# The cross-section of mutual fund fee dispersion

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This Version: September 8th, 2011

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## Abstract

In this paper, we empirically analyze the factors affecting the cross section of mutual fund fee dispersion. In the context of equity mutual funds, fee dispersion stems primarily from the heterogeneity of products, clienteles and production functions. However, the relevant theory predicts that search costs can also generate fee dispersion. By controlling for observable sources of heterogeneity, we find that fee dispersion decreases with fund size and age, as well as with the amount of assets under management of the investment company. In addition, we find lower levels of fee dispersion for funds that charge marketing and distribution fees. Although we cannot rule out the possibility that these factors are a proxy for some unobserved source of heterogeneity, our results are also consistent with the theoretical prediction that search costs positively affect fee dispersion.

*JEL classification:* G14; G23

*Keywords:* Mutual funds; Expense ratios; Price dispersion

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## 1. Introduction

Price dispersion for homogenous products is abundantly documented in the economic literature for different categories of consumer goods and is considered to be an indirect measure of market inefficiency. Prices are dispersed when market participants charge non-marginal prices for homogeneous products. Price dispersion is also documented in homogeneous investment services such as money market funds (Christoffersen and Musto, 2002) and index funds (Hortaçsu and Syverson, 2004). Christoffersen and Musto (2002) focus on money market funds and attribute fee dispersion to the heterogeneity of investors in terms of performance sensitivity. Funds that cater to less sensitive investors can charge higher fees for the same service than those that cater to more performance-sensitive investors. Hortaçsu and Syverson (2004) attribute the existence of price dispersion among S&P 500 index funds to the non-portfolio-related salient characteristics of the funds, switching costs and search costs.

Although US equity mutual funds do not offer a homogeneous investment service, Carhart (1997) shows that their price dispersion is not explained by the ex-post performance of the portfolio. Differences in expenses explain most of the variation in after-expense performance, thus suggesting that there is no positive relationship between the expense ratio and the gross performance of the portfolio. Gil-Bazo and Ruiz-Verdú (2009) show a negative relationship between gross performance and expenses after controlling for a number of funds' salient characteristics. Apart from the puzzle of the negative correlation with past performance, we can generally observe significant price dispersion. For example, Hortaçsu and Syverson (2004) report that the fees of a large sample of growth and income funds from 2000 have a coefficient of variation of 0.830 (at an average cost of 158.4 basis points), with a 90$^{th}$ to 10$^{th}$ percentile ratio of 5.5. In addition, the correlation between fees and performance is not significantly different from zero.

In this paper, we empirically analyze the factors affecting price dispersion in a sample of US equity funds. In contrast to previous studies on fee dispersion in mutual funds, the "products" in our sample can hardly be considered homogeneous. US equity funds differ in terms of portfolio composition, return, risk and other portfolio-related characteristics. Fund managers with greater stock selection ability should be able to charge more for their services (Chevalier and Ellison, 1999). Thus, if mutual fund managers have different degrees of investment ability, a certain degree of fee dispersion is to be expected (Gil-Bazo and Ruiz-Verdú, 2009). Moreover, economic theory suggests that heterogeneity of clienteles and production functions can generate price dispersion. As far as clientele heterogeneity is concerned, Salop and Stiglitz (1977) show that price dispersion may occur when "agents differ in their ability and willingness to make economical decisions in the market-place." In a similar vein, Stahl (1989) analyzes investors with different degrees of ability to search among sellers for better prices. When buyers are assumed to be identical, price dispersion can arise from heterogeneity among producers. Reinganum (1979), for example, shows that price dispersion can exist if firms have heterogeneous marginal costs. Of course, the two forms of heterogeneity (clientele and production function) are not mutually exclusive: both Carlson and McAfee (1983) and Benabou (1993) develop models where heterogeneities on both sides of the market cooperate in order to create equilibrium price dispersion.

Finally, a possible source of dispersion is the presence of search costs. Stigler (1961) first demonstrates that price dispersion can persist in a competitive market if the acquisition of information is costly. Consumers acquire information on a limited number of sellers and choose among them. As a result, even firms that sell their products for a non-marginal price face a positive demand. In this setting, the cost of acquiring information has a positive impact on price dispersion by reducing the sample of suppliers that consumers analyze in order to make their purchase decision.

In this paper, we model fund fees as a function of variables that are commonly used to explain the price of investment services. We therefore try to control for possible sources of heterogeneity. Admittedly, this approach has some limitations. All of our proxies for heterogeneity are ex-post variables. For example, we use past performance to proxy for the ability of the fund manager (a likely source of heterogeneity among funds). However, fund fees should reflect investors' *expectations* with regard to future performance, which clearly cannot be observed. If an investor believes that a fund manager is particularly good, irrespective of the manager's past performance, he or she will be willing to pay a higher fee. However, the extent of the limitations of using ex-post variables depends on how well these variables explain unobservable heterogeneity. Turning back to the example of the fund manager's ability, it is reasonable to assume that investors learn about managerial ability by observing the past performance of the fund (Berk and Green, 2004; Huang et al., 2007).

We find that around 40% of fee dispersion can be explained using observable sources of heterogeneity, such as past performance and other characteristics of the fund and of the investment company in question. By controlling for such observable sources of heterogeneity, we find that fee dispersion decreases with fund size and age, as well as with the amount of assets under management of the investment company. In addition, we find that the degree of residual fee dispersion is lower for funds that charge marketing and distribution fees. Our results are consistent with the theoretical prediction that search costs positively affect fee dispersion. However, we cannot rule out the alternative hypothesis that our results are driven by some unobserved source of heterogeneity.

The rest of the paper is organized as follows: in Section 2, we present our empirical methodology. The dataset is described in Section 3. In Section 4, we analyze the relationship between the pricing policy at the fund family level and fee dispersion. We discuss our empirical results in Section 5 and draw conclusions in Section 6.

## 2. Methodology

We employ the following heteroscedastic regression model, as proposed by Harvey (1976):

$$y_{it} = \mu_{it} + \sigma_{it} e_{it} \tag{1}$$
$$\mu_{it} = E(y_{it}) = \beta_0 + \beta_1 x_{it1} + \cdots + \beta_k x_{itk} \tag{2}$$
$$Log(\sigma_{it}^2) = Log[Var(y_{it})] = \gamma_0 + \gamma_1 z_{it1} + \cdots + \gamma_m z_{itm} \tag{3}$$

where $y_{it}$ is a random variable (the dependent variable) with mean $\mu_{it}$ and variance $\sigma^2_{it}$ , and $x_{it}$ and $z_{it}$ are (vectors of) covariates predicting the mean and log variance of $y$, respectively. Thus, we have a linear model for the expected value (mean) and a log-linear model for the variance of a response variable, which are conditional on a set of covariates that predict the mean and variance. The coefficients $\beta$ and $\gamma$ are to be estimated. In addition, the residuals $e_{it}$ are usually assumed to be standard, normally distributed and independent. As we have a panel dataset with multiple observations for every fund, we consider clustered residuals in order to increase the robustness of our estimates.

### *2.1. The mean equation*

Our dependent variable is the expense ratio net of 12b-1 fees for every fund/year in our sample.[1] The reader should note that for a significant number of funds in our database, the fiscal year is different from the calendar year, with the end of October being the most common non-conventional fiscal year closing date. This may affect our results because in the panel we consider as contemporary expense ratios that are actually measured on different horizons. In order to resolve this problem, we recalculate the expense ratios on a calendar year basis. If a fund closes the fiscal year for year $t$ at the end of October, the expense ratio for calendar year $t$ in our database is now a weighted average of the expense ratio of fiscal year $t$ and that

[1] We also run our model separately on the two main components of expense ratios, management fees and other administrative expenses, and obtain very similar results.

which was reported for fiscal year *t+1*. The weight of the latter is 2/12, which represents the number of months of calendar year *t* which are accounted for in fiscal year *t+1*. Admittedly, this procedure can only yield an estimate of the expense ratio paid by the investor in calendar year *t*; however, as the expense ratios in our sample tend to be stable, it can be considered a reasonable proxy. Indeed, the correlation coefficient between the expense ratios reported for the fiscal years and our estimated expense ratios for calendar years is above 0.99. Moreover, calendar year approximation for expense ratios is common practice in the relevant literature (see, for example, Gil-Bazo and Ruiz-Verdú, 2009; Huang et al., 2007).

Equation (2), henceforth the "mean equation", models the expected value of the expense ratio as a linear function of a certain number of explanatory variables which should reflect the degree of observable heterogeneity among funds. We can separate our covariates into four broad categories.

1. *Past performance*. If we assume that performance is not due to pure chance, a better-quality management will probably ask for a higher compensation. Moreover, many researchers have documented a positive and asymmetric relationship between mutual fund flows and past performance.[2] From a standard market perspective, products that are in high demand should cost more than products for which the demand is low. We model past performance with three different variables: (i) *RET*, the 36-month return (gross expense ratio) of the fund from year *t-3* to year *t-1*; (ii) *ALPHA*, the 36-month four-factor alpha estimated with the standard Fama, French and Carhart factors on monthly returns from *t-3* to *t-1*; and (iii) *RANK*, the fund's return ranking in relation to other funds with the same investment objective in the year *t-1*. The significance of all of these variables is proven in the existing flow-performance literature. We measure them on different time horizons in

[2] See, for example, Ippolito (1992), Gruber (1996), Chevalier and Ellison (1997), Sirri and Tufano (1998) and Huang et al. (2007).

order to capture different aspects of past performance. *RANK* is measured over the past year, because Sirri and Tufano (1998) show that this time frame has a higher explanatory power than a three-year period.[3] We use *ALPHA* and *RET* in different specifications of our model; as they are intended to capture the concept of managerial ability, three years is a reasonable midpoint in the tradeoff between the stability of the alpha estimate and the relevance to investors. We also test different specifications using up to 60 months of past returns without any material change in the results of the analysis. The results which are documented in the literature on the relationship between past performance and fees are mixed, and so we do not have a strong prior with regard to this variable;

2. *Cost structure of the investment company*. Baumol et al. (1990) and Latzko (1999) demonstrate that mutual fund management shows the presence of significant economies of scale. The average cost decreases with the fund's assets; nonetheless, the rate of reduction drops heavily at about $3.5 billion (Latzko 1999). In a competitive market, investment companies may pass these savings on to investors through a reduction in the expense ratios, thereby trading a higher unit profit margin for higher volumes of assets under management. In order to capture this phenomenon, we use *ICSIZE*, the natural logarithm of the size of the fund complex, and *SIZE*, the natural logarithm of the fund size. Both variables are defined at the end of year *t-1*. In accordance with the competition hypothesis, we should expect a negative relationship between both measures of size and the expense ratio.

   Khorana et al. (2009) show a negative relationship between expense ratios and the age of the fund due to experience economies that result in lower management costs. These savings are, at least in part, passed on to investors. We capture this effect with a dummy va-

[3] Investors seem to consider a fund's recent past performance to be more salient than older returns in their decision-making.

riable (*AGE*) which is set equal to 1 if at least 5 years have passed since the fund was first offered to the public.

3. *Heterogeneous clientele*. Many contributions to the literature show that mutual funds may cater to specific clientele defined by different levels of financial sophistication or different preferences. Funds may offer a different bundle of services to these clients and charge a different price. Hogue and Wellman (2007) argue that mutual funds use loads to differentiate customers with lower levels of financial sophistication and charge higher expense ratios. This idea is partially confirmed by a survey conducted by the Investment Company Institute in 2008 on the profile of mutual fund shareholders. This survey reveals that investors who buy mutual funds through a direct channel have a (slightly) higher level of education and income than investors who use the services of some sort of sales force. In addition, Capon et al. (1996) cluster investors according to the sources of information they use in their investment decision-making process; they document the presence of a group of "commission-based advisees" defined by the "the disproportionately high importance of commission-based financial advisors as an information source." On a related note, Bergstresser et al. (2009) find that loads/brokered funds deliver lower risk-adjusted returns (net of the expense ratio), even before subtracting the distribution costs, and display no better skills with regard to asset allocation. The authors conclude that this evidence is consistent with the fact that load funds deliver other intangible benefits or with the existence of a significant conflict of interests. Christoffersen et al. (2005) show that mutual fund flows in load funds are less prone to the disposition effect and consider this to be a valuable service provided by brokers to mutual fund investors who choose to invest in load funds.

We try to capture this clientele effect using a dummy variable (*FR_LOADS*), set equal to one if the fund charges front-end loads,[4] and two variables (*BACK_LOADS* and *LEV_LOADS*) that capture the effect of deferred loads. We use two different variables because it is well known that both back-end and level-load funds can charge deferred loads. In the latter case, the broker is compensated through a yearly charge, the 12b-1 fees, if the investor stays invested for more than one year, and otherwise a load is applied at the moment of the early redemption. In addition, our database (CRSP Mutual Funds) does not uniquely identify the type of share class, and we have to infer the type of distribution arrangement from the fee structure. Livingston and O'Neal (1998), O'Neal (1999) and Nanda et al. (2009) report the typical fee arrangements for different share classes, and it appears that level-load funds are characterized by lower deferred loads (typically 1%) and higher 12b-1 fees (again 1%) than back-end funds, which in turn report much higher loads (5% as a maximum level that typically decreases by 100 bp for each year of permanence in the fund) and marginally lower 12b-1 fees. We thus define a dummy variable for level-load funds (*LEV_LOADS*) when the deferred load is no higher than 1% and the 12b-1 fee is no lower than 1%. We also define a dummy variable for back-end load funds (*BACK_LOADS*) for when the funds charges a deferred load and the conditions mentioned above are not satisfied.[5] Based on the existing literature, we expect a positive relationship between loads and expense ratios.

In 1980, the Securities and Exchange Commission approved rule 12b-1, which authorizes mutual funds to deduct a sum of money from the net assets in order to remunerate bro-

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[4] In different specifications, we also used the actual value of the loads instead of dummy variables. All of the specifications led to the same conclusions.

[5] In order to test the robustness of our results with regard to the definition of the two dummy variables relating to deferred loads, we also tried different specifications, lowering the minimum 12-b1 fee requirement for level funds (to 0.5% and 0.25%) and dropping it altogether, thereby distinguishing between the two types solely on the basis of the size of the maximum deferred load. All of our results are robust to these different specifications.

kers. Both Ferris and Chance (1987) and Dukes et al. (2006) document a positive relationship between 12b-1 fees and the expense ratio (net of the distribution costs). As it is reasonable to assume that, to a certain extent, these fees can act as substitutes for loads, we include an additional variable (12b-1), which is defined as the actual distribution fees charged by the fund.

Christoffersen and Musto (2002) argue that mutual funds that cater to less performance-sensitive investors can charge higher fees. In order to capture this sensitivity of the clientele, we replicate their Q/MAX measure as the ratio of the assets under management at the end of the year *t-1* to the maximum value of the assets under management during the same year. The rationale behind this measure is that performance-sensitive investors are the first to leave the fund after a bad performance, and so the lower the measure, the higher the proportion of performance-sensitive investors that have left the fund in the last year and the lower the average performance sensitivity of the actual investors. The authors show, for money market funds, a negative relationship between this measure and the fee level;

4. *Portfolio structure*. The main service offered by investment companies is their participation in the return of the mutual fund portfolio; we should therefore expect different prices for different portfolios. Of course, part of this effect should be captured by the performance measure, but we can assume that, under certain market conditions, investors may demand certain types of stock (for example, small caps or growth stocks), regardless of their past performance. In our sample, we consider US domestic equity funds without industry specificities. In order to capture different portfolio effects, we use:

    a. The betas of a standard Fama, French and Carhart four-factor model estimated over the course of the 36 months from *t-3* to *t-1* (*MKT, SMB, HML, UMD*);

b. The standard deviation of fund returns (*DEV*), the $R^2$ of a four-factor model (*RSQ*), both calculated over the course of the 36 months from *t-3* to *t-1*, and the turnover of the fund in the year *t-1* (*TRN*);

c. A set of six dummy variables designed using Standard & Poor's objective codes in the CRSP database for aggressive growth, growth, growth and income, income and growth, midcaps and small caps.

We do not have a strong prior for the variable in sub-point (a), and consider these betas to be controls. With regard to the variables in (c), we could argue that some stocks, such as small cap or growth stocks, are more difficult to analyze and more expensive to trade. As far as the variables in (b) are concerned, we argue that high-volatility funds or funds that operate in a highly volatile context are more difficult to manage and should charge higher fees,[6] while funds with a high $R^2$ are *de facto* index funds and should charge lower fees (they require fewer managerial skills and a more passive management style). Finally, funds with a higher turnover should, for obvious reasons, charge a higher expense ratio.

We also use time dummy variables to control for variation over time in the level of market competition and investment-objective dummy variables to control for heterogeneity among different categories of mutual funds.

### *2.2. The variance equation*

The mean equation is intended to control for observable heterogeneity. In Equation (3), henceforth the "variance equation," the dependent variable is the log of the squared residual of the mean regression. We model the residual dispersion as a function of variables that should

[6] Moreover, investors in these funds should be less sensitive to fees as they are easily disguised by the highly volatile returns.

capture the level of search costs. As previously mentioned, we cannot rule out the possibility that such variables reflect some unobserved heterogeneity. Following the work of Huang et al. (2007), we consider three different aspects:

1. *Fund visibility*. Search costs are inversely related to the visibility of the fund, as it is easier and cheaper to acquire information on well-known and established funds. We therefore include the (natural logarithms of the) fund size (*SIZE*), the size of the investment complex (*ICSIZE*) and the age of the fund (*AGE*). We assume that larger (and older) funds and larger fund families would receive more media coverage and that investors would easily be able to acquire a significant amount of information on them. Moreover, a large number of investors already have information about these funds because they own, or have previously owned, funds managed by the same family (see Capon et al., 1996). This is particularly important as many investors seem to rely on word of mouth as a source of information. Alexander at al. (1998) show that, out of a sample of 2000 mutual fund investors, 37% use "family or friends" as a source of information (this was the second most popular source of information after fund prospectuses) and that 16.3% of the sample considered family or friends to be the best source of information. As all of these variables reduce information costs, they should be negatively related to fee dispersion;

2. *Fund sales effort*. Mutual funds can increase their own visibility by investing in incentives to encourage brokers and advisers to create and distribute information on the fund to the public. We cannot observe this effort directly; however, following the intuition of Sirri and Tufano (1998), we use the front loads (*FR_LOADS*) and the 12b-1 fees (*12b-1*) as proxies. The existing literature shows that brokers play an active role in producing information and helping investors with their investment decision-making process on the basis of this information. Alexander at al. (1998) report that 31% of the investors in their sample used the broker as a source of information and that 16.9% of the sample considered

the broker to be the best source of information, while Zhao (2005) demonstrates that brokers play a significant role in the decision-making of investors who buy shares in load funds. Our variables should measure the support that the fund receives from the sales channel in terms of information production and should be negatively related to fee dispersion;

3. *Switching costs*. Hortaçsu and Syverson (2004) argue that fee dispersion may be generated by a “switching-cost-induced parking behavior.” According to this hypothesis, investors are less sensitive to fees if they invest in funds with a significant switching cost. For these funds, we should therefore expect a greater degree of fee dispersion. We model switching cost using two dummy variables for back-end load (*BACK_LOADS*) and level-load (*LEV_LOADS*) funds. These are the share classes that may charge deferred loads.

Search costs in the mutual fund market can change over time. For example, new channels of information (e.g., the Internet) and the increasing level of investors’ financial education might have reduced search costs over time. As such, we include time fixed effects in the variance equation. In addition, search costs may differ between funds with different investment objectives. For example, more aggressive strategies might attract sophisticated investors with lower search costs. Similarly, the degree of competition between funds might change from one investment objective to another, thus affecting the level of transparency required by the market. We therefore include investment objective dummy variables as controls.

As noted above, one may argue that some of the variables used in the variance equation could reflect fund heterogeneity. For example, younger or smaller funds could manage less homogenous portfolios compared to larger and more established funds. In this case, an increase in fee dispersion would not originate from increased search costs. We attempt to minimize this potential problem by including in some of the specifications of the variance equation two additional variables: $ALPHA^2$, the squared value of the four-factor alpha, and *DIST*, a measure of the distance of the portfolio from the average equity portfolio. The starting point for this variable is the OLS estimation of a standard Fama, French and Carhart 4-factor model:[7]

$$r_{it} - rf_t = \alpha_i + \beta_i^{mkt}\left(r_{mt} - rf_t\right) + \beta_i^{smb}\left(r_{st} - r_{bt}\right) + \beta_i^{hml}\left(r_{ht} - r_{lt}\right) + \beta_i^{umd}\left(r_{ut} - r_{dt}\right) + \varepsilon_{it} \tag{4}$$

Where:

- $r_{it}$ is the monthly return of the mutual fund;
- $rf_t$ is the one-month treasury bill rate;
- $r_{mt}$ is the return of the US CRSP total market index (including NYSE, AMEX and NASDAQ);
- $r_{st}$ and $r_{bt}$ are the monthly returns of a small-cap and a large-cap portfolio (following Fama and French's (1993) definition, the size breakpoint for year *t* is the median NYSE market equity at the end of June in year *t*);
- $r_{ht}$ and $r_{lt}$ are the monthly returns of portfolios of stocks with high and low price-book value respectively (once again, following Fama and French's (1993) definition, the price-book value breakpoints are the 30th and 70th NYSE percentiles);
- $r_{ut}$ and $r_{dt}$ are the monthly returns of portfolios of stocks with high and low prior returns (from month *t-2* to *t-12*) respectively (the prior performance breakpoints are the 30th and 70th NYSE percentiles).

From the definition of the variables, it follows that running this model on a mutual fund that replicates the market index would produce a market beta equal to one and betas for the last three factors equal to zero. We can thus build a variable in order to measure the distance between a given fund and this "standard index fund" (that replicates the market portfolio) as the

[7] For a complete definition of these variables, see Fama and French (1993) and Carhart (1997).

sum of the squared values of the differences between the betas and their respective expected values, specifically:

$$DIST_i = \left(\beta_i^{mkt} - 1\right)^2 + \left(\beta_i^{smb} - 0\right)^2 + \left(\beta_i^{hml} - 0\right)^2 + \left(\beta_i^{umd} - 0\right)^2 \qquad (5)$$

We do not mean to cast these two additional variables (*ALPHA*$^2$ and *DIST*) as definitive controls with regard to the problem of unobserved heterogeneity. Nevertheless, the robustness of our results following the inclusion of these controls is reassuring.

## 3. Dataset

We use data from the Center for Research in Security Prices (CRSP) Survivorship Bias Free Mutual Fund Database, from which we obtain information about the net asset values, returns and characteristics of our funds. We collect data for the period from 1993 to 2006 on all non-industry-specific US domestic equity funds with assets under management which are no smaller than USD 10 million. As in our model we will use results from the estimation of a Fama-French-Carhart 4-factor model, we only consider funds with past data covering at least 36 months. The number of funds in our sample grows from 562 in 1993 to 3448 in 2006.

**[Insert Table 1 about here]**

Table 1 reports summary statistics for our entire sample. The percentage of no-load funds[8] is decreasing during our sample period, from around 44% to 33%. The average expense ratio grows from 1.21% in 1993 to 1.42% in 2003, and then decreases to 1.34% in 2006. In order

[8] These are defined as funds that do not charge front or deferred loads and do not charge 12b-1 fees above 25 bps.

to avoid possible errors, we dropped all the observations with non-positive expense ratios or expense ratios lower than the 12b-1 actually charged. The expense ratio net of these fees remains stable at around 1% (meaning that the volatility in the average expense ratio is mainly due to the 12b-1 fees). The cross-sectional volatility is, on average, 0.39, with a range of about 90 basis points between the $10^{th}$ and the $90^{th}$ percentiles.

We group the funds according to homogeneous categories using Standard & PoorS&P's investment objectives, provided by CRSP. Table 2 reports the summary statistics for the six different investment objectives which were considered.

**[Insert Table 2 about here]**

The average value of the expense ratio (net of the 12b-1 fees) varies across the different categories, with aggressive growth and small-cap funds predictably at the top of the ranking. These funds invest in the group of stocks with the highest cross-sectional volatility, and so it is reasonable to expect a higher cost for the management service. It is interesting to note that the same pattern does not apply for fee dispersion: by looking at the coefficients of variation, we can see that growth and income funds have the greatest dispersion, and that both growth and income and growth have higher levels of dispersion than small-cap funds.

Table 3 reports the correlation coefficients between the variables included in the variance equation as well as the p-values of the test against the null hypothesis of a lack of correlation.

Most of the coefficients are statistically different from zero, but the values are sufficiently low to reasonably rule out any problems of multicollinearity. In order to perform a more formal test of multicollinearity, we ran a two-stage estimation of our heteroscedastic model and calculated variance inflation factors (VIFs) for both the mean and the variance equation. The two-stage estimation is less efficient; however, as it performs two separate OLS estimations for the mean and the variance equations (instead of a single ML estimation), it allows us to perform separate tests for multicollinearity. All the VIFs are below 4, which is much lower than the usual critical level of 10 (see Hair et al., 2005). This rules out any concerns regarding multicollinearity.

**[Insert Table 3 about here]**

## 4. Fund families and pricing policies

Before moving to our multivariate test, we have to address an important issue related to the pricing policies of mutual fund families. It is common for investment companies to manage more than one fund within the same fund category, and in doing so the company may follow slightly different investment policies or cater to a different clientele. The relevant question then becomes whether the correct level of analysis for a study on fee dispersion is the mutual fund (share class) or the fund family/investment objective group. If a fund family chooses a common price for all of the funds with a given investment objective, we would end up relating mutual fund fees to fund characteristics (such as size and age), whereas actually we should consider explanatory variables relating to the fund family. The question is not whether there is a coordinated pricing policy within mutual fund families, but to what extent the pricing of a given mutual fund share is based on its own characteristics as opposed to family-related issues. If the weight of the latter is predominant, a fund-level analysis of fee dispersion would be fatally mis-specified.

We empirically address this problem in three ways. First of all, we run an ANOVA in order to determine the proportion of fee dispersion that can be explained at the fund level compared to the proportion that is determined by the family and investment objective of the fund.

Table 4 reports the sequential sum of squared errors generated considering the variability in expense ratios (net of 12b-1 fees) across different years, investment objectives and fund families. About 40.6% of fee dispersion can be explained simply by the fact that a fund belongs to a certain family and a certain strategy, whereas 46% of price dispersion is at the individual fund level. This analysis clearly confirms the existence of a family-level pricing strategy, but as a significant portion of price dispersion is explained by fund-level information, this also validates our fund-level approach.

**[Insert Table 4 about here]**

We also perform a less formal test by comparing the fee dispersion for funds with the same investment objective managed by the same investment company with the fee dispersion for all of the funds in the category in question. We restrict our analysis to family/strategy groups with at least five funds. The results in Table 5 show that only half of the family/strategy groups show a fee dispersion which is significantly lower (at the 5% level) than the strategy-wide dispersion, and that these low-dispersion groups account for around 53% of the funds in our sample. This percentage varies across investment objectives, ranging from around 43% for growth and income funds to 72% for aggressive growth funds. The table also shows that the average dispersion inside the “low-dispersion” group is around 63% (57% if weighted for the number of funds) lower than the corresponding strategy-wide fee dispersion.

**[Insert Table 5 about here]**

This analysis confirms that a significant amount of fee dispersion is generated at the individual fund level because half of the family-strategy groups revealed a dispersion level which was not significantly lower than the population-level one.

## 5. Empirical results

### *5.1. Heterogeneity and fee dispersion*

The results of the mean equation in Table 6[9] show that our explanatory variables explain around 40% of the variability of the expense ratio net of the 12b-1 fees. The signs of the coefficients confirm most of our predictions. The negative coefficients of *SIZE* and *ICSIZE* show that at least part of the reduction in costs which comes from economies of scale is passed along to investors. The result regarding experience economies is counterintuitive, with older funds charging, on average, higher expense ratios. We find evidence of significant clientele effects. We see that investors who avail themselves of brokerage services are charged higher expense ratios[10] (positive coefficients for *FR_LOADS*, *BACK_LOADS*, *LEV_LOADS* and *12b-1*), while investors who are less sensitive to performance are charged higher expense ratios (negative *Q/MAX* coefficient).

**[Insert Table 6 about here]**

[9] The results of the variance equation are reported in Table 8 and discussed later in the paper.

[10] This result is compatible with both the hypothesis of a straightforward rip-off of less sophisticated investors (Zhao, 2005) and the hypothesis that some additional benefits are delivered by brokers to these investors (Bergstresser et al., 2009).

We document significant effects of the portfolio structure on the expense ratio: predictably, funds with a low four-factor $R^2$ and funds with a high turnover charge more, as a result of more active management. In addition, funds with a higher degree of risk and funds that invest heavily in small caps charge more. This result may show a reverse causality problem. Families that charge lower expense ratios are more likely to have funds at the top of their category rankings. We also find a non-significant relationship between total return performance measures (past gross return and performance rank) and fees and a positive relationship between the four-factor alpha and the expense ratio, thus suggesting that investors are willing to remunerate managerial ability more than total return. The model has the same explanatory power regardless of the performance variable used. For the rest of our analysis, we will consider *ALPHA*, the variable with the most interesting and meaningful result. All of these results are robust to the inclusion of year and investment objective fixed effects.

### *5.2. Search costs and fee dispersion*

Assuming that the variables used in the mean equation are perfect controls for heterogeneity, the unexplained dispersion should reflect search costs.[11]

First, we test the heteroscedasticity of our mean equation, as heteroscedasticity would suggest that the dispersion of residual fees is not constant throughout the mutual fund population. We run both the standard Breusch and Pagan (1979) and the Koenker (1981) tests of heteroscedasticity on an OLS estimation of our mean equation. The first test assumes the normality of the residuals, while the second only assumes the residuals to be i.i.d. The two tests are run for the sample as a whole and also year-by-year. The results confirm the presence of heterosce-

[11] As we pointed out earlier in the paper, unobserved heterogeneity remains as an alternative hypothesis.

dasticity in each one of the years in our sample,[12] thus demonstrating that fee dispersion varies across the mutual fund population.

We then test whether or not search costs affect fee dispersion. An intuitive way to measure the relationship between fee dispersion and our search cost proxies is to look at the variance of (the unexplained portion of) expense ratios among the different groups of funds. Using our five proxy variables for search costs, we define high- and low-search cost mutual fund groups. For fund size (*SIZE*) and investment company size (*ICSIZE*), we define as having high search costs (low search costs) those funds in the lowest (highest) quartile. With regard to the *AGE* dummy variable, we define as having high search costs (low search costs) the funds with less than (more than or equal to) five years of past performance. For front-end loads and 12b-1 fees, we define as having high search costs (low search costs) the funds that do not (do) charge this kind of fee. We compute the variance of the residuals from model C.3 in Table 6 for the two groups and perform a standard F-test on the ratio between the two variances.

**[Insert Table 7 about here]**

The results of the F-tests in Table 7 show that for every proxy variable, the ratio between the standard deviations of the high- and low-search cost groups is always significantly greater than one, confirming that expense ratios are more dispersed among high-search cost funds. The differences are not only statistically but also economically significant. If we consider that the average expense ratio for our entire sample is around 1%, we can sense the relevance of

[12] Numerical results are available from the authors upon request.

the difference between the standard deviation of the expense ratio for the group of the largest funds (0.22%) and that of the group of the smallest funds (0.30%).

Moving on to our multivariate test, we now look at the variance equation of the model described in Section 2 (see Table 8). We consider two possible specifications of the mean equation. In models A.1–A.4 and C.4–E.4, we use the linear specification of model C.3 in Table 6, while in model B.4 we use a piecewise specification in which every continuous variable of the mean equation is broken into deciles. This second specification allows us to test whether the results of the variance equation are influenced by a non-linear relationship between the fee and the explanatory variables in the mean equation. In all of the models, we control for the year and investment objective effects.

Mutual fund fees are likely to be influenced by market-wide shocks across funds. It is thus reasonable to assume that funds are not (statistically) independent observations at a given point in time. The resulting residual cross-correlations across funds could be substantial, and thus an OLS estimation of our model would yield downward-biased standard errors. In order to address this problem, we perform three different robustness checks:

- In model C.4, we run our basic experiment by using a two-stage version of the Harvey (1976) model and clustering the residuals at both the year level *and* at the fund level, as opposed to the previous models in which only the latter dimension was considered. Both Petersen (2009) and Thompson (2011) show that this methodology leads to significantly more accurate inferences in panel estimations;
- In model D.4, for each year, we estimate a cross-sectional mean regression in order to obtain regression residuals. We then use the natural logarithm of the squared value of these residuals as the dependent variable in a series of cross-sectional variance regression estimations (again, one for each year). Finally, we use the time series of the estimated coeffi-

cients to conduct a t-test of their significance. This procedure yields a Fama and MacBeth (1973) estimation of our model, in which the mean and variance equations for each year are estimated separately (the two-stage version of the Harvey (1976) model). Petersen (2009) shows that Fama and MacBeth deal correctly with the bias induced in the standard errors by the correlation among individuals (funds) at a given point in time;

- In model E.4, we run the standard Harvey (1976) model separately for each year (as in the Fama-MacBeth approach). We then compute the mean of the time-series of the coefficients and test their significance. Unlike the previous approach, we now keep the simultaneous estimation of the mean and variance equations within a specific year.

The fact that the results are stable across specifications A.4–E.4 indicates that common, unobserved time-related factors do not play a significant role.

**[Insert Table 8 about here]**

Looking at Table 8, we can note that most of the variables show stable coefficients with the expected sign. Funds with a higher degree of visibility (larger and older funds and funds managed by larger investment companies) and funds with a higher degree of sales effort (non-zero front loads and high 12b-1 fees) show lower levels of residual fee dispersion.[13] In models A.4–E.4, we include $ALPHA^2$ and *DIST*, with no material change in the results.

In order to measure the practical relevance of these effects, we use the coefficients of the regression to estimate the expected fee (from the mean equation) and the mean absolute resi-

[13] We also find that funds with high switching costs (back-end load funds) have a higher level of price dispersion. The coefficient for level-load funds is always positive but not significant. This is reasonable if we consider that for these funds, the switching cost disappears after just 12 months of permanence.

dual fee (from the variance equation) for high- and low-search cost funds.[14] Table 9 reports the ratio between the unexpected and the expected fee for the two groups and the percentage increase in the ratio if a fund moves from the low- to the high-search cost group.

If we look at the change in the ratio of unexpected to expected fees, we can observe that for all of our proxy variables (except investment company size), moving from the low- to the high-search cost group would generate an increase in the relevance of the unexplained fee. The size of this increase ranges from 10% for the fund visibility proxies (size and age) to more than 20% for the sales effort variables (12b-1 fees and front loads).

**[Insert Table 9 about here]**

Overall, our results seem to suggest that a positive and significant relationship exists between search costs and price dispersion for equity mutual funds. One alternative explanation for these empirical findings is that our search cost variables are also proxies for unobserved heterogeneity. We therefore run a number of additional tests.

We run regressions including the fund $R^2$ (both as a substitution for and in addition to $ALPHA^2$ and *DIST*) as a (inverse) measure of fund heterogeneity with no change in the main results. In addition, we run our model on a subsample of funds with low heterogeneity ($R^2$

[14] We consider the fifth percentile value for *SIZE*, *ICSIZE* and 12b-1, a value of zero for the dummy variables *AGE* and *FR_LOADS* and a value of one for *BACK_LOADS* and *LEV_LOADS* (the fund has switching costs) to indicate high search costs. We consider the 95th percentile for the continuous variables, a value of one for the dummy variables *AGE* and *FR_LOADS* and a value of one for *BACK_LOADS* and *LEV_LOADS* to indicate low search costs. In order to capture the marginal effect of each variable, we consider changes in each proxy variable separately. For all of the other variables, we consider the median value and the results are averaged across years and fund complex/investment objective groups.

higher than 0.92, the median value in our sample) and again, all of our main results are confirmed.[15]

We explore the search cost interpretation, by looking at the asymmetry of the residual fee dispersion. A decrease in search costs should reduce both uncommonly high and uncommonly low expense ratios.

**[Insert Table 10 about here]**

We estimate our mean equation on a year-by-year basis in a quantile regression framework and use the residuals to build a discrete response variable that can assume three different values: "high" if the observation is in the top decile; "low" if it is in the bottom decile and "mid" if it is neither. We then measure the effect of our search cost proxies on the probability of a fund to charge particularly high or low fees. We run multinomial logit regressions using "mid" as the base case. Table 10 reports the coefficients of the two parts of the model and tests the significance of the difference between them. We can see that the effects of all of our proxies for search costs (with the exception of *ICSIZE*) are symmetrical in sign. They all reduce the probability that a fund will charge very high or very low fees.

Notwithstanding these robustness checks and additional tests, we cannot rule out the possibility that unobserved heterogeneity is partially responsible for our results.

[15] Numerical results are available from the authors upon request.

## 6. Conclusions

In this paper, we analyze the determinants of the cross section of mutual fund fee dispersion. Price dispersion for homogenous products is considered in the literature as an indirect measure of market inefficiency with a direct effect on consumer welfare. When prices are dispersed, there are sellers who charge a non-marginal price, thereby reducing the amount of surplus for consumers. Actively managed mutual funds cannot be considered to be homogeneous products. Indeed, a primary source of fee dispersion is heterogeneity of products, clienteles and production functions. We find that around 40% of fee dispersion can be explained by observable sources of heterogeneity, such as past performance and other characteristics of the fund and of the investment company in question.

However, the relevant theory predicts that search costs also can generate fee dispersion. By controlling for observable sources of heterogeneity, we find that fee dispersion decreases with fund size and age, as well as with the amount of assets under management of the investment company. In addition, we find that the level of fee dispersion is lower for funds that charge marketing and distribution fees. The effect of these proxy variables for search costs is economically meaningful and symmetrical. Although we cannot rule out the possibility that the search cost proxies used in this paper may also reflect some unobserved source of heterogeneity, our results are consistent with the theoretical prediction that search costs positively affect fee dispersion.

**Acknowledgements**

We would like to thank an anonymous referee, Ike Mathur (the editor), Jennifer Huang, Marco Pagani, Clemens Sialm, Laura Starks, Peter Tufano, seminar participants from the Financial Management Association, the European Financial Management Association, the Australasian Finance and Banking Conference, the Eastern Finance Association and the Midwest Finance Association for their helpful comments. An earlier draft of this paper was completed while Marco Navone was visiting the Finance Department of Red McCombs School of Business at the University of Texas at Austin. The authors gratefully acknowledge the financial support of the Centre for Applied Research in Finance (Carefin) of Bocconi University.

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## Table 1
## Summary statistics

This table reports the summary statistics of our sample from 1993 to 2006. At the end of each year, we calculate the cross-sectional mean value of the total net asset value, the age of the fund, the average number of no-load funds, the expense ratio and the expense ratio net of the 12b-1 fees charged during the year. For this last variable, we also provide cross-sectional standard deviations, coefficients of variation and the $10^{th}$ and $90^{th}$ percentiles.

| | | | | | | Expense ratio (net of 12b-1 fees) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Year** | **Number** | **Size (millions)** | **Age** | **No-load funds (%)** | **Expense ratio** | **Average value** | **Standard deviation** | **Coefficient of variation** | **$10^{th}$ percentile** | **$90^{th}$ percentile** |
| 1993 | 562 | 612.22 | 18.28 | 43.95 | 1.21 | 1.03 | 0.34 | 0.33 | 0.65 | 1.43 |
| 1994 | 609 | 753.35 | 18.96 | 45.48 | 1.18 | 1.01 | 0.35 | 0.34 | 0.64 | 1.38 |
| 1995 | 681 | 732.60 | 18.16 | 48.90 | 1.19 | 1.02 | 0.34 | 0.33 | 0.66 | 1.40 |
| 1996 | 863 | 897.53 | 15.77 | 52.03 | 1.19 | 1.01 | 0.39 | 0.38 | 0.63 | 1.39 |
| 1997 | 1110 | 966.09 | 13.86 | 48.56 | 1.21 | 0.98 | 0.34 | 0.35 | 0.61 | 1.37 |
| 1998 | 1358 | 1010.70 | 12.90 | 46.02 | 1.25 | 0.98 | 0.32 | 0.32 | 0.63 | 1.37 |
| 1999 | 1616 | 1071.43 | 12.38 | 44.68 | 1.30 | 0.99 | 0.32 | 0.32 | 0.63 | 1.37 |
| 2000 | 1996 | 1128.11 | 11.64 | 44.69 | 1.30 | 0.98 | 0.34 | 0.35 | 0.61 | 1.38 |
| 2001 | 2352 | 1039.09 | 11.20 | 43.15 | 1.32 | 0.99 | 0.35 | 0.35 | 0.57 | 1.40 |
| 2002 | 2649 | 818.36 | 11.16 | 42.32 | 1.37 | 1.02 | 0.35 | 0.34 | 0.60 | 1.43 |
| 2003 | 3016 | 558.65 | 10.60 | 38.93 | 1.42 | 1.05 | 0.37 | 0.35 | 0.6 | 1.49 |
| 2004 | 3191 | 728.90 | 10.81 | 37.86 | 1.41 | 1.05 | 0.38 | 0.36 | 0.59 | 1.46 |
| 2005 | 3437 | 791.57 | 10.98 | 35.03 | 1.36 | 1.01 | 0.36 | 0.36 | 0.55 | 1.41 |
| 2006 | 3448 | 688.51 | 11.13 | 32.57 | 1.34 | 0.98 | 0.36 | 0.37 | 0.55 | 1.38 |
| **Total** | **26902** | **827.57** | **12.00** | **40.64** | **1.33** | **1.01** | **0.36** | **0.35** | **0.6** | **1.41** |

## Table 2
## Summary statistics for investment objectives

This table reports the summary statistics for the six Standard & Poor's investment objectives included in our sample. For every group of funds, we calculate the cross-sectional mean value of the number of funds in the category, the total net asset value and the expense ratio net of the 12b-1 fees charged during the year. For this last variable, we also provide cross-sectional standard deviations, coefficients of variation and the $10^{th}$ and $90^{th}$ percentiles.

| | | | Expense ratio (net of 12b-1 Fees) | | | | |
|---|---|---|---|---|---|---|---|
| | **Average number** | **Size (millions)** | **Average value** | **Standard deviation** | **Coefficient of variation** | **$10^{th}$ percentile** | **$90^{th}$ percentile** |
| Aggressive growth | 122 | 670.50 | 1.24 | 0.45 | 0.36 | 0.80 | 1.75 |
| Growth | 199 | 495.43 | 1.04 | 0.29 | 0.28 | 0.70 | 1.40 |
| Growth and income | 456 | 1223.09 | 0.83 | 0.35 | 0.42 | 0.35 | 1.24 |
| Income and growth | 654 | 899.84 | 1.01 | 0.32 | 0.32 | 0.66 | 1.38 |
| Midcaps | 98 | 1184.49 | 0.90 | 0.26 | 0.29 | 0.64 | 1.21 |
| Small cap | 394 | 377.46 | 1.15 | 0.33 | 0.28 | 0.80 | 1.50 |
| **Total** | **1922** | **827.57** | **1.01** | **0.36** | **0.35** | **0.60** | **1.41** |

## Table 3
## Correlations between the independent variables in the variance equation

This table reports the correlation coefficients between the right-hand side variables in the variance equation of our heteroscedastic regression model (the p-values of tests against the null hypothesis of zero correlation are given in parentheses).

| | SIZE | ICSIZE | AGE | FR LOADS | 12B-1 | LEV LOADS | BACK LOADS | ALPHA$^2$ | DIST |
|---|---|---|---|---|---|---|---|---|---|
| SIZE | 1 | | | | | | | | |
| ICSIZE | 0.3590 *(0.000)* | 1 | | | | | | | |
| AGE | 0.1836 *(0.000)* | 0.0047 *(0.437)* | 1 | | | | | | |
| FR_LOADS | 0.0412 *(0.000)* | 0.0686 *(0.000)* | 0.0481 *(0.000)* | 1 | | | | | |
| 12B-1 | -0.2070 *(0.000)* | 0.1760 *(0.000)* | -0.0714 *(0.000)* | -0.0575 *(0.000)* | 1 | | | | |
| LEV_LOADS | -0.1423 *(0.000)* | 0.0875 *(0.000)* | -0.0567 *(0.000)* | -0.0377 *(0.000)* | 0.4779 *(0.000)* | 1 | | | |
| BACK_LOADS | -0.0746 *(0.000)* | 0.1514 *(0.000)* | 0.0179 *(0.003)* | 0.0558 *(0.000)* | 0.4342 *(0.000)* | -0.1981 *(0.000)* | 1 | | |
| ALPHA$^2$ | -0.0130 *(0.033)* | -0.0521 *(0.000)* | -0.0456 *(0.000)* | -0.0125 *(0.041)* | 0.0007 *(0.904)* | 0.0086 *(0.161)* | -0.0053 *(0.382)* | 1 | |
| DIST | -0.0056 *(0.359)* | -0.0181 *(0.003)* | -0.0065 *(0.284)* | -0.0121 *(0.047)* | -0.0088 *(0.148)* | -0.0032 *(0.600)* | -0.0085 *(0.163)* | 0.0355 *(0.000)* | 1 |

## Table 4
## Fee dispersion at the fund family level and at the individual fund level

This table reports the results of a univariate ANOVA in which the dependent variable is the expense ratio net of the 12b-1fees. On the right-hand side we consider dummy variables for year (*Year*), fund investment objective (*Strategy*), the interaction between the two (*Year*strategy*), fund family (*Family*) and the interaction between fund family and strategy (*Family*strategy*). The last column reports the percentage of fee dispersion explained by a given variable measured as the ratio of the sum of the squared errors.

| Source | Sequential sum of squared errors | Degrees of freedom | Mean squared error | F | P-value | % of dispersion |
|---|---|---|---|---|---|---|
| Model | 3907.498 | 1855 | 2.106 | 28.85 | 0.000 | 54.0 |
| | | | | | | |
| Year | 34.299 | 15 | 2.287 | 31.32 | 0.000 | 0.5 |
| Strategy | 909.184 | 5 | 181.837 | 2490.63 | 0.000 | 12.6 |
| Year*strategy | 25.410 | 73 | 0.348 | 4.77 | 0.000 | 0.4 |
| Family | 2354.518 | 631 | 3.731 | 51.11 | 0.000 | 32.5 |
| Family*strategy | 584.086 | 1131 | 0.516 | 7.07 | 0.000 | 8.1 |
| | | | | | | |
| Residual | 3331.959 | 45638 | 0.073 | | | 46.0 |
| **Total** | **7239.456** | **47493** | **0.152** | | | **100.0** |

## Table 5
## Summary statistics for investment objectives

This table reports the results of a test of the dispersion of expense ratios (net of 12-b1 fees) within fund families with more than five funds with the same investment objective. The second column reports the percentage of family/strategy groups with a dispersion level which is significantly lower (at the 5% level) than the dispersion level of all of the funds in the same category for the given year. The third column reports the percentage of the number of funds managed by low-dispersion families. The last two columns report the weighted average (the difference between fee dispersion within low-dispersion family/strategy groups and the strategy-wide dispersion divided by the strategy-wide dispersion level).

| Investment objective | % of families with low dispersion | % of funds managed by low-dispersion families | Weighted average dispersion reduction | |
|---|---|---|---|---|
| | | | Equally weighted | Weighted on no. of funds |
| Aggressive growth | 72.04 | 75.84 | -72.32 | -71.52 |
| Midcaps | 43.87 | 46.86 | -61.31 | -56.74 |
| Growth and income | 42.92 | 45.26 | -64.72 | -59.50 |
| Growth | 52.31 | 56.41 | -58.84 | -51.96 |
| Income and growth | 61.29 | 62.96 | -72.45 | -69.03 |
| Small caps | 51.62 | 53.72 | -64.01 | -58.91 |
| **Total sample** | **50.51** | **53.27** | **-63.36** | **-57.21** |

## Table 6
## Determinants of the expected fee

This table reports the results of the mean equation from the maximum likelihood estimation of a multiplicative heteroscedastic regression. The dependent variable is the expense ratio net of the 12b-1 fees. The right-hand side variables capture: (1) *The past performance of the fund*: the 36-month return of the fund gross of the expense ratio (*RET*) in models A.1–A.3, the fund's return ranking in relation to other funds with the same investment objective (*RANK*) in models B.1–B.3 and the 36-month 4-factor alpha estimated with the standard Fama, French and Carhart factors (*ALPHA*) in models C.1–C.3; (2) *The cost structure of the investment company*: the natural logarithm of the fund size (*SIZE*), the natural logarithm of the fund complex size (*ICSIZE*) and a dummy variable for funds of at least five years of age (*AGE*); (3) *The catering of the fund to heterogeneous clientele*: dummy variables for front-end (*FR_LOADS*), back-end (*BACK_LOADS*) and level load (*LEV_LOADS*) funds, the actual distribution fees charged by the fund (12b-1) and the ratio between the assets under management at the end of year *t-1* and the maximum value of the assets under management during year *t-1* (Q/MAX); (4) *The portfolio structure of the fund*: the betas of a standard Fama, French and Carhart 4-factor model estimated over the 36 months (*MKT, SMB, HML, UMD*), the 36-month standard deviation of the portfolio (*DEV*), the $R^2$ of a 4-factor model (*RSQ*) estimated over 36 months and the turnover of the fund (*TRN*). All the explanatory variables are lagged with regard to the year when the dependent variable is measured. All the models include investment objective fixed effects. In order to properly address possible time-related effects, the heteroscedastic model is estimated year-by-year *à la* Fama and MacBeth (1973). The standard errors have been estimated by clustering the residuals at the fund level. T-statistics are reported in brackets. ***, ** and * represent significance at the 1%, 5% and 10% levels.

*[Table follows on the next page]*

**Table 6** *(Description on previous page)*

| | (A.1) | (A.2) | (A.3) | (B.1) | (B.2) | (B.3) | (C.1) | (C.2) | (C.3) |
|---|---|---|---|---|---|---|---|---|---|
| Constant | 1.859*** | 1.941*** | 2.262*** | 1.901*** | 1.95*** | 2.28*** | 1.869*** | 1.959*** | 2.261*** |
| | (129.204) | (103.940) | (34.722) | (72.894) | (84.379) | (33.129) | (104.034) | (99.420) | (35.220) |
| RET | -0.069 | -0.006 | 0.041 | | | | | | |
| | (-1.278) | (-0.113) | (1.036) | | | | | | |
| RANK | | | | -0.067** | 0.001 | -0.021 | | | |
| | | | | (-1.681) | (0.041) | (-0.805) | | | |
| ALPHA | | | | | | | 3.108*** | 4.539*** | 3.489*** |
| | | | | | | | (2.771) | (4.113) | (3.675) |
| SIZE | -0.059*** | -0.050*** | -0.047*** | -0.058*** | -0.05*** | -0.046*** | -0.060*** | -0.051*** | -0.047*** |
| | (-20.450) | (-23.223) | (-23.809) | (-19.048) | (-18.535) | (-18.479) | (-20.334) | (-19.185) | (-19.297) |
| ICSIZE | -0.042*** | -0.048*** | -0.043*** | -0.042*** | -0.048*** | -0.043*** | -0.041*** | -0.048*** | -0.043*** |
| | (-22.822) | (-21.984) | (-33.600) | (-22.261) | (-24.580) | (-36.210) | (-21.907) | (-23.941) | (-36.567) |
| AGE | 0.015** | -0.001 | 0.004 | 0.014* | -0.001 | 0.005 | 0.016** | -0.001 | 0.007 |
| | (1.690) | (-0.163) | (0.604) | (1.530) | (-0.101) | (0.668) | (1.854) | (-0.089) | (0.899) |
| FR_LOADS | | 0.069*** | 0.067*** | | 0.069*** | 0.067*** | | 0.068*** | 0.067*** |
| | | (11.311) | (11.551) | | (10.980) | (11.599) | | (11.393) | (11.684) |
| LEV_LOADS | | 0.093*** | 0.081*** | | 0.094*** | 0.081*** | | 0.091*** | 0.078*** |
| | | (4.389) | (3.319) | | (4.554) | (3.271) | | (4.558) | (3.193) |
| BACK_LOADS | | 0.123*** | 0.120*** | | 0.123*** | 0.119*** | | 0.122*** | 0.119*** |
| | | (7.774) | (7.496) | | (7.854) | (7.452) | | (7.836) | (7.493) |
| 12b-1 | | -2.862 | -2.815 | | -2.838 | -2.838 | | -2.650 | -2.828 |
| | | (-1.246) | (-1.208) | | (-1.235) | (-1.231) | | (-1.149) | (-1.226) |
| Q/MAX | | -0.146*** | -0.118*** | | -0.142*** | -0.111*** | | -0.158*** | -0.128*** |
| | | (-10.270) | (-8.846) | | (-9.318) | (-7.716) | | (-11.664) | (-7.414) |
| MKT | | | -0.018 | | | -0.019 | | | -0.013 |
| | | | (-0.764) | | | (-0.844) | | | (-0.542) |
| SMB | | | 0.105*** | | | 0.104*** | | | 0.104*** |
| | | | (9.117) | | | (8.463) | | | (9.793) |
| HML | | | -0.024** | | | -0.016* | | | -0.017* |
| | | | (-1.894) | | | (-1.343) | | | (-1.359) |
| UMD | | | -0.017 | | | -0.017 | | | -0.010 |
| | | | (-0.724) | | | (-0.761) | | | (-0.433) |
| RSQ | | | -0.656*** | | | -0.660*** | | | -0.645*** |
| | | | (-8.246) | | | (-8.009) | | | (-8.240) |
| DEV | | | 1.467*** | | | 1.305*** | | | 1.381*** |
| | | | (2.869) | | | (2.537) | | | (2.671) |
| TRN | | | 0.058*** | | | 0.058*** | | | 0.060*** |
| | | | (13.203) | | | (13.946) | | | (13.003) |
| *Year control variables (CVs)* | *Yes* | *Yes* | *Yes* | *Yes* | *Yes* | *Yes* | *Yes* | *Yes* | *Yes* |
| *Investment objective CVs* | *Yes* | *Yes* | *Yes* | *Yes* | *Yes* | *Yes* | *Yes* | *Yes* | *Yes* |
| Observations | 26922 | 26922 | 26922 | 26922 | 26922 | 26922 | 26922 | 26922 | 26922 |
| R-squared | 0.332 | 0.365 | 0.423 | 0.333 | 0.365 | 0.423 | 0.332 | 0.366 | 0.423 |

## Table 7

## Univariate tests for search costs and residual fee dispersion

This table reports the results of F-tests of the equality of variance of residual fees across different samples. Residual fees are defined as the residuals of model C.3 in Table 6. In order to avoid bias due to residual time-dependent cross-correlation, we run the model year-by-year. This table reports the standard deviations of residual fees for funds with high search costs and funds with low search costs as well as the variance ratio and the F-stat relative to the test of the null hypothesis of the ratio being equal to one. We use five variables as proxies for search costs. The first three are related to fund visibility: natural logarithms of fund size and investment company size and a dummy variable for funds which are at least five years old. For the size-related variables, we define as high-search cost funds those in the lowest quartile and as low-search cost funds those in the highest quartile, while for the dummy variable for age, we considered old funds as being low-search cost and young funds as being high-search cost. The last two variables are related to the fund sales effort: front-end loads and 12b-1 fees. We defined as having high search costs the funds that do not charge this kind of fee, and as having low search costs the funds that do. For every test, we report the F-stat. ***, ** and * represent significance at the 1%, 5% and 10% levels.

| | High search cost | Low search cost | Variance ratio | F-stat |
|---|---|---|---|---|
| **Fund visibility measures** | | | | |
| **Log of fund size** | 0.304 | 0.225 | 1.352*** | 1.827 |
| **Log of investment Company size** | 0.295 | 0.239 | 1.230*** | 1.513 |
| **Age** | 0.279 | 0.254 | 1.099*** | 1.208 |
| **Sales effort measures** | | | | |
| **Front loads** | 0.267 | 0.235 | 1.134*** | 1.286 |
| **12b-1 fees** | 0.281 | 0.238 | 1.180*** | 1.392 |

## Table 8
## Residual fee dispersion

This table reports the results of the variance equation from the maximum likelihood estimation of a multiplicative heteroscedastic regression. The dependent variable in the variance equation is the natural logarithm of the squared values of the residuals of the mean equation. The right-hand side variables capture: (1) *The visibility of the fund*: the natural logarithm of the fund size (*SIZE*), the natural logarithm of the fund complex size (*ICSIZE*) and a dummy variable which is equal to one if the fund has more than five years of past performance (*AGE*); (2) *The sales effort*: a dummy variable for front-end loads (*FR_LOADS*) and the actual distribution fees charged by the fund (*12b-1*). In models A.4 and B.4, we also control for: (3) *Switching costs*: dummy variables for back-end load (*BACK_LOADS*) and level-load funds (*LEV_LOADS*); (4) *Heterogeneity* of the managed portfolios including the squared value of the alpha of a 4-factor model (*ALPHA*$^2$) and the sum of the squared values of the excess values of the beta of a four-factor model (*DIST*). We also use year and investment objective fixed effects for all of the specifications. All of the explanatory variables are lagged with regard to the year when the dependent variable is measured. The structure of the mean equation is that of model C.3 in Table 6, except for model B.4 for which we use a piecewise specification in which all of the continuous variables in the mean equation are broken into deciles. In model C.4, we use the two-stage version of the Harvey (1976) model and cluster the residuals both at the year and at the fund level. In model D.4, the mean and the variance equations are estimated separately on a year-by-year basis, while in model E.4 we run a year-by-year simultaneous estimation of the two. In both cases, the table reports Fama and MacBeth's (1973) coefficients and t-statistics for the variance equation. The standard errors have been estimated in the first five models by clustering the residuals at the fund level. T-statistics are reported in brackets. ***, ** and * represent significance at the 1%, 5% and 10% levels.

| | (A.1) | (A.2) | (A.3) | (A.4) | (B.4) | (C.4) | (D.4) | (E.4) |
|---|---|---|---|---|---|---|---|---|
| CONSTANT | -1.153*** | -2.029*** | -0.948*** | -1.028*** | -0.994*** | -3.476*** | -3.348*** | -1.329*** |
| | (-3.383) | (-7.344) | (-2.970) | (-3.593) | (-3.148) | (-21.371) | (-21.992) | (-7.470) |
| SIZE | -0.0872*** | | -0.126*** | -0.128*** | -0.136*** | -0.0765*** | -0.0807*** | -0.099*** |
| | (-4.648) | | (-6.594) | (-6.763) | (-7.110) | (-4.463) | (-5.629) | (-9.048) |
| ICSIZE | -0.0635*** | | -0.0430* | -0.0393* | -0.0545*** | -0.00517 | -0.0082 | -0.058*** |
| | (-2.889) | | (-1.910) | (-1.862) | (-2.712) | (-0.345) | (-0.804) | (-6.012) |
| AGE | -0.169*** | | -0.172*** | -0.172*** | -0.155*** | -0.182*** | -0.103 | -0.130** |
| | (-3.898) | | (-4.025) | (-4.063) | (-3.601) | (-3.411) | (-1.362) | (-1.946) |
| FR_LOADS | | -0.253*** | -0.290*** | -0.298*** | -0.255*** | -0.259*** | -0.142*** | -0.253*** |
| | | (-2.845) | (-3.797) | (-4.025) | (-3.555) | (-4.358) | (-4.119) | (-7.483) |
| 12B-1 | | -34.65*** | -43.280*** | -55.99*** | -46.86*** | -51.61*** | -68.890*** | -74.275*** |
| | | (-4.136) | (-5.623) | (-5.440) | (-4.543) | (-5.620) | (-8.669) | (-8.333) |
| LEV_LOADS | | | | 0.121 | 0.109 | -0.0346 | 0.184 | 0.020 |
| | | | | (0.934) | (0.871) | (-0.268) | (1.681) | 0.0728 |
| BACK_LOADS | | | | 0.187*** | 0.147** | 0.0443 | 0.482*** | 0.275** |
| | | | | (2.845) | (2.174) | (0.474) | (3.227) | (2.280) |
| ALPHA$^2$ | | | | 852.2* | 625.900 | 20.90 | 1.188** | 479.114 |
| | | | | (1.946) | (1.432) | (0.084) | (2.452) | (0.794) |
| DIST | | | | 0.0217*** | 0.00803 | 0.0186*** | 0.0599 | 0.146* |
| | | | | (3.322) | (1.352) | (12.443) | (0.757) | (1.333) |
| *Strategy control variables* | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *Time control variables* | Yes | Yes | Yes | Yes | Yes | Yes | No | No |
| *Specification of the mean equation* | Linear | Linear | Linear | Linear | Piecewise | Linear | Linear | Linear |

## Table 9
## Economic significance

This table reports the expected fee and the mean absolute residual fee calculated with the coefficients estimated in model A.4 of Table 8 for the mean equation and the variance equation respectively, together with the ratio of the expected to the residual fee. Fees are calculated using the median value for each independent variable. The results are averaged across years and investment objective groups. For every search cost proxy variable, we estimate two values of the fees: (1) *High search costs: SIZE*, *ICSIZE* and *12b-1* are at the fifth percentile of their distribution, the *AGE* and *FR_LOADS* dummy variables are equal to zero and the *BACK_LOADS* and *LEV_LOADS* dummy variables are equal to one; and (2) *Low search costs: SIZE*, *ICSIZE* and *12b-1* are at the 95$^{th}$ percentile of their distribution, the *AGE* and *FR_LOADS* dummy variables are equal to one and the *BACK_LOADS* and *LEV_LOADS* dummy variables are equal to zero. The last two columns report the percentage change of the residual fee and the ratio of the residual to the expected fee if a fund moves from the low to the high search cost group.

| | Expected fee | | Residual fee | | Ratio | | Residual fee | Ratio |
|---|---|---|---|---|---|---|---|---|
| | High SC | Low SC | High SC | Low SC | High SC | Low SC | % change | % change |
| SIZE | 1.046 | 0.821 | 0.338 | 0.240 | 0.324 | 0.292 | 41.0 | 10.8 |
| ICSIZE | 1.167 | 0.839 | 0.321 | 0.279 | 0.275 | 0.333 | 14.8 | -17.5 |
| AGE | 0.940 | 0.952 | 0.319 | 0.293 | 0.339 | 0.308 | 9.0 | 10.3 |
| FR_LOADS | 0.952 | 1.009 | 0.293 | 0.252 | 0.308 | 0.250 | 16.1 | 23.1 |
| 12b-1 | 0.948 | 0.964 | 0.314 | 0.237 | 0.332 | 0.246 | 32.3 | 34.6 |
| LEV_LOADS | 0.999 | 0.952 | 0.311 | 0.293 | 0.311 | 0.308 | 5.9 | 1.2 |
| BACK_LOADS | 1.035 | 0.952 | 0.322 | 0.293 | 0.311 | 0.308 | 8.9 | 1.0 |

## Table 10
## Asymmetry of residual fee dispersion

This table reports the results of a multinomial logistic regression in which the response variable is able to assume three different values depending on whether the residual fee of the fund is (1) in the top quintile of the distribution; (2) in the bottom quintile of the distribution; or (3) in the central part of the distribution (the base case). The residual fee has been estimated using model C.3 in Table 6 via a quintile regression approach. In order to avoid bias due to residual time-dependent cross-correlations, we run the model on a year-by-year basis. The right-hand side variables of the logistic model capture: (1) *The visibility of the fund*: the natural logarithm of the fund size (*SIZE*), the natural logarithm of the fund complex size (*ICSIZE*) and a dummy variable for funds of at least five years of age (*AGE*); (2) *The sales effort*: a dummy variable for front-end loads (*FR_LOADS*) and the actual distribution fees charged by the fund (*12b-1*); (3) *Switching costs*: dummy variables for back-end load (*BACK_LOADS*) and level load (*LEV_LOADS*) funds. We also used year and investment objective control variables. All the explanatory variables are lagged with regard to the year when the dependent variable is measured. The third column reports the difference between the coefficients in the first two columns together with a chi-squared statistic on this difference being different from zero. ***, ** and * represent significance at the 1%, 5% and 10% levels.

| | (1)<br>Top quintile | (2)<br>Bottom quintile | (3)<br>Difference |
|---|---|---|---|
| SIZE | -0.103*** | -0.0549*** | -0.048*** |
| | (-8.963) | (-4.814) | (11.690) |
| ICSIZE | 0.0123 | 0.00453 | 0.008 |
| | (1.474) | (0.544) | (0.590) |
| AGE | -0.102** | -0.228*** | 0.126** |
| | (-2.278) | (-5.139) | (5.560) |
| FR_LOADS | -0.161*** | -0.365*** | 0.204*** |
| | (-4.483) | (-9.799) | (20.500) |
| 12b-1 | -44.140*** | -71.65*** | 27.510*** |
| | (-7.088) | (-11.348) | (12.930) |
| LEV_LOADS | -0.0531 | 0.0948 | -0.148 |
| | (-0.609) | (1.055) | (1.810) |
| BACK_LOADS | 0.0880* | 0.154*** | -0.066 |
| | (1.867) | (3.283) | (1.350) |