhibit such high loyalty to a specific fund manager as retail investors.

We also link the differences in performance between the optimal portfolio of funds that fully informed investors might select and the actual structure of the mutual fund markets to the welfare loss associated with imperfect competition and the different costs incurred by the investor in the process of allocating his/her wealth in the universe of funds. We proxy the welfare loss from investing in a suboptimal actual portfolio using different metrics, such as: the difference in the certainty equivalent, average return and Sharpe ratio, alpha and information ratio between the actual investor's optimal portfolio and the optimal portfolio. Alternative approaches not explored in this paper include assuming that the investor is indeed acting optimally and therefore finding the investor's preferences more appropriate to explain their investment decisions given the costs faced, or assuming that investors are not really rational or may be affected by behavioural biases (Bailey et al., 2011).

The methodology applied in our paper follows that in the papers by Brandt et al. (2009) and Barroso and Santa Clara (2015). Brandt et al. (2009) tackle a similar problem and compare the optimal allocation weights for U.S. equities with the observed market capitalization weights, exploiting size, value and momentum anomalies. Barroso and Santa Clara (2015) use different technical and fundamental variables that are common across currencies to form optimal currency portfolios. Following the Brandt et al. (2009) methodology we assume that the optimal portfolio weight allocated to each fund is a linear function of the fund's characteristics standardized cross-sectionally allowing us to obtain the optimal portfolio of funds without estimating the expected returns, volatilities and higher order moments of the mutual funds' return distribution. The coefficients that link the common characteristics across funds with the optimal portfolio of funds also allow us to investigate different aspects of the mutual fund market, like the existence of hot hands, smart money and the role played by relevant factors in a fund such as age or size.

Our empirical analysis focuses on the Spanish mutual fund market but the Brandt et al. (2009) methodology could easily be applied to any mutual fund market regardless of its specific characteristics. In addition, our empirical results are interesting per se. As can be derived from Golez and Marin (2015), Spain constitutes a good representative of the European markets for mutual funds[1]. This is a market whose structure shares the main features as the mutual fund markets of Continental Europe. It is a market driven by fixed income mutual funds, where retail investors own the majority of the assets under management and where funds are placed mainly through branches of national credit institutions. According to the European Fund and Asset Management Association, Spain ranked as the 9th largest market in Europe at the end of 2015. Stripping out the U.K., Luxembourg and Ireland and controlling for country size, the amount of assets managed in the Spanish market is comparable to other European countries like France, Germany and Italy. Regarding competition, the Spanish market is also comparable to other European markets. Ferreira and Ramos (2009) calculated a Herfindahl index for the fund industry in Spain of 0.11 in 2006, which was very close to the average index in a sample of euro zone countries (0.12), composed of Austria, Belgium, Finland, France, Germany, Italy, the Netherlands and Portugal.

Our empirical analysis of the Spanish mutual fund market shows that there is only one characteristic common to the whole universe of funds that affects all optimal portfolios in the same negative way, regardless of the type of investor at which the fund is aimed and the investor's risk profile: the fees. This suggests that fees do not seem to be fair compensation for the value added by the funds' managers. The funds' age also has a very substantial impact on optimized portfolios but with different signs depending on the investor's risk profile, regardless of the type of investor that the fund targets. More risk-averse investors, who are likely to invest in more

1 As already stated in Otten and Schweitzer (2002), the Continental European fund markets and U.S. fund markets differ. In the U.S., the industry is much larger and the number of funds is lower, which results in a larger average size of individual funds in the U.S. market. Moreover, as mentioned, the channels for fund distribution are also different. In Europe, with the exception of the U.K., mutual funds are mainly brokered through branches of commercial banks, which, in most cases, belong to the same financial conglomerate as the funds' management company. In the U.S. and the U.K., mutual funds are mainly brokered by independent financial advisors.

conservative funds, are better off choosing funds that are older than average and may profit from greater experience. On the contrary, less risk-averse investors, who are likely to invest in more aggressive funds, are better off choosing younger-than-average funds. These young funds are likely to adopt a more active and successful strategy to gain market share and are usually run by independent management companies. Interestingly, in the wholesale market only, market share is positively (negatively) related to the optimal portfolios when we consider the more (less) risk-averse investors. In the retail segment, market share is only negatively significant for more risk-averse investors. Finally, we find evidence that wholesale investors also seem to be more skilful than retail investors and direct flows to the outperforming funds, especially in the conservative segment. In summary, our results provide evidence for the importance of considering both funds' characteristics and the structure of the mutual fund market jointly to create an optimal portfolio of funds. The investor's welfare loss from investing in a suboptimal current portfolio of funds is substantial. We find an economically significant in-the-sample and out-of-the-sample difference in the certainty equivalent, average return and Sharpe ratio between the current investor's optimal portfolio and the optimal portfolio, which also delivers a positive, significant alpha and a high information ratio with a low beta.

From the regulatory point of view, the implications of our study are straightforward. Although the feasibility of achieving the optimal portfolio is extremely low due to the presence of frictions, especially short-selling restrictions and search costs, it would be possible to improve the investor's market allocation by providing easier access to information about a few fund characteristics, like fees, age, market share or investors' flows.

The remainder of the paper proceeds as follows. Section 2 presents the theoretical framework. Section 3 describes the state variables or fund characteristics used in our empirical analysis, the Spanish mutual fund market and the data used. Section 4 presents the results of the empirical study. Finally, section 5 sets out the conclusions.

2. The theoretical framework: The optimal portfolio of mutual funds

This section describes the methodology used to form an optimal portfolio of funds. We follow Brandt et al. (2009), who propose a methodology that is suitable for optimizing portfolios with a large number of assets. Instead of analysing a portfolio of stocks, we assume that an investor wants to optimize a portfolio with a large number of funds. This active portfolio manager searches for an optimized portfolio that could outperform the benchmark performance.

On each date t there is a large number of funds, F_t, which can vary across time. Each fund i has a return of $r_{i,t+1}$ from date t to date $t+1$ and a vector of characteristics, $x_{i,t}$, is observed on date t for all the funds. These characteristics are expected to be related to the fund's return distribution moments and convey valuable information for the purpose of optimizing the portfolio of funds.

The investor's problem is to choose the portfolio weights, $\alpha_{i,t}$, to maximize the conditional expected utility of the portfolio's return, $r_{p,t+1}$, which is connected to all the moments of the distribution of the portfolio's return (Brandt et al., 2009):

$$\max_{\{\alpha_{i,t}\}_{i=1}^{F_t}} \quad E_t\left[U\left(r_{p,t+1}\right)\middle|\Omega_t\right]=E_t\left[U\left(\sum_{i=1}^{F_t}\alpha_{i,t}r_{i,t+1}\right)\middle|\Omega_t\right], \tag{1}$$

with $U(.)$ denoting the investor's utility, Ω_t the corresponding sigma algebra and $E\left[\bullet\middle|\Omega_t\right]$ the mathematical expectation conditional on Ω_t.

Like Brandt et al. (2009), we parameterize the optimal portfolio weights as a linear function of the fund characteristics, assuming that the investor's benchmark portfolio is the value-weighted portfolio of funds:

$$\alpha_{i,t}=f\left(x_{i,t};\theta\right)=\overline{\alpha_{i,t}}+\frac{1}{\mathrm{F_t}}\theta^T\overline{x_{i,t}}, \tag{2}$$

with θ a constant vector of coefficients to be estimated and $\overline{\alpha_{i,t}}$ the weight of fund i on date t in the value-weighted benchmark portfolio. $x_{i,t}$ are the characteristics of fund i standardized cross-sectionally to have zero mean and unit standard deviation across all funds on date t. This standardization ensures stationarity through time and that on each date t the quantity $\theta^T\overline{x_{i,t}}$ is zero. Therefore, the optimal deviations from the value-weighted portfolio to each fund sum to zero and the optimal portfolio weights sum to one (Brandt et al., 2009).

The optimal portfolio weights are a function of characteristics that are common to all the funds, making the estimation problem dependent on the number of characteristics rather than the number of funds. Hence, the number of estimated parameters, the constant vector θ, equals the number of considered characteristics; consequently the computational burden of the estimation problem is very low.

The assumption that the coefficients θ are constant across funds and through time guarantees that the conditional problem can be rewritten in terms of the unconditional problem (Brandt et al., 2009):

$$\underset{\theta}{Max}\, E\left[U\left(r_{p,t+1}\right)\middle|\Omega_t\right]=E\left[U\left(\sum_{i=1}^{F_t}\left(\overline{\alpha_{i,t}}+\frac{1}{\mathrm{F_t}}\theta^T\overline{x_{i,t}}\right)r_{i,t+1}\right)\middle|\Omega_t\right]. \quad (3)$$

The estimation of the vector θ is performed by maximizing the sample analogue:

$$\underset{\theta}{Max}\frac{1}{T}\sum_{t=0}^{T-1}\left[U\left(r_{p,t+1}\right)\middle|\Omega_t\right]=\frac{1}{T}\sum_{t=0}^{T-1}\left[U\left(\sum_{i=1}^{F_t}\left(\overline{\alpha_{i,t}}+\frac{1}{\mathrm{F_t}}\theta^T\overline{x_{i,t}}\right)r_{i,t+1}\right)\middle|\Omega_t\right]. \quad (4)$$

The first-order condition of this problem is stated as follows:

$$\frac{1}{T}\sum_{t=0}^{T-1}\left[U^{'}\left(r_{p,t+1}\right)\left(\overline{x_{i,t}}^T r_{t+1}\right)\middle|\Omega_t\right]=0. \quad (5)$$

Assuming that the investor's information set in period t is $W_t = Z_t$, condition (5) defines the following system of equations:

$$\frac{1}{T}\sum_{t=0}^{T-1}\left[U^{'}\left(r_{p,t+1}\right)\left(\overline{x_{i,t}}^T r_{t+1}\right)\otimes Z_t\right]=0, \quad (6)$$

with $\otimes$ denoting element-by-element multiplication.[2]

Therefore, condition (6) yields a testable representation that can be implemented using the generalized method of moments (GMM) technique (Hansen, 1982). Let $c\left(R_{p,t+1},Z_t;\beta\right)=U^{'}\left(r_{p,t+1}\right)\left(\overline{x_{i,t}}^T r_{t+1}\right)\otimes Z_t$ be a $k \times 1$ vector, with k being the length of Z_t. The sample analogue of expression (6) is

$$\frac{1}{T}\sum_{t=0}^{T-1}c\left(R_{p,t+1},Z_t;\beta\right)=0. \quad (7)$$

The idea behind the generalized method of moments (GMM) is to choose θ so as to make the sample moment $\frac{1}{T}\sum_{t=0}^{T-1}c\left(r_{p,t+1},x_t,\theta\right)$ as close to zero as possible. This is achieved by minimizing the scalar:

2 This is known as a Kronecker product.

$$\left[\frac{1}{T}\sum_{t=0}^{T-1}c\left(r_{t+1},x_t,\theta\right)\right]' V_T^{-1}\left[\frac{1}{T}\sum_{t=0}^{T-1}c\left(r_{t+1},x_t,\theta\right)\right], \tag{8}$$

where V_T admits different choices for the covariance matrix. In principle, in the first stage V_T is the identity matrix and in the second stage, to gain efficiency, this matrix is replaced by a consistent estimator of the asymptotic covariance matrix, V, of the random vector $c\left(r_{t+1},x_t,\theta\right)$.

To make these theoretical results operational, we assume that the investor's utility function is isoelastic and takes the following form:

$$U\left(r_{p,t+1}\right)=\frac{(1+r_{p,t+1})^{1-\gamma}}{1-\gamma}, \tag{9}$$

where γ is the investor's constant relative risk aversion (CRRA) coefficient. It is important to point out that if $\gamma = 1$ the utility function becomes $U(R_{p,t+1})=\log\ (1+R_{p,t+1})$.

It is also interesting to outline that

$$r_{p,t+1}=\left(\sum_{i=1}^{F_t}\left(\overline{\alpha_{i,t}}+\frac{1}{\mathrm{F_t}}\theta^T\overline{x_{i,t}}\right)r_{i,t+1}\right)=\left(\sum_{i=1}^{F_t}\left(\overline{\alpha_{i,t}}r_{i,t+1}\right)\right)+\left(\sum_{i=1}^{F_t}\left(\frac{1}{\mathrm{F_t}}\theta^T\overline{x_{i,t}}\right)r_{i,t+1}\right)=r_{m,t+1}+r_{h,t+1}.$$

Therefore, the optimized portfolio return is the sum of the market return, $r_{m,t+1}$, and the return of a long/short hedge fund, $r_{h,t+1}$, with weights that always add up to one (Brandt et al., 2009). Thus, problem (3) can be reinterpreted as the problem of a hedge fund that maximizes the expected utility of an investor who already holds the market portfolio.

3. Data

The section commences by describing the state variables used in the empirical analysis and briefly describes the mutual fund industry in Spain. It continues by presenting the data used in the paper.

3.1 The choice of characteristics common across the universe of funds

This section discusses the choice of the fund characteristics or state variables used to create the optimal portfolio of funds. The enormous literature that attempts to explain mutual funds' performance uncovers different variables or factors that are helpful in our framework. The variables used in our empirical application are:

– **Momentum**: defined as the average of the fund's returns in the three previous months. The phenomenon of persistence or the "hot hands phenomenon" (Hendricks et al., 1993) tries to determine whether the funds that obtain better (worse) results also obtain systematically better (worse) results, giving support to the existence (lack) of skilled or informed mutual fund managers. The empirical results provide mixed evidence that may also depend on the stage of the cycle (Hendrick et al., 1993; Carhart, 1997; Ferreira et al., 2012; Kacperczyk et al. 2014)

– **Net subscriptions**: defined as the change in the fund's total net assets between the close of one month and the close of the previous month. A belief in the persistence of fund performance would motivate a nonlinear relationship between funds' flows and their performance in the presence of search costs (see Ippolito, 1992; Sirri and Tufano, 1998). A related question is whether investors have the ability to predict future fund performance and consequently direct money flows to these funds. The study of the existence of a "smart money effect" also yields inconclusive results (see Gruber, 1996; Zheng, 1999; Frazzini and Lamont, 2008; Ferreira et al. 2012).

– **Fees**: defined as the sum of the management fees, the deposit fee, one-seventh of the subscription fee and one-seventh of the redemption fee of each fund in each of the periods making up the sample.[3] If a manager is able to generate superior risk-adjusted returns after the fees are charged, it can be said that the fund adds value to the investor. However, the empirical evidence about the relationship between fees and mutual fund performance is

3 This variable is defined in a similar manner to that used by Gavazza (2011) and Cambon and Losada (2014), who assume that investors make their investments on a time horizon of seven years.

also mixed and inconclusive (see Gil-Bazo and Verdú, 2009; Chen et al., 2004; Ferreira et al., 2012).

- **Age**: defined as the number of years the fund has existed in each of the months under consideration. Fund age, which determines a fund's longevity and might be a proxy for the fund manager's ability, could also affect the fund's performance. However, younger mutual funds are expected to be more prone to achieving a better performance to survive but also face higher costs and suffer from a lack of experience. The empirical evidence also depends on the market under consideration (see Chen et al., 2004; Ferreira et al., 2012).

- **Size of the fund**: the assets of the fund at the close of each month. The relationship between mutual fund size and performance has been extensively researched by studies analysing the role of economies of scale in active management. However, another thread suggests that the trading costs associated with liquidity or price impact force large funds to invest in assets that are not so good. According to this illiquidity hypothesis, the negative relationship between fund size and fund performance would be larger in funds that have to invest in more illiquid assets, such as small cap stocks (Chen et al., 2004; Pollet and Wilson, 2008; Ferreira et al., 2012).

- **Market share**: defined as the ratio between the total assets of the funds managed by a management company in a month and the total assets of all funds in that month. There is a relationship between the degree of price competition and product competition and the structure of the mutual fund industry in the performance (Gavazza, 2011; Cambón and Losada, 2014). In industries in which consumers prefer to make all their purchases from a single company, companies tend to offer a greater variety of products rather than lower prices (Gavazza, 2011). If demand spillovers are important, a form of industry concentration can arise, with a few large firms offering many products. Assuming that this behaviour applies to the financial industry, in which consumers tend to concentrate all their operations in a single entity, an increase is to be expected in the fees charged and therefore the value added for investors is reduced. Gavazza (2011) documents strong (weak) demand spillovers in the retail (institutional) segment of the U.S. mutual fund industry, in which fees are non-trivial (lower), families offer a large (small) number of funds and the market is quite concentrated (fragmented). Cambón and Losada (2014) also offer evidence for the Spanish mutual fund industry, especially drawn from the retail segment.

- **Volatility**: defined as the standard deviation of the fund's daily returns over the previous month. This is a standard risk measure used to assess the profile of mutual funds.

3.2 The mutual fund industry in Spain

In this section we briefly describe the Spanish mutual fund market. Cambón and Losada (2014) report very special characteristics in the competition found in the Spanish mutual fund market, which is mainly characterized by a low level of competition and a high level of concentration.[4] It is also observed that credit institutions enjoy a larger market share than elsewhere, which highlights the importance of this type of institution in the Spanish mutual fund industry. Indeed, the Spanish economy, like other European countries, is characterized by a bank-oriented financial system based on the proximity to clients of commercial branches offering a full range of financial products. This retail distribution makes it easier for the demand for financial assets to be concentrated in a few entities.

For the purposes of this article, conservative funds are defined as those that invest in money market assets, fixed-income funds and guaranteed funds. Aggressive funds are equity, global and mixed funds. A fund is considered to be a wholesale fund when over 50% of its assets have their origin in sufficiently large holdings. Specifically, we define wholesale funds as those in which the holdings are greater than 180,000 euros in the period 1995–1998 and 150,000 thereafter. The second period includes an exception for money market funds and short-term fixed-income funds, for which a minimum holding of 300,000 euros is considered.[5] In the sector as a whole, the proportion of retail funds was much higher than that of wholesale funds.

As stated before, the Spanish financial economy relies mainly on banks. Thus, we can divide this sector into two: fund management companies may belong to a credit institution or may be independent. Considering the type of management company, we would point out that bank fund management companies accounted for the greatest proportion of mutual funds. On average, between 1995 and 2014, these management companies offered 83.7% of all funds.

For credit institutions' management companies, the proportion of conservative funds, which can be seen as close in nature to bank deposits, was greater than that of more aggressive funds throughout the period under consideration. In contrast, independent management companies mainly ran aggressive funds, which averaged over 65% of their funds in the period, peaking at 80% in 2010. Regarding type of investors, credit institutions' management companies marketed mainly retail funds, while independent management companies specialized, in relative terms, in wholesale funds.

The most important source of income for management companies is the management fees charged to investors in mutual funds[6]. These fees are generally established as a percentage of the fund's assets under management, of its return or of both variables (mixed fees), with the first formula being the most common. The maximum fees that management companies may apply are set by law. The fees

4 As was pointed out before, Ferreira and Ramos (2009) calculated a Herfindahl index for the mutual fund industry in Spain of 0.11 for 2006, which is very close to the average index of a sample of Eurozone countries (0.12), composed of Austria, Belgium, Finland, France, Germany, Italy, the Netherlands and Portugal.

5 The change in the investment limits in different time periods is related to the modification of the reserved statements submitted to the CIS since 2000, which conditions the availability of data for making this type of distinction.

6 International studies on the characteristics of the mutual fund sector reveal that the fees paid for Spanish mutual funds are in line with those for Italian ones but higher than those for funds in Germany, France and the United Kingdom and much higher than those in the United States (Ferreira and Ramos, 2009).

charged by independent management companies have risen since 2005, indicating that they have changed their business model to one with a greater weighting of aggressive funds. The downward trend observed in the fees of the non-independent management companies was caused by the fall in the maximum applicable fees and a certain increase in competition within the sector.

3.3 Data description

Our empirical application considers the Spanish mutual fund market. The original source of the data set is the CNMV, the Spanish equivalent of the U.S. Securities and Exchange Commission. This institution periodically collects information as part of its duty to supervise collective investment schemes. Data on all existing mutual funds and investment management companies were obtained on a monthly basis from January 1995 to December 2014 (240 months), including those that are now defunct or merged. Treating each mutual fund/year as a single observation, the total sample size is 498,330 observations. The total number of mutual funds that are part of the database is 4,571. To be part of this database, all observations had to meet a set of criteria to guarantee their quality. Firstly, all the mutual funds had net total assets above 2 million euros. Secondly, all the mutual funds reported monthly volatility. Lastly, all the mutual funds had been operating in the market for at least 12 months.

The database built for the analysis uses variables that characterize the mutual funds and the management companies in each of the months under consideration. These variables are defined for each mutual fund, bearing in mind the management company that it belongs to and the month. With regard to the category, the funds are grouped into two major categories depending on their risk profile and their capacity to substitute bank deposits. As explained earlier, “conservative funds” are considered to include money market funds, short-term fixed-income funds, long-term fixed-income funds and guaranteed funds. Within the “aggressive funds” are mixed funds, pure equity funds and global funds.

Table 1 summarizes the main descriptive statistics of the variables considered in the empirical analysis. This table considers both the sample as a whole and broken down into retail/conservative, retail/aggressive, wholesale/conservative and wholesale/aggressive segments. The average monthly return of the total sample was 0.20% between January 1995 and December 2014. As we can observe from the different submarkets, most of their return came from conservative funds, which enjoyed high returns from fixed income during the early years of the sample. However, the standard deviation of returns was 3.13%, reflecting the high range of riskiness in the mutual funds’ portfolios.

Descriptive statistics of the sample

TABLE 1

Table 1.a. Total mutual fund market

Funds	Average	Standard Deviation
Return (%)	0.20	3.13
Net Subscriptions (Thousand Euros)	147.82	19,338.68
Momentum (%)	0.28	0.95
Volatility (%)	1.81	2.46
Total Assets (Thousand Euros)	83,428.70	230,700.43
Fees (%)	1.39	0.57
Age (Number of Months)	80.78	27.52
Management Companies	**Average**	**Standard Deviation**
Market Share (%)	4.96	7.05
Number of Observations	498,330	
Number of Funds	4,571	

Table 1.b. Retail/conservative mutual fund market

Funds	Average	Standard Deviation
Return (%)	0.23	2.32
Net Subscriptions (Thousand Euros)	-71.65	20,511.83
Momentum (%)	0.27	0.37
Volatility (%)	0.71	1.06
Total Assets (Thousand Euros)	100,185.06	269,138.85
Fees (%)	1.26	0.42
Age (Number of Months)	78.15	23.26
Management Companies	**Average**	**Standard Deviation**
Market Share (%)	6.28	7.63
Number of Observations	224,377	
Number of Funds	2,383	

Table 1.c. Retail/aggressive mutual fund market

Funds	Average	Standard Deviation
Return (%)	0.14	4.32
Net Subscriptions (Thousand Euros)	257.49	18,689.73
Momentum (%)	0.36	2.08
Volatility (%)	3.57	3.04
Total Assets (Thousands Euros)	60,936.21	145,735.17
Fees (%)	1.81	0.51
Age (Number of Months)	89.69	34.10
Management Companies	**Average**	**Standard Deviation**
Market Share (%)	5.55	8.37
Number of Observations	125,913	
Number of Funds	1,373	

Table 1.d. Wholesale/conservative mutual fund market

Funds	Average	Standard Deviation
Return (%)	0.22	1.16
Net Subscriptions (Thousand Euros)	455.15	25,354.49
Momentum (%)	0.28	0.28
Volatility (%)	0.53	1.00
Total Assets (Thousand Euros)	128,408.90	312,900.16
Fees (%)	0.91	0.53
Age (Number of Months)	80.24	26.29
Management Companies	**Average**	**Standard Deviation**
Market Share (%)	4.64	7.13
Number of Observations	63,389	
Number of Funds	832	

Table 1.e. Wholesale/aggressive mutual fund market

Funds	Average	Standard Deviation
Return (%)	0.16	3.80
Net Subscriptions (Thousand Euros)	336.31	9,230.47
Momentum (%)	0.33	1.69
Volatility (%)	3.05	2.76
Total Assets (Thousand Euros)	38,787.83	106,804.41
Fees (%)	1.45	0.61
Age (Number of Months)	80.64	37.83
Management Companies	**Average**	**Standard Deviation**
Market Share	2.90	4.95
Number of Observations	84,652	
Number of Funds	925	

The tables report the average and standard deviation of the following variables: a) monthly return, defined as the percentage change in the asset value of the unit of each fund between the close of one month and the close of the previous month; b) net subscriptions, defined as the change in the fund's total net assets between the close of one month and the close of the previous month; c) momentum, defined as the average of the fund's returns in the three previous months; d) volatility, defined as the typical deviation of the fund's daily returns over the previous month, which is a standard risk measure used to assess the profile of mutual funds; e) age, defined as the number of years the fund has existed in each of the months under consideration; f) fees, defined as the sum of the management fees, the deposit fee, one-seventh of the subscription fee and one-seventh of the redemption fee of each fund in each of the periods making up the sample[1]; and g) market share, defined as the ratio between the total assets of the funds managed by a management company in a month and the total assets of the funds in that month. This table considers the total sample and the retail/conservative, retail/aggressive, wholesale/conservative and wholesale/aggressive segments. Mutual funds are classified as wholesale funds if the holdings per investor are above a given minimum amount for more than 50% of the total fund assets. Funds that do not satisfy these criteria are then considered as retail funds.[2] Finally, the type of financial group to which the management company belongs is considered: this information allows the separation of the funds into two groups, one consisting of the funds of the management companies that belong to credit institutions and the other containing the funds of the independent management companies.

1 This variable is defined in a similar manner to that in Gavazza (2011) and Cambon and Losada (2014), in which it is assumed that investors make their investments with a time horizon of seven years.

2 Following Cambon and Losada (2014), who take into consideration the regulatory changes during the sample period that are relevant to this purpose, the minimum holdings mentioned for wholesale funds are set at 180,000 euros between 1995 and 1998 and at 300,000 euros if they are money market and short-term fixed-income funds or 150,000 euros otherwise for the rest of the period.

It is also important to point out that the average fee paid by investors was 1.39%, with a standard deviation of 0.57%. The fees were higher in the aggressive markets for two different reasons: on the one hand, the costs of running an aggressive portfolio are higher, and on the other hand, in the Spanish market, there are fee caps at work that are lower for money market funds.[7] Furthermore, the average fees paid in the wholesale markets are lower (0.91% and 1.45%) than in the retail markets (1.26% and 1.81%).

The average monthly volatility accounted for 1.81%, with a standard deviation of 2.46%. As one would expect, most of the volatility came from the aggressive markets. However, reported volatility was lower in the wholesale market (3.05%) than in the retail market (3.57%).

The average size of the mutual funds was 83.4 million euros. When we divide the sample into submarkets, we observe that the funds with conservative portfolios were larger than those with aggressive profiles.

The last noteworthy feature is that the average market size of the management companies in charge of mutual funds was larger in the case of the retail markets. The average market shares in wholesale markets were 4.64% and 2.90%, compared to 6.28% and 5.55% in the retail markets. This could be a signal of lower competition in the retail segments, as shown by Cambon and Losada (2014).

7 In 2000 there was a reduction in the maximum fees that fund managers could apply to funds. In the case of fixed income funds, the maximum fee fell from 2.5% to 2.25%, while the maximum fee on results fell from 20% to 18%. For money market funds, the maximum management fees fell from 1.5% to 1% and the maximum fee on results fell from 15% to 10%. The official classification of money market funds no longer exists in the Spanish market, so, currently, for all funds, the maximum management fees are 2.25% when the fee is based solely on a fund's assets, 18% if it is calculated on the results and, in the case of mixed fees, 1.35% on assets and 9% on results. The maximum deposit fees that may be applied are also set by law.

4 Empirical analysis

This section analyses the optimal portfolio allocated to the funds by studying the relationship between the optimal portfolio weight in Equation (2) and the cross-section of fund characteristics described above. Firstly, section 4.1 analyses the optimal portfolio allocation to the whole universe of funds. Secondly, section 4.2 solves the in-sample optimal portfolio allocation to the funds using the cross-section of fund characteristics depending on the different market segments and fund profiles. As discussed previously, we consider four different cases intended to represent the heterogeneity of the Spanish mutual fund market:

1) retail/conservative,
2) retail/more aggressive,
3) wholesale/conservative,
4) wholesale/more aggressive.

By so doing, we seek to uncover the relationship between the cross-section of fund characteristics and the optimal portfolio allocated to each fund depending on the type of investors targeted (retail vs. wholesale) and the funds' risk profile (conservative vs. more aggressive). Differences across market segments in the Spanish mutual fund market could convey valuable information about investment advice for investors that is masked when considering the entire universe of funds. Section 4.3 tests the robustness of our results by implementing an out-of-sample strategy.

4.1 The optimal portfolio using all mutual funds

Tables 2 and 3 report the results for the base case, which considers the formation of the optimal portfolio of funds considering all existing funds. We use a two-step estimator and a weight matrix that allows for heteroskedasticity and autocorrelation up to six lags using the Bartlett kernel.

Table 2 presents the in-sample parameter estimates in Equation (2) optimized for a power utility function defined by the CRRA parameters $\gamma = (5,10,100)$ considering the fund characteristics separately. The purpose is to check the relevance of each variable separately in forming the optimal portfolio of funds. The sign is consistent across gamma, with the exception of the size variable. Increasing estimates of the beta coefficients associated with decreasing values of gamma reveal an inverse relationship between the degree of investor risk aversion and the responsiveness to changes in the information set. The results provide evidence that the optimal portfolio weight allocated to the funds is significantly related to different fund characteristics when considered separately. Thus, the optimal portfolio weight allocated to the funds is positively and significantly related to the momentum variable and the market share given any possible value of CRRA. Interestingly, the optimal portfolio weight is also negatively related to the total fees, the flows variable and volatility for more risk-averse investors.

Simple linear portfolio policy. In-sample results

TABLE 2

Variable	CRRA = 5	CRRA = 10	CRRA = 100
$\beta_{\text{Net Subscriptions}}$	-6.95	-5.16	-2.54
t-stat	(-0.88)	(-1.34)	**(-5.92)**
β_{Momentum}	1.81	1.02	0.35
t-stat	**(2.74)**	**(3.08)**	**(7.37)**
$\beta_{\text{Volatility}}$	-0.25	-0.36	-0.46
t-stat	(-0.42)	(-1.16)	**(-14.43)**
$\beta_{\text{Assets of the Fund}}$	-2.25	0.52	3.01
t-stat	(-0.44)	(0.20)	**(10.54)**
$\beta_{\text{Total Fees}}$	-1.47	-1.17	-0.92
t-stat	(-1.27)	**(-2.03)**	**(-15.05)**
$\beta_{\text{Market Share}}$	18.07	10.86	4.23
t-stat	**(2.18)**	**(2.58)**	**(6.60)**
β_{Age}	0.54	0.47	0.52
t-stat	(0.15)	(0.25)	(1.78)

This table shows estimates of the optimal investment strategy policy specified in Equation (2) and optimized for a power utility function with different CRRA coefficients (γ = 5, 10 and 100) using the fund characteristics separately: net subscriptions, three-month fund return (momentum), volatility, assets of the fund or size, total fees, market share and age of the fund. We use data from the CNMV database from January 1994 to December 2014.

Table 3 reports the in-sample parameter estimates in Equation (2) optimized for a power utility function defined by the CRRA parameters $\gamma = (5,10,100)$ considering all fund characteristics. We drop the size and volatility variables hereafter because they are specifically correlated with the market share variable and are only significant in the individual analysis where CRRA = 100.

Simple linear portfolio policy. In-sample results

TABLE 3

Variable	CRRA = 5	CRRA = 10	CRRA = 100
$\beta_{\text{Net Subscriptions}}$	-11.80	-6.17	-1.33
t-stat	(-1.85)	**(-1.93)**	**(-3.90)**
β_{Momentum}	2.24	1.15	0.08
t-stat	**(3.37)**	**(3.49)**	**(2.50)**
$\beta_{\text{Total Fees}}$	0.38	-0.14	-0.74
t-stat	(0.29)	(-0.22)	**(-10.84)**
$\beta_{\text{Market Share}}$	-6.58	-2.91	-0.12
t-stat	(-0.76)	(-0.67)	**(-0.28)**
β_{Age}	1.79	1.45	0.75
t-stat	(0.69)	(1.12)	**(5.84)**
χ^2	30.67	30.60	29.98
p-value	0.99	0.99	0.99

This table shows estimates of the optimal investment strategy policy specified in Equation (2) and optimized for a power utility function with different CRRA coefficients (γ = 5, 10 and 100) using all the fund characteristics: net subscriptions, three-month fund return (momentum), volatility, assets of the fund or size, total fees, market share and age of the fund. We use data from the CNMV database from January 1994 to December 2014.

Table 3 shows that the optimal portfolio weight allocated to the funds is positively related to the momentum variable and negatively related to the flows variable. Therefore, the optimal portfolio overweights funds with a higher-than-average momentum and underweights funds with higher-than-average net subscriptions given any CRRA. As the variables are standardized cross-sectionally, we can compare the magnitudes of the coefficients, and quantitatively the funds that display higher-than-average net subscriptions lead to the greatest underweighting of a fund. The general portfolio advice is consequently consistent with the possible existence of the hot hands effect in the Spanish mutual fund industry. However, investors do not seem to be able to profit from this momentum effect, as, interpreting the optimal portfolio rule, their money seems to flow to underperforming funds. Table 3 also reports that the optimal portfolio weight allocated to the funds is not related to market share. For very risk-averse investors (CRRA = 100), who are expected to invest in the safest assets or in conservative funds, the optimal portfolio weight allocated to the funds is also negatively related to the total fees charged and positively related to the age of the fund. Thus, very risk-averse investors should also allocate a larger fraction of their wealth to the funds that charge lower-than-average total fees and are older than the average age. This could be interpreted as indirect evidence of the possible negative relationship between fees and performance discovered by the literature (Gil-Bazo and Verdú, 2009) in the Spanish market. Old funds also seem to enjoy economies of experience.

4.2 The optimal portfolio of funds. The impact of market structure and investors' risk profile on the role of the cross-section of fund characteristics

In this section we establish the relationship between the optimal allocation to funds and their characteristics depending on the structure of the mutual fund market. To characterize this market structure, we focus on two dimensions: the type of investor at which a fund is aimed, retail vs. wholesale, and the fund's risk profile, conservative vs. more aggressive.

4.2.1 Retail and conservative investors' optimal portfolio

Table 4 reports the optimal portfolio allocation to funds using fund characteristics in the market segment targeting retail and conservative investors. The test of overidentifying restrictions shows that the asset allocation model estimated with different values of the CRAA is well specified. Interestingly, the optimal portfolio allocation to the funds is negatively related to the total fees charged and the net flows and positively related to the funds' age. Therefore, investors should overweight funds that charge lower fees, receive fewer net inflows and are older than the average across all funds. The magnitudes of the coefficients show that, quantitatively, those funds that display higher-than-average net flows should be most heavily underweighted. Very conservative investors, who are likely to be classified in this segment, should also underweight funds that have a larger market share than the average.

Simple linear portfolio policy. Retail and equity/mixed. In-sample results TABLE 4

Variable	CRRA = 5	CRRA = 10	CRRA = 100
$\beta_{\text{Net Subscriptions}}$	2.82	0.99	-0.22
t-stat	(0.95)	(0.67)	(-1.38)
β_{Momentum}	0.16	0.06	-0.03
t-stat	(0.31)	(0.23)	(-1.01)
$\beta_{\text{Total Fees}}$	-6.07	-4.80	-3.86
t-stat	**(-4.62)**	**(-7.33)**	**(-47.04)**
$\beta_{\text{Market Share}}$	4.20	1.38	-1.65
t-stat	(0.84)	(0.55)	**(-5.62)**
β_{Age}	-10.38	-5.48	-0.6
t-stat	**(-3.69)**	**(-3.88)**	**(-4.14)**
χ^2	32.52	32.54	32.32
p-value	0.99	0.99	0.99

This table shows estimates of the optimal investment strategy policy specified in Equation (2) and optimized for a power utility function with different CRRA coefficients (γ = 5, 10 and 100) using the following fund characteristics: net subscriptions, three-month fund return (momentum), total fees, market share and age of the fund. We use data from the CNMV database from January 1994 to December 2014. We consider "more aggressive funds", which are pure equity funds, "mixed funds", which invest in fixed income and equity, and global funds, which are aimed at retail investors.

Remarkably, we can infer implicitly from the optimal portfolio rule that retail and conservative investors are not too smart or able to detect outperforming funds. They simply chase returns that are not correlated with future fund returns. The differences in the total fees charged across funds are economically meaningful, as they do not seem to be a reward linked to higher fund returns. This implies that investors would be better off choosing funds that charge lower-than-average fees. Investors could also benefit from the greater experience of fund managers who face an investment opportunity set characterized by bounded risk.

4.2.2 Retail and aggressive investors' optimal portfolio

Table 5 reports the optimal portfolio allocation to funds using the fund characteristics in the market segment targeting retail and more aggressive investors who invest in equity/mixed funds. The test of overidentifying restrictions shows that the asset allocation model estimated with different values of the CRAA is well specified. As in the retail and conservative segment, the optimal portfolio allocation to the funds is negatively related to the total fees charged; however, it is also negatively related to the fund's age. Consequently, investors should overweight the funds that charge lower fees and are younger than the average across funds. Table 5 also shows that the optimal portfolio allocated to the funds in the retail and equity/mixed segment is not related to the net flows, market share or momentum variables. The magnitudes of the coefficients allow us to determine that, quantitatively, the funds that are younger than average should be most heavily overweighted. The young funds in the "more aggressive" segment seem to try to attain a larger market share by implementing more active and successful strategies.

Simple linear portfolio policy. Retail and conservative. In-sample results TABLE 5

Variable	CRRA=5	CRRA=10	CRRA=100
$\beta_{\text{Net Subscriptions}}$	-33.55	-28.75	-3.33
t-stat	**(-2.81)**	**(-4.78)**	**(-5.46)**
β_{Momentum}	-0.66	-0.01	-0.17
t-stat	(-0.53)	(-4.57)	**(-2.71)**
$\beta_{\text{Total Fees}}$	-18.27	-10.58	-2.02
t-stat	**(-3.33)**	**(-3.79)**	**(-7.79)**
$\beta_{\text{Market Share}}$	-3.91	3.23	-0.64
t-stat	**(-0.63)**	(1.07)	**(-2.12)**
β_{Age}	16.20	8.05	0.88
t-stat	**(4.47)**	**(4.51)**	**(4.74)**
χ^2	32.65	29.70	32.29
p-value	0.99	0.99	0.99

This table shows estimates of the optimal investment strategy policy specified in equation (2) and optimized for a power utility function with different CRRA coefficients (γ=5, 10 and 100) using the following fund's characteristics: net subscriptions, three-month fund's return (momentum), total fees, market share and age of the fund. We use data from the CNMV database from January 1994 to December 2014. We consider the "conservative funds", which are the money market funds, fixed-income funds and guaranteed funds, which are aimed at retail investors.

Broadly speaking, the fund managers in the market segment oriented toward retail investors do not seem to generate superior risk-adjusted returns due to their higher skill level and then charge higher fees than other competing funds delivering lower risk-adjusted returns. Our empirical evidence for the Spanish mutual fund industry favours Gil-Bazo and Verdú's (2009) hypothesis that fund managers seem to charge fees strategically to investors who are insensitive to performance in the Spanish retail mutual fund market. The overall results in the retail segment also reveal evidence about the absence of the hot hands effect or persistence in the Spanish retail mutual fund market.

4.2.3 Wholesale and conservative investors' optimal portfolio

We now turn our attention to the market segment oriented toward wholesale and conservative investors. Table 6 reports the relationship between the fund characteristics and the optimal portfolio allocation to funds. Wholesale investors who invest in conservative funds should overweight the funds that are older, receive higher net flows, have a larger market share and charge lower fees than the average for all funds. The momentum variable is only positively related to the optimal portfolio rule for very highly risk-averse investors (CRRA = 100). The interpretation of the optimal portfolio allows us to infer that wholesale investors seem to direct flows to outperforming funds, in clear contrast to retail investors. Thus, wholesale investors seem to be smarter than retail investors in the conservative market segment. To screen the conservative funds better, wholesale investors should also pay special attention to old funds that are likely to be positively related to the acquisition of experience scales and to funds that display a larger market share and again to avoid funds that charge high total fees.

Simple linear portfolio policy. Wholesale and conservative. In-sample results TABLE 6

Variable	CRRA = 5	CRRA = 10	CRRA = 100
$\beta_{\text{Net Subscriptions}}$	69.35	38.75	1.68
t-stat	**(4.86)**	**(5.44)**	**(2.41)**
β_{Momentum}	2.31	1.12	0.16
t-stat	(1.34)	(1.32)	**(1.95)**
$\beta_{\text{Total Fees}}$	-23.37	-13.86	-1.46
t-stat	**(-5.25)**	**(-6.30)**	**(-6.64)**
$\beta_{\text{Market Share}}$	39.17	19.07	0.53
t-stat	**(3.18)**	**(3.14)**	**(0.89)**
β_{Age}	77.69	41.72	5.45
t-stat	**(6.87)**	**(7.41)**	**(9.59)**
χ^2	31.61	31.54	31.42
p-value	0.99	0.99	0.99

This table shows estimates of the optimal investment strategy policy specified in Equation (2) and optimized for a power utility function with different CRRA coefficients (γ = 5, 10 and 100) using the following fund characteristics: net subscriptions, three-month fund return (momentum), total fees, market share and age of the fund. We use data from the CNMV database from January 1994 to December 2014. We consider "conservative funds", which are money market funds, fixed-income funds and guaranteed funds aimed at wholesale investors.

4.2.4 Wholesale and aggressive investors' optimal portfolio

Table 7 reports the relationship between fund characteristics and the optimal portfolio allocation to the funds in the market segment oriented toward wholesale and more aggressive investors. Wholesale investors who invest in more aggressive funds should overweight the funds that are younger, have a smaller market share and charge lower fees than the average for all funds. The magnitudes of the coefficients allow us to determine that, quantitatively, funds that are younger than average should be most heavily overweighted. Wholesale investors in the equity/mixed market segment should also pay attention to the funds that have a smaller market share and are likely, as young funds, to be more aggressive and more prone to achieve better performance to survive and gain market share. Interestingly, wholesale investors should also underweight the funds that charge higher-than-average fees.

Simple linear portfolio policy. Wholesale and equity/mixed. In-sample results TABLE 7

Variable	CRRA = 5	CRRA = 10	CRRA = 100
β Net Subscriptions	2.92	2.01	0.90
t-stat	(0.73)	(1.00)	(3.76)
β Momentum	0.06	-0.06	-0.09
t-stat	(0.10)	(-0.22)	**(-2.49)**
β Total Fees	-2.65	-3.02	-3.13
t-stat	**(-1.86)**	**(-4.28)**	**(-41.4)**
β Market Share	-8.41	-4.79	-0.51
t-stat	**(-2.23)**	**(-2.52)**	**(-2.40)**
β Age	-12.49	-7.67	-3.06
t-stat	**(-3.76)**	**(-4.75)**	**(-16.75)**
$\chi2$	32.24	32.25	32.24
p-value	0.99	0.99	0.99

This table shows estimates of the optimal investment strategy policy specified in Equation (2) and optimized for a power utility function with different CRRA coefficients (γ = 5, 10 and 100) using the following fund characteristics: net subscriptions, three-month fund return (momentum), total fees, market share and age of the fund. We use data from the CNMV database from January 1994 to December 2014. We consider "more aggressive funds", which are pure equity funds, "mixed funds", which invest in fixed income and equity, and global funds, which are aimed at wholesale investors.

The above analyses indicate the importance of screening funds considered for inclusion in an optimized portfolio by target investor type (retail vs. wholesale) and by the fund's risk profile (conservative vs. more aggressive). More risk-averse investors, who are likely to consider more conservative funds, are better off choosing funds that are older than average. On the contrary, less risk-averse investors, who are likely to consider more aggressive funds, would benefit from choosing younger-than-average funds. This is a signal that young funds, which are expected to account for a small market share, are successful in offering more attractive financial products that invest in risky securities to gain market share. This contrasts with the funds that offer the safest securities, where experience stands as a key element likely to generate a large market share. Interestingly, market share is positively (negatively) related to the optimal portfolio for more (less) risk-averse investors in the wholesale market only. In the retail segment, market share is only negatively significant for more risk-averse investors. Interestingly, wholesale investors also seem to be more skilful than retail investors in directing flows to outperforming funds, as the sign and the magnitude of the net subscription coefficients show, especially in the conservative segment. Finally, it is remarkable that there is only one characteristic that is common across the universe of funds that affects the optimal portfolios in a negative way: the fees.

Finally, we focus on the distribution of portfolio weights, the performance of the optimal portfolio relative to the value-weighted portfolio of funds and the average characteristics of the portfolio. Table 8 shows the main results. The first few rows of Table 8 describe the weights of the optimized portfolio and compare them with the value-weighted portfolio. Tables A and B show the results for retail and wholesale investors who consider conservative (CRRA = 100) and more aggressive (CRRA = 5) funds, respectively. An important result is that the optimal portfolio includes no extreme bets on individual funds, especially for conservative funds.

Simple linear portfolio policy. Statistics of the portfolio weights, portfolio performance and average characteristics of the portfolios. In-sample results

TABLE 8

Panel A. Retail and wholesale investors. Conservative funds

	Value-weighted portfolio (retail)	Retail and conservative	Value-weighted portfolio (wholesale)	Wholesale and conservative
$\lvert\omega_i\rvert \times 100$	0.001	0.001	0.004	0.01
$\max\ \varpi_i \times 100$	4.77	7.07	1.06	2.89
$\min\ \varpi_i \times 100$	0.000	-3.68	0.000	-1.98
$\sum \varpi_i\ I\left(\varpi_i < 0\right)$	0.000	-0.84	0.000	-2.32
$\sum I\left(\varpi_i < 0\right) / N_t$	0.000	0.39	0.000	0.426
CE	0.016	0.026	0.027	0.032
$\bar{r}$	0.031	0.036	0.033	0.054
$\bar{\sigma}$	0.016	0.015	0.011	0.025
SR	1.960	2.464	3.029	2.584
α		0.023		0.031
β		0.420		0.71
IR		1.75		1.57
Momentum	-0.030	-0.108	0.002	0.464
Total fees	-0.186	-2.113	-0.351	3.109
Market share	0.510	0.182	0.830	1.593
Net subscriptions	-0.241	-3.187	0.137	2.075
Age	-0.218	0.859	-0.226	5.502

This table shows the in-sample distribution of portfolio weights, the performance of the optimal portfolio relative to the value-weighted portfolio of funds and the average characteristics of the portfolio. The optimal investment strategy policy specified in Equation (2) is optimized for a power utility function with CRRA coefficients (γ = 100) using the following fund characteristics: net subscriptions, three-month fund return (momentum), total fees, market share and age of the fund. We use data from the CNMV database from January 1994 to December 2014. We consider "conservative funds", which are money market funds, fixed-income funds and guaranteed funds aimed at retail and wholesale investors. The first set of rows shows the statistics of the portfolio weights averaged across time. These statistics include the average absolute portfolio weight, the average minimum and maximum portfolio weights, the average sum of negative weights in the portfolio, the average fraction of negative weights in the portfolio and the turnover in the portfolio. The third set of rows displays the average portfolio return statistics: certainty-equivalent return, average return, standard deviation and Sharpe ratio of returns as well as the alpha, the beta and the information ratio. The final set of rows displays the average normalized characteristics of the portfolio.

Panel B. Retail and wholesale investors. Aggressive funds

	Value-weighted portfolio (retail)	Retail and more aggressive	Value-weighted portfolio (wholesale)	Wholesale and conservative
$\lvert\omega_i\rvert \times 100$	0.002	0.002	0.003	0.005
$\max\ \varpi_i \times 100$	4.81	10.7	8.36	15.04
$\min\ \varpi_i \times 100$	0.000	-5.82	0.000	-15.15
$\sum \varpi_i\ I\left(\varpi_i < 0\right) \times 100$	0.000	-3.77	0.000	-5.04
$\sum I\left(\varpi_i < 0\right) / N_t$	0.000	-0.511	0.000	0.485
CE	0.012	0.041	0.016	0.053
$\bar{r}$	0.035	0.069	0.037	0.118
$\bar{\sigma}$	0.093	0.106	0.088	0.188
SR	0.375	0.645	0.418	0.626
α		0.081		0.136
β		-0.33		-0.51
IR		0.789		0.747
Momentum	0.029	0.336	0.135	0.211
Total fees	0.019	-2.641	-0.085	-0.866
Market share	0.678	4.240	0.772	-6.901
Net subscriptions	-0.158	1.287	0.269	1.161
Age	-0.266	-7.656	-0.304	-12.148

This table shows the in-sample distribution of portfolio weights, the performance of the optimal portfolio relative to the value-weighted portfolio of funds and the average characteristics of the portfolio. The optimal investment strategy policy specified in Equation (2) is optimized for a power utility function with CRRA coefficients ($\gamma = 5$) using the following fund characteristics: net subscriptions, three-month fund return (momentum), total fees, market share and age of the fund. We use data from the CNMV database from January 1994 to December 2014. We consider "more aggressive funds", which are pure equity funds, "mixed funds", which invest in fixed income and equity, and global funds, which are aimed at retail and wholesale investors. The first set of rows shows the statistics of the portfolio weights averaged across time. These statistics include the average absolute portfolio weight, the average minimum and maximum portfolio weights, the average sum of negative weights in the portfolio, the average fraction of negative weights in the portfolio and the turnover in the portfolio. The third set of rows displays the average portfolio return statistics: certainty-equivalent return, average return, standard deviation and Sharpe ratio of returns, as well as the alpha, the beta and the information ratio. The final set of rows displays the average normalized characteristics of the portfolio.

The following rows of Table 8 show the performance of the optimal portfolio relative to the value-weighted portfolio, displaying the average portfolio return statistics: the certainty-equivalent return, average return, standard deviation and Sharpe ratio of returns, as well as the alpha, beta and information ratio.

As expected, the optimal portfolios deliver a higher certainty equivalent and Sharpe ratio, especially in the more aggressive funds. The optimal portfolio policies offer a certainty equivalent gain of roughly 1% for conservative funds and larger than 3% for more aggressive funds relative to the value-weighted portfolios. The optimal portfolio alpha ranges from 2.3%–3.1% in the conservative fund market to

8%–13.6% in the more aggressive fund market for retail and wholesale investors, respectively, with a low market beta. In all the cases the information ratio, which is obtained by dividing the alpha by the residual volatility, is larger than 0.75. All these measures reflect that investors, especially retail ones, currently suffer a welfare loss compared with investors who could invest in the optimal portfolio, regardless of their investor risk profile.

The last five rows of Table 8 report the characteristics of the optimized portfolio vs. the value-weighted portfolio averaged through time. For every month we compute these characteristics, the weighted characteristics of the portfolio, as $\mathrm{F_t}\sum_{i=1}^{\mathrm{F_t}}\theta^T\overline{x_{i,t}}$. As expected, panels A and B show that the differences between the characteristics of the optimized portfolios and the corresponding value-weighted portfolios are closely related to the sign of the parameter estimates. For example, wholesale investors who optimally consider more aggressive funds are especially biased toward young funds with a small market share that charge lower fees. In contrast, the market is biased toward funds that have a larger market share and is almost neutral with respect to funds' age and the fees charged.

4.3 Out-of-sample analysis

In this section we present an out-of-sample experiment to lend robustness to our results. We use data from January 1994 to December 2006, before the beginning of the U.S. subprime crisis, to estimate the first optimal parametric portfolio. After this, the model is re-estimated for every year using an expanding window of data until the end of the sample. The investor uses the estimates in period t to form the optimal portfolio of funds every month between t and $t + 12$, given the observed realization of the state variables.

The out-of-sample results are presented in Table 9. We focus on the out-of-sample estimates and the out-of-sample performance of the optimal portfolio relative to the value-weighted portfolio of funds. The out-of-sample estimates and t-statistics are the time series average from each out-of-sample estimation of the optimal portfolio policy.

Simple linear portfolio policy and portfolio performance. Out-of-sample results

TABLE 9

Panel A. Retail and wholesale investors. Conservative funds

	Value-weighted portfolio (retail)	Retail and conservative	Value-weighted portfolio (wholesale)	Wholesale and conservative
β_{Momentum}		-0.14		0.05
t-stat		(-2.28)		(0.54)
$\beta_{\text{Total Fees}}$		-2.06		-1.99
t-stat		(-7.01)		(-8.06)
$\beta_{\text{Market Share}}$		-0.09		2.21
t-stat		(-0.37)		(2.78)
$\beta_{\text{Net Subscriptions}}$		-3.51		4.07
t-stat		(-5.99)		(4.91)
β_{Age}		0.71		5.47
t-stat		(3.72)		(8.28)
CE	0.001	0.012	0.001	0.001
$\bar{r}$	0.020	0.021	0.021	0.039
$\bar{\sigma}$	0.019	0.014	0.012	0.025
SR	1.07	1.56	1.88	1.59
α		0.142		0.17
β		0.211		0.85
IR		1.29		0.88

This table shows the out-of-sample estimates of the optimal investment strategy policy specified in Equation (2) and the performance of the optimal portfolio relative to the value-weighted portfolio of funds. The optimal investment strategy policy specified in Equation (2) is optimized for a power utility function with CRRA coefficients (γ = 100) using the following fund characteristics: net subscriptions, three-month fund return (momentum), total fees, market share and age of the fund. We use data from the CNMV database from January 1994 to December 2014. We use data from January 1994 to December 2006, before the beginning of the US subprime crisis, to estimate the first optimal parametric portfolio. After this, the model is re-estimated for every year using an expanding window of data until the end of the sample. The investor uses the estimates in period t to form the optimal portfolio of funds in every month between t and t + 12, given the observed realization of the state variables. We consider "conservative funds", which are money market funds, fixed-income funds and guaranteed funds aimed at retail and wholesale investors. The first set of rows shows the out-of-sample estimates and t-statistics averaged across time. The second set of rows displays the average portfolio return statistics: certainty-equivalent return, average return, standard deviation and Sharpe ratio of returns, as well as the alpha, the beta and the information ratio.

Panel B. Retail and wholesale investors. Aggressive funds

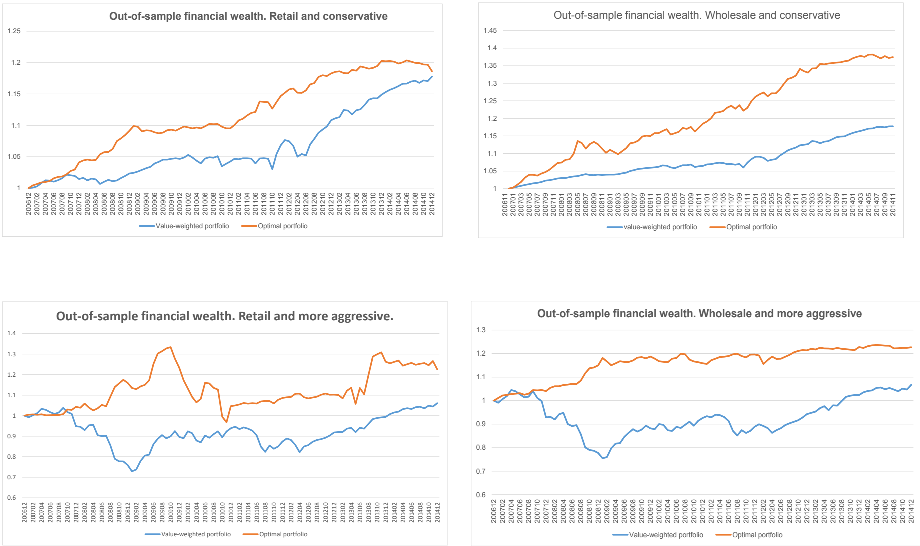
	Value-weighted portfolio (retail)	Retail and more aggressive	Value-weighted portfolio (wholesale)	Wholesale and more aggressive
β_{Momentum}		-0.01		-0.04
t-stat		(-0.305)		(-1.06)
$\beta_{\text{Total Fees}}$		-3.42		-3.50
t-stat		(-55.12)		(-40.27)
$\beta_{\text{Market Share}}$		2.69		-0.63
t-stat		(6.70)		(-3.04)
$\beta_{\text{Net Subscriptions}}$		0.18		0.75
t-stat		(1.02)		(3.66)
β_{Age}		-3.53		-2.24
t-stat		(-16.10)		(-12.69)
CE	-0.007	0.010	0.000	0.024
$\bar{r}$	0.011	0.030	0.010	0.026
$\bar{\sigma}$	0.085	0.099	0.068	0.029
SR	0.129	0.304	0.153	0.895
α		0.234		0.22
β		0.205		-0.13
IR		0.29		0.98

This table shows the out-of-sample estimates of the optimal investment strategy policy specified in Equation (2) and the performance of the optimal portfolio relative to the value-weighted portfolio of funds. The optimal investment strategy policy specified in Equation (2) is optimized for a power utility function with CRRA coefficients ($\gamma = 5$) using the following fund characteristics: net subscriptions, three-month fund return (momentum), total fees, market share and age of the fund. We use data from the CNMV database from January 1994 to December 2014 from January 1994 to December 2006, before the beginning of the US subprime crisis, to estimate the first optimal parametric portfolio. After this, the model is re-estimated for every year using an expanding window of data until the end of the sample. The investor uses the estimates in period t to form the optimal portfolio of funds in every month between t and t + 12, given the observed realization of the state variables. We consider "more aggressive funds", which are pure equity funds, "mixed funds", which invest in fixed income and equity, and global funds, which are aimed at retail and wholesale investors. The first set of rows shows the out-of-sample estimates and t-statistics averaged across time. The second set of rows displays the average portfolio return statistics: certainty-equivalent return, average return, standard deviation and Sharpe ratio of returns; the alpha, the beta and the information ratio.

Almost all the coefficients are still significant and preserve their sign. Therefore, the portfolio advice for investors would remain the same. However, the magnitude of the coefficients can vary depending on the segment of the market due to the changes in the Spanish mutual fund industry's structure triggered by the economic and financial crisis in the out-of-sample estimation. More interestingly, the optimized portfolios offer return statistics that still constitute an improvement in terms of the Sharpe ratio, information ratio and certainty equivalent in a period characterized by a high level of uncertainty in the Spanish financial market funds, relative to the value-weighted portfolios. Figure 1 plots the evolution of the out-of-sample financial wealth of 1 euro invested in each case. As can easily be seen from the plot, the optimized strategies deliver a good performance overall, especially for wholesale investors. Again, we find evidence that investors are still far from having the optimum portfolio.

Evolution of out-of-sample financial wealth

FIGURE 1



This figure plots the out-of-sample financial wealth dynamics. The investment strategy consists of investing $1 in the optimal portfolio of funds vs. the value-weighted portfolio of funds. We use data from the CNMV database from January 1994 to December 2006, before the beginning of the US subprime crisis, to estimate the first optimal parametric portfolio. After this, the model is re-estimated for every year using an expanding window of data until the end of the sample. The investor uses the estimates in period t to form the optimal portfolio of funds in every month between t and t + 12, given the observed realization of the state variables. We consider "conservative funds" and "more aggressive funds" that are aimed at retail and wholesale investors.

5 Conclusions

In this paper we analyse why the current structure of the mutual fund markets differs from the optimal portfolio of funds that fully informed investors might select. We focus on the main drivers that explain this difference. We establish the relationship between the optimal allocation to the funds and their characteristics as regards target investor type, retail vs. wholesale, and risk profile (conservative vs. more aggressive) in the Spanish market. We find that, with the exception of fees, the relationship between the fund characteristics and the optimal portfolio of funds depends on the investor's risk profile and/or the type of investor at which a fund is aimed. This means that investors do not take into account that the heterogeneity of the mutual fund market structure could result in misleading portfolios. The welfare consequences of ignoring an approach that integrates fund characteristics and the mutual market structure are substantial. Although the feasibility of achieving the optimal portfolio is low due to the presence of frictions, especially short-selling restrictions and search costs, it would be possible to improve investors' market allocation by providing easier access to information about a few fund characteristics, like fees, age, market share or investors' inflows.

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