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Essays on Mutual Funds

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PhD in Finance

Supervisor:
PhD António Freitas Miguel, Professor Associado com Agregação,
ISCTE-IUL

December, 2021

BUSINESS
SCHOOL

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Resumo

Esta tese estuda fundos de investimento em ações geridos de forma ativa em três artigos separados e independentes. O primeiro artigo analisa a importância da afiliação dos fundos de investimento com grandes famílias para relação fluxo-desempenho a nível internacional, o segundo e o terceiro artigos estudam diferenças entre fundos norte-americanos quantitativos e não quantitativos.

No primeiro artigo, apresentado no Capítulo 2, usamos dados de 33 países para estudar o impacto que a afiliação dos fundos de investimento com grandes famílias tem na relação fluxo-desempenho. Os resultados mostram que este impacto depende do grau de sofisticação dos investidores de cada país. Enquanto que os investidores menos sofisticados são persuadidos pela grande visibilidade e pelas estratégias dos fundos afiliados com famílias de grande dimensão, isso não acontece com os investidores mais sofisticados. A afiliação com grandes famílias aumenta a convexidade da relação fluxo-desempenho em países onde os investidores são menos sofisticados, mas essa convexidade diminui em países com investidores mais sofisticados. Os resultados deste estudo são importantes para investidores, sociedades gestoras e reguladores, uma vez que a sensibilidade ao fluxo-desempenho determina os ativos sob gestão, o nível de comissões cobradas, a maior ou menor assunção de risco e, assim, o desempenho do fundo.

O segundo artigo, apresentado no Capítulo 3, tem como objetivo estudar as diferenças na sensibilidade do fluxo-desempenho entre fundos de ações norte-americanos quantitativos e não-quantitativos geridos de forma ativa. Os resultados encontrados mostram que, tal como os investidores em fundos não quantitativos, os investidores em fundos quantitativos investem mais nos fundos com melhor desempenho do que vendem as suas participações nos fundos que apresentam fraco desempenho. Quando analisamos as diferenças na convexidade do fluxo-desempenho entre fundos quantitativos e não quantitativos, encontramos homogeneidade em vez de heterogeneidade nas preferências dos investidores. Os nossos resultados são importantes, uma vez que sugerem que quaisquer diferenças encontradas nas comissões cobradas, na assunção de risco ou no desempenho entre fundos quantitativos e não quantitativos provêm dos gestores de fundos e das decisões e estratégias das sociedades gestoras, e não das preferências dos investidores.

No terceiro artigo, apresentado no Capítulo 4, estudamos as diferenças de *Active Share* entre fundos de ações norte-americanos quantitativos e não-quantitativos. Os resultados mostram que o *Active Share* é mais baixo nos fundos quantitativos. Ao testarmos as diferenças no impacto do *Active Share* no desempenho de fundos quantitativos e não quantitativos, verificamos que, tal como expresso na literatura, o *Active Share* prevê o desempenho dos fundos não quantitativos, mas reduz o desempenho dos fundos quantitativos. Essa diferença permanece estatística e economicamente importante para fundos com diferentes *benchmarks*.

Classificação JEL: G11, G15, G23, G40

Palavras-chave: Fundos de investimento, Dimensão da família dos fundos, Análise quantitativa, Sensibilidade fluxo-desempenho, *Active Share*.

Abstract

This thesis addresses the research on actively managed mutual funds in three separate and self-contained papers. The first paper studies how a fund's affiliation with large families shapes the flow–performance relationship internationally, and the second and third papers study differences between quantitative and non–quantitative US funds.

In the first paper, presented in Chapter 2, we use data from 33 countries to study how a fund's affiliation with large families shapes the flow–performance relationship internationally. Our results show that the effect of family size on the fund flows' response to performance depends on the sophistication of investors in a country. While less sophisticated investors are persuaded by the great visibility and strategies of funds that are affiliated with large and established families, more sophisticated investors are not. Affiliation with a large family increases the convexity of the flow–performance relationship in countries where investors are less sophisticated, but decreases this convexity in countries with more sophisticated investors. These results are important for investors, mutual fund companies and regulators because the flow–performance sensitivity determines the assets under management, the level of fees, risk–taking, and the performance of the fund.

The second paper, presented in Chapter 3, aims to study differences in the flow-performance sensitivity between quantitative and non–quantitative actively managed US equity funds. We show that quantitative investors buy more top performing funds and sell less poor performers, which is no different from the main findings in the mutual fund literature. When testing for differences in flow-performance convexity between quantitative and non–quantitative funds, we find homogeneity rather than heterogeneity in investors preferences. Our results are important as they suggest that any differences to be found in fees, risk-taking or performance between quantitative and non-quantitative funds originate from fund managers and fund management companies' decisions and strategies rather from investors preferences.

In the third paper, presented in Chapter 4, we study differences in *Active share* between quantitative and non–quantitative actively managed US equity funds. Our results show that the *Active share* is lower for quantitative funds. When testing for differences in the impact of *Active share* on the performance of quantitative and non–quantitative funds we find that, consistent with the literature, *Active share* predicts the performance of non–quantitative funds, but decreases the performance of quantitative funds. This difference remains statistically and economically important for funds with different benchmark types.

JEL classification: G11, G15, G23, G40
Keywords: Mutual funds, Fund family size, Quantitative analysis, Mutual fund flow-performance sensitivity, Active share.

Index

List of Tables

List of Figures

1. Introduction

This thesis is organized into three self-contained empirical papers. In the first paper, we use an international sample of mutual funds to study the role of family size on the flow–performance relationship. The second and third paper focus on quantitative funds, i.e., those funds that use mathematical and statistical models as well as automated algorithms to make investment decisions and execute trades.

The mutual fund industry outside the US has grown significantly in recent years. The world share of assets under management outside the US grew from 38% in 1997 to about 52% in 2015 (European Fund and Asset Management Association [EFAMA], 2015; Investment Company Institute [ICI], 2015). However, the mutual fund literature shows that the US–based evidence does not apply to other environments, notably countries where financial markets are less developed and investors less sophisticated. Our first study aims to explain differences in the way family size shapes the flow–performance relationship across countries. We use a global sample of mutual funds from 33 countries to study cross–country variation in the influence of family size on investor decision–making. Using a sample of countries with investors at different stages of sophistication sheds light on the likely evolution of the impact of family size on the flow–performance convexity in a given country.

We posit that the sophistication of the investors in the country affects the impact of family size on the flow–performance sensitivity. To measure flow performance sensitivity, we use a piecewise–linear specification allowing for different flow–performance sensitivities at different levels of performance (e.g., Sirri & Tufano, 1998). We run panel regressions to examine the impact of family size on the sensitivity of flows to past performance. We calculate robust t–statistics that are twoway–clustered by fund and quarter (Petersen, 2009). We use weighted least squares to avoid giving excessive weight to countries in our sample with a greater fraction of the number of funds, weighting each fund by the inverse of the number of funds in that country–quarter. Additionally, we report the change in convexity due to a fund's affiliation with large families and p–values from a Wald–test, testing whether this change is statistically significant.

This paper contributes to the mutual fund literature in several ways. To the best of our knowledge, we are the first to study the effect of fund family size on the flow–performance relationship in an international context. Second, we show that there are marked differences in how a fund's affiliation with large families shapes the flow–performance relationship across countries and that the US–based evidence does not apply universally. The US evidence holds for countries with more sophisticated investors but not for countries where investors are less sophisticated. Moreover, our tests show that the observed differences in the impact of family size on the convexity of the flow–performance across countries are not only statistically significant but also economically relevant. Third, we contribute to the growing literature studying the investment decisions of mutual fund investors to determine whether they are sophisticated and whether they act rationally. Finally, we also add to literature investigating the family−based structure of the mutual fund industry and its implications for the investment decisions of individual investors.

Quantitative funds have come to play an increasing role in the mutual fund industry. Advances in machine learning and big data analysis together with investor's belief that quantitative models are less susceptible to cognitive errors and biases have contributed to the increasing popularity of quantitative funds. While emotions and cognitive errors, influence individuals' trading decisions, quantitative funds remove the emotional and cognitive input from the decision process, as they rely on objective mathematical and statistical models to select securities. Despite the rising interest of investors in quantitative funds, very little is known about the impact of quantitative analysis on the mutual fund industry and on the overall market stability.

Our second paper sheds light on differences in the flow-performance sensitivity between quantitative and non–quantitative actively managed US equity funds. We use two different approaches to test for differences in the flow-performance sensitivity between quantitative and non-quantitative investors, using both relative and absolute fund flow and measuring performance with raw returns and four-factor alpha. We also run our tests with both quarterly and annual data. In the first approach, we examine flows of funds for bottom and top performance quintiles, like in Berk and Tonks (2007). At the end of each period, we start by sorting funds into quintiles based on their raw returns over the previous year. We then compute the average relative and absolute net flow over the period of the quintile formation and test whether it is statistically different from zero. We next follow Berk and Tonks (2007) and Del Guercio and Reuter (2014) and use a regression–based approach that allows to control for different fund characteristics when investigating differences in the flow–performance sensitivity between quantitative and non-quantitative funds.

This paper makes important contributions to the literature. We contribute to the literature on the mutual fund flow-performance sensitivity by being the first to study the flow performance relationship for quantitative funds. Additionally, we contribute to the better understanding of quantitative funds, as the literature on this type of funds is rather scarce. By showing no differences in the flow-performance sensitivity of quantitative and non-quantitative investors our results indicate homogeneity rather than heterogeneity in investors preferences.

In the third paper, we study differences in *Active share* between quantitative and non–quantitative funds. We specifically start by understanding how active quantitative funds are and whether these funds deviate more or less than non–quantitative funds from their benchmarks. Next, and more important, we look at the impact of *Active share* on the performance of quantitative and non–quantitative funds. The main research question of our study is therefore whether there are differences in the impact of *Active share* on the performance of quantitative and non–quantitative funds.

To study differences in *Active share* between quantitative and non–quantitative funds, we start by running a panel regression of *Active share* on a quantitative dummy variable. Next, we add a number of lagged controls known to influence fund *Active share* to the regression. To understand whether fund and market characteristics affect mutual fund *Active share* differently for quantitative and non–quantitative funds and test for the significance of these differences, we rerun a panel regression and remove the quantitative dummy variable from the regression. To test for differences in *Active share* between quantitative and non–quantitative funds, we follow Del Guercio and Reuter (2014), and pool quantitative and non–quantitative funds in a single regression. We then run a t–test to determine the differences in the coefficients on prior–period four–factor alpha (and prior–period control variables) between quantitative and non–quantitative funds. These regressions include time fixed effects and benchmark fixed effects, and we account for cross–sectional correlation and for the time series autocorrelation within funds computing robust standard errors clustered by fund and time. Finally, because the literature has shown differences in *Active share* between fund benchmark types (e.g., Frazzini et al., 2016), we run additional tests, where we add to our previous regressions dummy variables for the different benchmark types. We conduct a number of tests to confirm the robustness of our results. We find that our results do not change.

Our study makes significant contributions. First, we add to the scarce literature on quantitative funds. Second, to the best of our knowledge, we are the first to study *Active share* for quantitative funds. Third, our results have significant implications for both investors and practitioners. *Active share* has become a widely used concept in fund analysis and, consistent with the main findings in the literature, market participants believe that the attempt to outperform a fund's benchmark (i.e., to create value to investor) depends on fund manager's ability to deviate from the benchmark. Our findings indicate that not only quantitative funds deviate less from their benchmarks but that greater benchmark differentiation results in underperformance rather than outperformance for these funds. These conclusions suggest that quantitative funds do not adequately diversify portfolios and, contrary to investors' expectations, quantitative funds do not overcome the inability of human–managed active funds to beat their benchmarks. Moreover, our results in the second paper find no differences in the flow-performance sensitivity of quantitative and non-quantitative investors, which indicates that the observed differences in *Active share* originate from fund managers and fund management companies' decisions and strategies and cannot be attributed to differences in investors preferences.

2. Does mutual fund family size matter? International evidence

Abstract: We use data from 33 countries to study how a fund's affiliation with large families shapes the flow–performance relationship internationally. Our results show that the effect of family size on the fund flows' response to performance depends on the sophistication of investors in a country. While less sophisticated investors are persuaded by the great visibility and strategies of funds that are affiliated with large and established families, more sophisticated investors are not. Affiliation with a large family increases the convexity of the flow–performance relationship in countries where investors are less sophisticated, but decreases this convexity in countries with more sophisticated investors. These results are important for investors, mutual fund companies and regulators because the flow–performance sensitivity determines the assets under management, the level of fees, risk–taking, and the performance of the fund.

JEL classification: G15, G23

Keywords: Mutual funds, Flow–performance relationship, Fund family size, Investor sophistication.

2.1. Introduction

A fund family is a group of funds managed and marketed by the same company. Virtually all funds are part of a fund family (Brown & Wu, 2016).[1] Family ties bind funds in many different ways, affecting how mutual funds are managed and also how mutual fund investors allocate their money (e.g., Massa, 1998, 2003; Gaspar et al., 2006; Huang et al., 2007). Family size increases fund visibility and brand awareness (e.g., Sirri & Tufano, 1998). The literature also shows that fund families exploit the patterns in investor behavior and fund flows to increase their assets under management and that these family–level strategies are more common in large fund complexes (e.g., Sirri & Tufano 1998; Chen et al., 2004; Gaspar et al., 2006; Bhattacharya et al., 2013).

We use a global sample of mutual funds from 33 countries to study cross–country variation in the influence of family size on investor decision–making. More specifically, we focus on the effect of family size on the convexity of the flow–performance sensitivity across countries. Prior research on this relationship concentrates on the US market, and there is a lack of evidence on how family size affects the flow–performance convexity internationally.[2]

The mutual fund literature shows that the US–based evidence does not apply to other environments, notably countries where financial markets are less developed and investors less sophisticated; it is therefore particularly important to understand cross–country variation in the relation between family size and flow–performance convexity.[3, 4] Using a sample of countries with investors at different stages of sophistication sheds light on the likely evolution of the impact of family size on the flow–performance convexity in a given country, which would be difficult to study in a single country setting. Studying mutual funds internationally is also

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[1] Massa (2003, p. 249) classifies the increasing number of funds differentiated into market categories and belonging to only a few families as "*the most glaring stylized fact about mutual fund industry*".

[2] The literature on the impact of family size on flows outside the US is quite scarce. Benson et al. (2008) study the role of fund families in the determination of money flows to Australian funds and Jank and Wedow (2013) look at the effect of fund families in purchases and redemptions of German equity funds, but there are no cross–country studies examining how family size affects flows.

[3] Many studies show that there are statistically and economically significant differences in the conduct of mutual funds around the world and that the features of the US fund industry are not necessarily the same as those of other countries. The seminal studies by Khorana et al. (2005, 2009) find differences in fund size and fees across countries, respectively. Ferreira et al. (2012, 2013, 2019) study alterations in the flow–performance relationship, mutual fund performance, and mutual fund persistence, respectively. Miguel (2021) finds differences in how fund flows eliminate future abnormal performance and persistence across countries. Keswani et al. (2020) use a sample of 25 countries to show that cultural differences explain differences in the flow–performance sensitivity, fund performance, and fund risk–taking.

[4] Ferreira et al. (2012) study differences in the flow–performance sensitivity around the world, but their work does not examine the impact of mutual fund family size on the flow–performance relationship.

important given the significant growth of the mutual fund industry outside the US in recent years. The world share of assets under management outside the US grew from 38% in 1997 to about 52% in 2015 (EFAMA, 2015; ICI, 2015).

Different studies address the role of fund families in the mutual fund industry. Evidence indicates that the interests of fund families and investors are not always aligned. Chevalier and Ellison (1997) argue that this misalignment is a classic example of an agency problem. As most fees are proportional to funds' managed assets, the main goal of fund families is to maximize their assets under management rather than maximize risk–adjusted performance. Massa (1998) argues that fund families use market segmentation and fund proliferation as marketing strategies to exploit investors' heterogeneity. Khorana and Servaes (1999, 2012) show that large families are more likely to open new funds and that the family–level decision to start a new fund is strategically related to fee and flow maximization considerations. Massa (2003) finds that enhancing performance is not necessarily the optimal strategy for fund families, and that large complexes can still attract investors to poorly performing funds by reducing fees or increasing the number of funds within the family.

There is also evidence that fund complexes increase market share by actively exploiting performance spillover effects across funds within a family. Sirri and Tufano (1998) and Evans (2010) find that fund families choose to advertise only the best performing funds within the family to take advantage of the convexity of the flow–performance relationship.[5,6] Nanda et al. (2004) show that a star performer not only attracts flows to itself but also to the other funds in the family, which encourages families to create stars even at the expense of poorly performing funds. Gaspar et al. (2006) find that fund families strategically transfer performance from low–fee to high–fee funds in order to increase overall family profits. Bhattacharya et al. (2013) observe that affiliated funds–of–funds serve to provide liquidity support to other funds, as fund families use these funds to absorb liquidity shocks in the family.

While the family–base structure of the mutual fund industry allows large complexes to implement a number of family–level strategies designed to influence investors' allocation decisions, the literature also shows that family size leads to brand recognition, allowing for

[5] The convexity of the flow–performance relationship encourages fund families to produce top performers even if it harms the performance of other funds. The non–linear relation between mutual fund performance and flows is well documented in the literature, both in the US (e.g., Ippolito, 1992; Chevalier & Ellison, 1997; Goetzman & Peles, 1997; Sirri & Tufano, 1998; Del Guercio & Tkac, 2002; Huang et al., 2007) and around the world (Ferreira et al., 2012).

[6] The influence of advertisement on fund flows is amplified for larger fund complexes, as indicated by the results of Gallaher et al. (2015) that, at the family level, flows have a convex relation with advertising expenditure with a significant positive impact for high relative advertisers only.

investors' convenience. Investors can recognize large and established families such as Fidelity or Vanguard more easily (e.g., Capon et al.,1996; Goetzmann & Peles, 1997), which reduces participation costs (transaction costs and information costs) and also helps explain the asymmetric response of fund flows to past performance (Sirri & Tufano, 1998; Huang et al., 2007). On the other hand, the literature also shows that investors tend to concentrate on their investments within the same families of funds (Capon et al., 1996), and seem to pick a fund family first and then the individual fund in which to invest (Massa, 2003). These results are consistent with the findings that fund flows are "*dumb money*" that is driven by behavioral biases instead of rational learning about managerial skill (Frazzini & Lamont, 2008; Bailey et al., 2011).[7]

There is also evidence that more sophisticated investors are less likely to be influenced by behavioral tendencies, namely familiarity bias (Dumitrescu & Gil–Bazo, 2016). In the US, Gruber (1996) states that while sophisticated investors make decisions based on performance, *"disadvantaged"* investors are subjected to sales pressure or other constraints. Bailey et al. (2011) observe that sophisticated investors engage less in trend–chasing. Huang et al. (2007) argue that unsophisticated investors prefer to passively accumulate knowledge rather than actively seek out the relevant information about the fund. They also find that participation costs decrease with the level of investor sophistication and that more sophisticated investors have a less convex flow–performance relationship. Outside the US, Ferreira et al. (2012) use a worldwide sample to confirm that more sophisticated investors are less behaviorally biased. They observe significant differences in the flow–performance sensitivities across countries and show that investor sophistication explains these differences, as countries with more sophisticated investors present lower convexity in their flow–performance relationship.

The literature shows that fund family size influences investor behavior and that this behavior depends on investor sophistication. Prior studies also find that investor sophistication varies internationally and has implications for the way fund flows respond to past performance. Thus, we expect that family size is of varying importance to the flow–performance relationship across countries. Specifically, we posit that family size: (1) increases the convexity of the flow–performance sensitivity in countries where investors are less sophisticated; and (2) decreases the flow sensitivity to performance in countries with more sophisticated investors. Our evidence confirms these predictions. We show that family size affects the convexity of the flow–

[7] Bailey et al. (2011) also conclude that the familiarity behavioral bias leads to sub–optimal investment decisions.

performance sensitivity differently in countries with more and less sophisticated investors. Affiliation with large families increases (decreases) the convexity of the flow–performance relationship in countries where mutual fund investors are less (more) sophisticated.

Huang et al. (2007) state that sophisticated investors demand superior performance before investing in a fund, even when the fund is affiliated with a large family. They argue that sophisticated investors are less *naïve* and actively seek relevant information or they at least use the available information more rationally than other investors. However, it will be more difficult for unsophisticated investors to process the information and make objective judgments when allocating their money, as they will be more persuaded by the strategies of funds affiliated with large and established fund families. Hence, in countries with less sophisticated investors, we expect fund flows to flock disproportionally more to top performers affiliated with larger families, increasing the convexity of the flow–performance relationship at the top of the performance scale (*High–Mid*). On the other hand, in countries with more sophisticated investors, funds with larger families are expected to present a less convex flow–performance relationship at the upper end of the performance scale, i.e., these funds will increase the slope of the flow–performance relationship in the middle section and decrease it in the top section. Our tests confirm this prediction. We examine the impact of family size on the sensitivity of flows for countries with more sophisticated investors and those with less sophisticated investors separately and find that the flows in the latter are less sensitive to mid–range performers affiliated with larger families, while they flock to top performers that are part of larger families. In the case of countries with more sophisticated investors, family size increases the sensitivity to middle–range performance and decreases the sensitivity to top performers. When we test for differences in the flow–performance convexity between the two groups of countries, we find that family size significantly decreases (increases) the convexity of (*High–Mid*) performance range in countries with more (less) sophisticated investors. These differences are economically important as the increase in the convexity of (*High–Mid*) performance range that results from being affiliated with a large family in the group of countries with less sophisticated investors is approximately 20%; in contrast, affiliation with larger families decreases the convexity of (*High–Mid*) by more than 32% in countries with more sophisticated investors, regardless of the proxy used for measuring investor sophistication.

Ferreira et al. (2012) show that less sophisticated investors react less to poor performance. Thus, we expect less sophisticated investors to be even less sensitive to poorly–performing funds affiliated with a large family. We anticipate that poor performers belonging to a large family experience fewer outflows in countries with less sophisticated investors. Less sophisticated investors also react more to top performers, which increases the convexity of the flow–performance relationship between low– and high–performance ranges (*High–Low*). Our third hypothesis tests this prediction. We find that flows in countries with less sophisticated investors are less sensitive to bottom performers when funds are affiliated with larger families. We also find that family size increases the convexity of the (*High–Low*) performance range. Additionally, our results show that family size decreases (*High–Low*) convexity in countries where investors are more sophisticated. This change in convexity is explained by the lower sensitivity of flows to the top–performing funds affiliated with larger families.[8] Our results are economically important. For example, affiliation with larger families increases (decreases) the convexity of (*High–Low*) performance range by 40% (42%) when we use the percentage of population owning shares as a proxy for investor sophistication in the group of countries with less (more) sophisticated investors.

We document the robustness of our results in various ways. We start by examining the combined effect of family size with other fund characteristics that have been shown to be correlated with family size, including total fees, star affiliation, and the number of fund categories offered by the affiliated family. We find that our results are maintained. We next control for the level of switching costs in a country, as larger families offer investors the flexibility to transfer money between different funds at reduced or even zero costs. This also leaves our results unchanged. Many mutual funds are run by asset management divisions of groups whose primary activity is commercial banking, particularly in less developed countries. This allows banks to follow cross–selling strategies and therefore many bank–affiliated fund investors are also clients of other financial products the bank offers. It is possible that captive investors react differently to the performance of funds managed by large complexes that are part of financial conglomerates. To assess this possibility, we run our tests separately for bank–affiliated and non–affiliated funds and observe that our main results are preserved. We repeat our tests individually for domestic and international funds and we find robust results in both sub–samples. To examine whether our results are driven by the US dominance of our sample, we exclude the US and observe that our results remain robust. We address concerns of cross–

[8] Given that investors in more developed financial markets presumably have better channels for information processing and face fewer investment barriers, we would expect our country–level proxies for investor sophistication to also capture differences in information costs or investment barriers that vary across countries. Khorana et al. (2005) show that countries where investors have access to better information and where fund companies face lower barriers to entry have larger mutual fund industries. This is more relevant for equity funds, because information asymmetries are more pronounced for equities than for other investments.

sectional dependence by running our main tests using the Fama–Macbeth estimation procedure and find that our main conclusions are maintained. Finally, we also run regressions using additional proxies for the level of investor sophistication in a country, and our results do not change.

Our paper contributes to the mutual fund literature in several ways. To the best of our knowledge, we are the first to study the effect of fund family size on the flow–performance relationship in an international context. Second, we show that there are marked differences in how a fund's affiliation with large families shapes the flow–performance relationship across countries and that the US–based evidence does not apply universally. The US evidence holds for countries with more sophisticated investors but not for countries where investors are less sophisticated. Moreover, our tests show that the observed differences in the impact of family size on the convexity of the flow–performance across countries are not only statistically significant but also economically relevant. Third, we contribute to the growing literature studying the investment decisions of mutual fund investors to determine whether they are sophisticated and whether they act rationally. Finally, we also add to literature investigating the family–based structure of the mutual fund industry and its implications for the investment decisions of individual investors.

The results of our study are important for mutual fund companies and investors because flow–performance sensitivity determines the assets under management, the level of fees and risk–taking, and, ultimately, the performance of the fund. As the mutual fund industry continues to grow worldwide, fund management companies use international comparisons to understand the relative efficiency of the different parts of their business. The development of the mutual fund industry imposes new challenges to both fund managers and investors. Investment decisions are increasingly demanding for the average retail investor, not only because of the rising number of alternative investments but also because of the increasing complexity of information investors need to understand.

2.2. Data and variables construction

2.2.1. Sample description

We use data from 33 countries spanning the period 2000 to 2015. Our data on mutual funds comes from the Lipper Hindsight database, includes both domestic and international actively managed equity funds, and is free of survivorship–bias.[9] Although multiple share classes are

[9] This dataset is used in Demirci et al. (2021).

listed separately in the Lipper dataset, they have the same returns before expenses and loads, the same manager, and the same holdings. To avoid counting the same fund twice, we follow Ferreira et al. (2013), and Demirci et al. (2021), and use the primary share class identified by Lipper. Table 2.1 presents the number of unique funds and the total net assets (TNA) of our sample by country at the end of 2015.[10]

Table 2.1: Mutual fund industry sample by country

This table presents the number of unique funds in our sample, the total net assets (TNA) under management (sum of all share classes in millions of US dollars at the end of 2015), and the market share (percentage of TNA sum) of the top five management companies (equity funds) in each country. The sample is restricted to open–end and actively managed equity funds drawn from the Lipper database. The sample period is 2000–2015.

Country	Number of Funds	TNA ($ million)	Fund industry top five share (%)
Argentina	65	476	68.83
Australia	1,343	130,519	38.39
Austria	232	10,638	60.03
Belgium	814	19,624	83.52
Brazil	935	21,231	57.64
Canada	1,385	267,596	44.11
China	27	6,117	59.65
Denmark	261	33,217	51.75
Finland	210	26,568	77.16
France	1,509	159,864	46.47
Germany	476	120,833	81.94
Greece	46	915	84.20
Hong Kong	107	32,944	61.78
India	320	44,084	61.04
Indonesia	66	4,686	84.26
Italy	349	21,872	66.51
Japan	1,268	111,690	67.37
Malaysia	268	15,130	86.28
Netherlands	158	25,013	74.10
New Zealand	48	1,872	76.79
Norway	192	36,296	79.75
Poland	111	7,481	68.99
Portugal	72	1,690	87.93
Singapore	166	8,674	69.44
South Africa	178	21,614	64.92
South Korea	845	24,412	63.06
Spain	360	19,639	61.39
Sweden	319	116,759	63.90
Switzerland	349	50,779	79.55
Taiwan	370	12,577	52.16
Thailand	210	11,498	66.74
UK	1,290	523,944	27.97
US	4,378	5,265,178	43.76
All countries	18,727	7,155,433	65.34

[10] Table B.1 in Appendix B presents the number of unique funds in our sample and TNA for domestic and international mutual funds.

The US is the country with the most funds and the largest total TNA. The US funds represent 23% of the total number of funds and 74% of TNA in our sample. France (9%) and Canada (7%) have the second and third highest number of funds, while UK (7%) and Canada (4%) have the second and third largest TNA. China and Argentina have the lowest number of funds and the lowest TNA, respectively.

The last column of Table 2.1 also presents the market share of the top five management companies across fund industries, which allows us to understand the importance of the largest mutual fund families internationally. From Table 2.1, we observe that, in most countries, the majority of assets under management is concentrated in the top five management companies. In 28 out of 33 countries, the market share of these companies represents more than half of the assets under management in the equity mutual fund industry. Only in five countries, namely the UK, Australia, the US, Canada, and France, do the top five companies manage less than 50% of the total assets managed by the country's equity mutual fund industry. Table 2.1 also shows a substantial variation in the fraction of assets managed by the largest fund management companies around the world. In the UK equity mutual fund industry, these companies concentrate only 28% of the assets under management, while in Portugal this number goes up to nearly 90%.

2.2.2. Fund–level variables construction

2.2.2.1. Fund flow

We follow the literature (e.g., Sirri & Tufano, 1998) and calculate fund flow as the new money growth rate that is due to new external money. Fund flow for fund *i* in country *c* at quarter *t* is calculated as:

$$Flow_{i,c,t} = \frac{TNA_{i,c,t} - TNA_{i,c,t-1}(1+R_{i,c,t})}{TNA_{i,c,t-1}}, \tag{2.1}$$

where $TNA_{i,c,t}$ is the total net asset value in the local currency of fund *i* in country *c* at the end of quarter *t*, and $R_{i,c,t}$ is fund *i*'s raw return from country *c* in quarter *t*. Panel A of Table 2.2 presents descriptive statistics of the fund–level variables aggregated across countries and shows that the average quarterly flow in our sample is negative (–0.48%), as in Ferreira et al. (2012), and Ferreira et al. (2018).[11]

[11] For completeness, Table B.2, Panel A in Appendix B shows summary statistics by country.

Table 2.2: Mutual fund and country characteristics

This table presents mean, median, standard deviation, minimum, maximum, and number of observations of the fund–level characteristics in Panel A, and country–level characteristics in Panel B. Panel C presents pairwise correlations among fund characteristics, while Panel D presents pairwise correlations among country characteristics. The sample is restricted to open–end and actively managed equity funds drawn from the Lipper database. The sample period is 2000–2015. See Appendix A for variable definitions.

Variable	Mean	Median	Standard deviation	Percentile 10th	Percentile 90th	Number of Observations
Panel A – Fund characteristics						
Raw return (% quarter)	1.73	2.33	10.96	–12.59	14.39	570,432
Benchmark–adjusted return (% quarter)	–0.08	–0.17	3.97	–4.23	4.18	564,933
Four–factor alpha (% quarter)	–0.43	–0.52	5.36	–6.35	5.52	570,432
Flows (% quarter)	–0.48	–1.80	15.67	–10.82	9.14	570,432
Size ($ million)	563	73	3,076	5.26	975	570,432
Family size ($ million)	23,429	3,633	87,601	143.40	38,256	570,432
Age (years)	12.20	9.58	9.25	4.42	22.08	570,432
Expense ratio (%)	1.63	1.56	0.72	0.84	2.54	570,432
Loads (%)	2.47	2.00	2.54	0.00	5.25	570,432
SMB	0.13	0.05	0.47	–0.37	0.78	570,432
HML	–0.06	–0.04	0.54	–0.70	0.53	570,432
Countries sold	1.31	1.00	1.30	1.00	2.00	570,432
Volatility	0.41	0.38	0.16	0.23	0.63	570,432
Panel B – Country characteristics						
Population owning shares (%)	13.70	11.97	9.15	2.39	30.75	570,432
Trading costs (basis points)	31.28	29.30	11.05	20.14	49.78	570,432
Emerging market dummy	0.14	0.00	0.35	0.00	1.00	570,432

Panel C – Pairwise correlations among fund characteristics

		1	2	3	4	5	6	7	8	9	10	11	12
Raw return (% quarter)	1	1											
Four–factor alpha (% quarter)	2	0.39	1										
Flows (% quarter)	3	0.06	0.05	1									
Size ($ million)	4	0.01	0.01	0.01	1								
Family size ($ million)	5	0.01	0.02	0.02	0.35	1							
Age (years)	6	–0.01	0.01	–0.03	0.23	0.14	1						
Expense ratio (%)	7	–0.01	–0.02	–0.01	–0.13	–0.15	–0.10	1					
Loads (%)	8	–0.03	0.00	–0.01	–0.03	–0.06	0.05	0.28	1				
SMB	9	0.02	0.01	–0.01	–0.03	0.00	–0.04	0.08	–0.02	1			
HML	10	–0.03	–0.02	0.01	0.01	0.01	0.02	–0.07	0.003	–0.19	1		
Countries sold	11	0.01	0.01	0.01	0.02	–0.02	0.08	–0.01	0.09	–0.01	–0.02	1	
Volatility	12	0.03	0.00	–0.01	–0.07	–0.07	–0.10	0.18	–0.10	0.25	–0.21	0.003	1

Panel D – Pairwise correlations among country characteristics

		1	2	3
Population owning shares	1	1		
Trading costs	2	–0.48	1	
Emerging markets	3	–0.33	0.73	1

2.2.2.2. Fund performance

We measure fund performance using both raw returns and risk–adjusted returns (i.e., Carhart, 1997, four–factor alpha). We follow Bekaert et al. (2009), and Demirci et al. (2021), and estimate four–factor alpha for domestic, foreign country, and regional funds by using regional factors based on a fund's investment region (Asia–Pacific, Europe, North America, and

Emerging Markets). In the case of global funds, we use world factors.[12]

We run the following regression:

$$R_{i,t} = \alpha_i + \beta_1 MKT_{i,t} + \beta_2 SMB_{i,t} + \beta_3 HML_{i,t} + \beta_4 MOM_{i,t} + \varepsilon_{i,t}\,. \tag{2.2}$$

In Equation (2.2), $R_{i,t}$ is the return net of fees in US dollars of fund *i* in month *t* in excess of the one–month US Treasury bill rate; $MKT_{i,t}$ (*market)* is the excess return in the fund's investment region in month *t*; $SMB_{i,t}$ (*small minus big*) is the average return on the small–capitalization stock portfolio minus the average return on the large–capitalization stock portfolio in the fund's investment region; $HML_{i,t}$ (*high minus low*) is the average return on high book–to–market stock portfolio minus the average return on low book–to–market stock portfolio in the fund's investment region; and $MOM_{i,t}$ (*momentum*) is the average return on past 12–month winners portfolio minus the average return on past 12–month losers portfolio in the fund's investment region. The previous 36 months of net fund returns are used to estimate the time series regression of monthly excess returns based on the fund's factor portfolios. Next, we compare the difference between the fund's expected return and realized return and use this to estimate the fund's abnormal return (or alpha) in each month. We compound monthly alphas to calculate quarterly alphas. Panel A of Table 2.2 shows that the average raw return in our sample is positive (1.73%), and the average four–factor alpha is negative (–0.43%), which is comparable with the findings in Demirci et al. (2021).

2.2.2.3. Additional control variables

The literature shows that mutual fund characteristics other than past performance affect mutual fund flows. These characteristics include fund size, age and its interaction with performance, and fees (Chevalier & Ellison, 1997; Sirri & Tufano, 1998; Huang et al., 2007; Ferreira et al., 2012). Sirri and Tufano (1998) and Huang et al. (2007) include volatility in their tests, measured by the standard deviation of fund returns. Ferreira et al. (2012) use the number of countries where a fund is registered to sell and also use loadings on SMB and HML factors to control for fund style. Because of the serial correlation of fund flows, Ferreira et al. (2012) and Keswani et al. (2020) also control for past flows. We add the aggregate flow into each fund category to our tests to control for other unobserved factors that can potentially influence fund flows, such as sentiment shifts (Sirri & Tufano, 1998). Nanda et al. (2004) show that a star performer not

[12] The classification is based on the fund´s investment region using data on the fund's domicile country and geographic investment style provided by the Lipper database.

only attracts flows to itself but also to other funds in the family. We therefore control for funds affiliated with star families (but that are not stars themselves) in our regressions, following Huang et al. (2007), and Ferreira et al. (2018).

Panel A of Table 2.2 presents summary statistics for fund–level characteristics, while Appendix A contains definitions.[13] Table 2.2, Panel C, exhibits pairwise correlations among fund characteristics. Consistent with Ferreira et al. (2012), fund flows are positively correlated with both raw returns and four–factor alpha, family size, HML and the number of countries where the fund is sold, but negatively correlated with age, fees, and SMB. The pairwise correlation matrix among fund control variables also shows that using these variables together in our tests does not raise concerns of multicollinearity.

2.2.3. Country–level characteristics

We follow Ferreira et al. (2012) and proxy for investor sophistication by using measures of financial market development. These authors argue that the more developed the financial markets in a country, the more sophisticated their investors are. Our first measure is the percentage of the population owning shares, from Grout et al. (2009), as investors own more stocks in more developed financial markets. Our second measure is stock market trading costs. Countries with less developed financial markets are countries with higher trading costs (Khorana et al., 2005; Ferreira et al., 2012). Stock market trading costs are given by the annual average stock market transaction cost in basis points (including commissions, fees, and price impact) from the Global Universe Data–ElkinsMcSherry database. Finally, we also use a dummy variable that takes the value of one if the country is considered an emerging market country (following the MSCI criteria) in our baseline tests. Our proxies for investor sophistication have been widely used in cross–country studies (e.g., Khorana et al., 2005, 2009; Ferreira et al., 2012, 2013; Cremers et al., 2016; Keswani et al., 2020; Demirci et al., 2021).

In Table 2.2, Panels B and D present descriptive statistics and a pairwise correlation matrix for country–level characteristics, respectively. Table B.2, Panel B, in Appendix B reports detailed numbers by country.[14] Canada has the highest percentage of population owning shares, while Indonesia has the smallest proportion of population investing in shares. Indonesia also has the highest trading costs, while Japan and the US have the lowest. Following the MSCI criteria, one–third of the countries in our sample are classified as emerging markets.

[13] Table B.2, Panel A in Appendix B presents summary statistics by country.

[14] Panel B of Table B.10 in Appendix B presents means of additional country–level characteristics by country.

Ferreira et al. (2012) argue that mutual fund investors are more familiar with financial products in countries with more developed financial markets. Investors in these countries also have a better understanding of mutual funds as the mutual fund industry is older, larger and more pervasive, and they are also expected to adopt innovative methods of investing more quickly.

In the robustness tests, we employ additional proxies for investor sophistication. We use financial literacy, measured as the percentage of adults who are financially literate, from Klapper et al. (2015); we measure financial openness using the index of Chinn and Ito (2006), which measures a country's degree of capital account openness; and we use GDP per capita as a measure of a country's wealth, with data obtained from the World Development Indicators (WDI) database.

Education and GDP per capita capture investor sophistication, as high–income countries and countries with more educated populations have more sophisticated investors (Ferreira et al., 2012). These arguments are consistent with the findings in Khorana et al. (2005) that show that the mutual fund industry is larger in countries with wealthier and more educated populations and that this effect is more pronounced for equity funds as they require a higher level of investor sophistication. This is also in line with the findings in the US literature. Bailey et al. (2011) show that investors with a higher income and higher educational levels are more likely to use mutual funds and benefit from their choices. Campbell (2006) and Calvet et al. (2009) find that wealthier households exhibit more financial sophistication and make fewer investment mistakes. Chinn and Ito (2006) show that financial openness leads to financial development, particularly in equity markets, which indicates a direct link between financial openness and investor sophistication.

2.3. The effect of family size on the flow–performance sensitivity

This section provides details of our empirical tests and their results. Our aim is to explain differences in the way family size shapes the flow–performance relationship across countries in our sample. We posit that the sophistication of the investors in the country affects the impact of family size on the flow–performance sensitivity.

To measure flow performance sensitivity, we use a piecewise–linear specification allowing for different flow–performance sensitivities at different levels of performance (e.g., Sirri & Tufano, 1998). A fund's performance rank ranging from zero (poorest performance) to one (best performance) is assigned in each country c, investment region r, and quarter t, on the basis of its performance in the prior year as measured by raw returns or four–factor alpha.[15]

We allow slopes to differ for the lowest quintile [$Low_{i,c,r,t-1}=min(0.2, Rank)$], middle three quintiles [$Mid_{i,c,r,t-1}=min(0.6, Rank-Low_{i,c,r,t-1})$], and the top quintile [$High_{i,c,r,t-1}=Rank-(Low_{i,c,r,t-1}+Mid_{i,c,r,t-1})$] of the fractional fund performance rank. The coefficients on these piecewise decompositions of fractional ranks represent the marginal fund–flow response to the performance. To examine the impact of family size on the sensitivity of flows to past performance, we estimate the following regression:

$$\begin{aligned} Flows_{i,r,t} \;=\; & a + \beta_1\, Low_{i,r,t-1} \\ & + \beta_2\, Low_{i,r,t-1} \times\; Large\,fund\,family_{i,r,t-1} \;+ \beta_3\, Mid_{i,r,t-1} \\ & + \beta_4\, Mid_{i,r,t-1} \times\; Large\,fund\,family_{i,r,t-1} \;+ \beta_5\, High_{i,r,t-1} \\ & + \beta_6\, High_{i,r,t-1} \times\; Large\,fund\,family_{i,r,t-1} \\ & + \delta\, Large\,fund\,family_{i,r,t-1} +\; \theta X_{t-1} \;+ \varepsilon_t, \end{aligned} \tag{2.3}$$

where quarterly fund flows are regressed on piecewise past performance, a dummy variable that takes the value of one if the fund family size is above the median fund family size in the country, prior quarter (*t–1*), and investment region (*r*) concerned ($Large\,fund\,family_{i,r,t-1}$), and past performance interacted with $Large\,fund\,family_{i,r,t-1}$. X_{t-1} represents a set of lagged controls known to influence the flow–performance relationship. These variables are presented in Section 2.2 and include *Flows category, Star affiliation, Age* and its interaction with performance (*Age x Performance*), *Volatility*, fund s*ize*, *Flows*, *Expense ratio*, *Loads*, *SMB*, *HML*, and the number of countries where the fund is sold (*Countries sold)*. Regressions also include country, investment region, benchmark, and fund type (domestic, foreign, regional, and global) fixed effects as part of the controls. We calculate robust *t*–statistics that are twoway–clustered by fund and quarter (Petersen, 2009).[16] We use weighted least squares to avoid giving excessive weight to countries in our sample with a greater fraction of the number of funds, weighting each fund by the inverse of the number of funds in that country–quarter. Additionally, we report the change in convexity due to a fund's affiliation with large families (*High–Mid* and *High–Low*) and *p*–values from a *Wald–test*, testing whether this change is statistically significant.

[15] In untabulated results, we obtain consistent results if we use ranks based on the previous three years' performance.

[16] Fund investment regions are based on the fund's domicile country and geographic investment style provided by the Lipper database, and includes Asia–Pacific, Europe, North America, Emerging Markets, and Global, in the case of world funds.

We start by estimating the regression in Equation (2.3) with funds pooled across the 33 countries in our sample. Column (1) of Panels A and B of Table 2.3 report the results with performance measured using raw returns and four–factor alpha, respectively.[17]

In Column (1) of Table 2.3, we find no evidence that family size has a significant impact on the convexity of the flow–performance relationship when we pool funds from all countries together.

[17] We refer to the numbers in Panel A of Table 2.3, but we find identical results for four–factor–alpha.

Table 2.3: Flow–performance sensitivity and fund's affiliation with large families across countries – Investor sophistication

This table presents the results of panel regressions examining the aggregate flow–performance relationship for all countries in our sample (in Column 1) and for funds pooled across countries with below and above median values of the country variable concerned (in Columns 2–7). Panels A and B present the results when fund performance is measured using *raw return*s and *four–factor alpha*, respectively. Country–level variables proxy for investor sophistication and include, *Population owning shares, Trading costs,* and *Emerging markets*. Weighted least squares are used where each fund is weighted by the inverse of the number of funds in each country–quarter. The dependent variable is *fund flows* and the independent variables are past performance, *Large fund family*, and a dummy variable that takes the value of one if the fund family size is above the median fund family size in the country–quarter and investment region concerned, past performance interacted with *Large fund family*, and control variables lagged by one quarter. A piecewise linear regression is used to define three linear segments in the flow–performance relationship. In each quarter, by country, and investment region, fractional performance ranks ranging from zero to one are assigned to funds according to their average performance in the past year. This procedure designates three performance variables: $Low_{i,c,r,t-1}=min(0.2,Rank_{i,c,r,t-1})$, $Mid_{i,c,r,t-1}=min(0.6,Rank-Low_{i,c,r,t-1})$, and $High_{i,c,r,t-1}=Rank-(Low_{i,c,r,t-1}+Mid_{i,c,r,t-1})$. Control variables include: *Flows category*; *Star affiliation*; *Age*; *Age x Performance; Volatility*; *Size*; *Flows*; *Expense ratio*; *Loads*; *SMB*, *HML*; and *Countries sold*. Regressions also include country, time, investment region, benchmark, and fund type fixed effects. Robust t–statistics twoway–clustered by fund and time are reported in parentheses. At the bottom of the table, we report the increase in convexity due to a fund's affiliation with large families (*High–Mid* and *High–Low*) and p–values from a *Wald–test* testing whether this change is statistically significant. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. See Appendix A for variable definitions.

Panel A– Raw returns

		Population owning shares		Trading Costs		Emerging markets	
	All Countries	Below	Above	Above	Below	Yes	No
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Low	0.0458***	0.0302**	0.0354***	0.0335**	0.0390***	0.0646***	0.0490***
	(4.87)	(2.09)	(3.38)	(2.44)	(3.72)	(2.70)	(4.65)
Low x Family size	0.0064	–0.0456**	0.0185*	–0.0474**	0.0181*	–0.0432**	0.0245**
	(0.77)	(–2.16)	(1.73)	(–2.34)	(1.67)	(–2.47)	(2.46)
Mid	0.0394***	0.0406***	0.0394***	0.0349***	0.0414***	0.0401***	0.0393***
	(8.42)	(9.12)	(16.44)	(8.85)	(14.54)	(8.38)	(14.50)
Mid x Family size	0.0021	–0.0078*	0.0062**	–0.0056*	0.0071**	–0.0084	0.0037
	(0.59)	(–1.73)	(2.35)	(–1.68)	(1.75)	(–1.17)	(1.44)
High	0.2042***	0.2307***	0.1833***	0.2395***	0.1717***	0.2545***	0.1827***
	(10.46)	(10.06)	(15.45)	(11.30)	(14.76)	(9.12)	(16.41)
High x Family size	–0.0041	0.0351**	–0.0438***	0.0387**	–0.0449***	0.0341*	–0.0423**
	(–0.38)	(2.09)	(–2.74)	(2.27)	(–2.61)	(1.72)	(–2.52)
Large fund family	0.0068***	0.0073***	0.0066***	0.0069***	0.0066***	0.0056***	0.0071***
	(8.97)	(5.16)	(8.47)	(5.41)	(9.54)	(3.80)	(10.37)
Flows category	0.2301**	0.3482***	0.0778	0.1579*	0.0383	0.3679*	0.0309
	(2.33)	(3.36)	(1.55)	(1.88)	(0.68)	(1.79)	(0.54)
Star affiliation	–0.0019	–0.0031***	–0.0025***	–0.0051***	–0.0017***	–0.0084***	–0.0016***
	(–1.62)	(–2.68)	(–4.46)	(–4.14)	(–3.23)	(–4.41)	(–3.42)
Age (log)	–0.0127***	–0.0067***	–0.0140***	–0.0058***	–0.0144***	–0.0058***	–0.0134***
	(–5.66)	(–6.41)	(–23.03)	(–6.65)	(–18.76)	(–5.36)	(–21.14)
Age x Performance	0.0399***	0.0392***	0.0395***	0.0433***	0.0404***	0.0469***	0.0416***
	(5.71)	(4.31)	(8.42)	(6.16)	(9.08)	(4.40)	(9.25)
Volatility	–0.0118	0.0040	–0.0227***	0.0153	–0.0240***	0.0255	–0.0215**
	(–0.89)	(0.37)	(–2.61)	(1.03)	(–2.73)	(1.47)	(–2.44)
Size (log)	–0.0057***	–0.0070***	–0.0055***	–0.0059***	–0.0057***	–0.0048***	–0.0058***
	(–10.88)	(–10.21)	(–15.66)	(–9.82)	(–20.21)	(–7.86)	(–19.44)
Flows	0.1934***	0.1574***	0.2034***	0.1690***	0.2023***	0.1932***	0.1908***
	(7.67)	(15.01)	(30.39)	(18.97)	(27.94)	(19.90)	(28.87)
TER	–0.2581**	–0.0847	–0.3926***	–0.3311***	–0.2307***	–0.2138**	–0.2487***
	(–1.99)	(–0.92)	(–7.35)	(–3.16)	(–3.59)	(–2.02)	(–4.31)
Loads	–0.0241	–0.0659**	–0.0119	–0.0265	–0.0207	0.1023*	–0.0318*
	(–0.55)	(–2.36)	(–0.61)	(–0.76)	(–1.13)	(1.87)	(–1.78)
SMB	–0.0058**	–0.0106***	–0.0037**	–0.0131***	–0.0041**	–0.0155***	0.0001
	(–2.08)	(–4.07)	(–2.19)	(–5.07)	(–2.33)	(–5.40)	(0.09)
HML	–0.0003	–0.0052**	0.0024**	–0.0060***	0.0029**	–0.0068**	0.0027**
	(–0.18)	(–2.32)	(2.18)	(–3.47)	(2.29)	(–2.52)	(2.23)
Countries sold	0.0023***	0.0050***	0.0015***	0.0007**	0.0040***	–0.0007	0.0023***
	(2.79)	(8.02)	(5.62)	(2.28)	(9.76)	(–0.19)	(8.61)
Benchmark fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund type fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Investment region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Change in convexity *(High–Mid)*	–0.0061	0.0429*	–0.0492**	0.0443**	–0.0511**	0.0421*	–0.0457**
Wald test (p–value)	(0.81)	(0.06)	(0.02)	(0.04)	(0.04)	(0.08)	(0.02)
Change in convexity *(High–Low)*	–0.0104	0.0807***	–0.0615***	0.0857***	–0.0621***	0.0771***	–0.0665***
Wald test (p–value)	(0.47)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)
Adjusted R–squared	0.085	0.067	0.093	0.082	0.089	0.118	0.081
Number of observations	570,432	108,078	462,354	143,579	426,853	79,997	490,435

Panel B – Four–factor alpha

	All Countries	Population owning shares		Trading Costs		Emerging markets	
		Below	Above	Above	Below	Yes	No
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Low	0.0405***	0.0296**	0.0397***	0.0302**	0.0426***	0.0632**	0.0354***
	(4.73)	(2.14)	(4.08)	(2.11)	(4.08)	(2.58)	(2.70)
Low x Family size	–0.0200*	–0.0336**	0.0179	–0.0425**	0.0127	–0.0452**	0.0167
	(–1.69)	(–2.28)	(1.49)	(–2.05)	(1.14)	(–2.32)	(1.55)
Mid	0.0366***	0.0257***	0.0404***	0.0353***	0.0368***	0.0397***	0.0360***
	(18.83)	(5.72)	(17.93)	(7.44)	(13.97)	(6.12)	(15.09)
Mid x Family size	–0.0011	–0.0098**	0.0061**	–0.0106**	0.0042*	–0.0123	0.0014
	(–0.41)	(–1.99)	(2.09)	(–2.10)	(1.78)	(–1.56)	(0.45)
High	0.1602***	0.2121***	0.1693***	0.2175***	0.1443***	0.2307***	0.1526***
	(12.93)	(8.96)	(11.89)	(9.06)	(10.50)	(8.27)	(11.64)
High x Family size	–0.0132	0.0408**	–0.0502***	0.0391**	–0.0363**	0.0118	–0.0418***
	(–1.09)	(2.55)	(–3.00)	(2.38)	(–2.20)	(0.67)	(–2.59)
Large fund family	0.0117***	0.0186***	0.0100***	0.0173***	0.0097***	0.0188***	0.0109***
	(5.85)	(4.55)	(4.64)	(4.63)	(4.44)	(4.05)	(5.22)
Flows category	0.2550***	0.4073***	0.2417***	0.2297**	0.2253***	0.4243*	0.2258***
	(5.04)	(3.79)	(4.90)	(2.55)	(4.38)	(1.95)	(4.15)
Star affiliation	–0.0028***	–0.0028**	–0.0028***	–0.0056***	–0.0019***	–0.0081***	–0.0019***
	(–5.01)	(–2.41)	(–4.80)	(–4.47)	(–3.34)	(–4.30)	(–3.78)
Age (log)	–0.0126***	–0.0064***	–0.0139***	–0.0061***	–0.0143***	–0.0060***	–0.0133***
	(–21.60)	(–6.17)	(–22.50)	(–6.57)	(–18.35)	(–5.17)	(–20.61)
Age x Performance	0.0268***	0.0326***	0.0238***	0.0358***	0.0235***	0.0448***	0.0240***
	(5.51)	(3.22)	(4.84)	(4.76)	(4.62)	(4.05)	(4.73)
Volatility	–0.0053	0.0056	–0.0126*	0.0204	–0.0152**	0.0316*	–0.0124*
	(–0.88)	(0.55)	(–1.86)	(1.42)	(–2.42)	(1.77)	(–1.96)
Size (log)	–0.0054***	–0.0066***	–0.0052***	–0.0055***	–0.0054***	–0.0046***	–0.0055***
	(–17.37)	(–9.69)	(–15.52)	(–9.70)	(–19.94)	(–7.41)	(–19.55)
Flows	0.1967***	0.1607***	0.2069***	0.1723***	0.2059***	0.1971***	0.1941***
	(29.99)	(15.20)	(29.76)	(18.90)	(27.44)	(20.06)	(28.28)
TER	–0.2726***	–0.1059	–0.4024***	–0.3413***	–0.2466***	–0.2391**	–0.2600***
	(–5.27)	(–1.15)	(–7.45)	(–3.33)	(–3.76)	(–2.32)	(–4.42)
Loads	–0.0259	–0.0727**	–0.0113	–0.0207	–0.0222	0.1021*	–0.0331*
	(–1.49)	(–2.58)	(–0.58)	(–0.60)	(–1.20)	(1.88)	(–1.85)
SMB	–0.0047***	–0.0098***	–0.0027	–0.0123***	0.0010	–0.0154***	0.0013
	(–2.73)	(–3.43)	(–1.48)	(–4.38)	(0.61)	(–5.00)	(0.80)
HML	0.0023	–0.0015	0.0035**	–0.0050***	0.0069***	–0.0069**	0.0068***
	(1.48)	(–0.85)	(2.12)	(–2.64)	(3.69)	(–2.41)	(3.64)
Countries sold	0.0024***	0.0050***	0.0016***	0.0008***	0.0040***	–0.0005	0.0024***
	(8.70)	(8.31)	(6.06)	(2.78)	(9.83)	(–0.14)	(9.12)
Benchmark fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund type fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Investment region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Change in convexity *(High–Mid)*	–0.0120	0.0506***	–0.0561***	0.0497***	–0.0402**	0.0238	–0.0424**
Wald test (*p*–value)	(0.36)	(0.00)	(0.00)	(0.01)	(0.04)	(0.17)	(0.02)
Change in convexity *(High–Low)*	0.0070	0.0738***	–0.0679***	0.0811***	–0.0487**	0.0568**	–0.0577***
Wald test (*p*–value)	(0.68)	(0.00)	(0.00)	(0.00)	(0.02)	(0.03)	(0.00)
Adjusted R–squared	0.082	0.065	0.090	0.080	0.087	0.116	0.078
Number of observations	570,432	108,078	462,354	143,579	426,853	79,997	490,435

Our first hypothesis states that family size affects the response of fund flows to performance across countries differently. We also anticipate that family size: (1) increases the convexity of the flow–performance sensitivity in countries where investors are less sophisticated; and (2) decreases the flow sensitivity to performance in countries with more sophisticated investors.

To test this conjecture, we repeat the regression in Equation (2.3), except that we partition countries into two groups based on proxies for investor sophistication presented in Section 2.2.3. These proxies include the percentage of the population owning shares, stock market trading costs, and an emerging market dummy that equals one if the country is an emerging market (following the MSCI Emerging Markets Index criteria). [18] Below and above refer to the group of countries with below– and above–median values for the country variable concerned.

The results for raw returns and four–factor alpha are presented in Columns (2–7) of Panels A and B of Table 2.3, respectively. We find fundamental differences in the way family size affects the levels of convexity for countries with more and less sophisticated investors. Consistent with our predictions, family size increases the convexity of the flow–performance sensitivity in the group of countries where investors are less sophisticated (in Columns 2, 4, and 6). Contrarily, in countries with more sophisticated investors (in Columns 3, 5, and 7), family size decreases convexity.

Our second hypothesis postulates that family size affects the sensitivity of flows in the middle and top performance ranges. We expect family size to increase (decrease) the convexity at the upper end of the performance scale (*High–Mid*) in countries where investors are less (more) sophisticated. Less sophisticated investors have less sensitivity to mid–range performing funds that are affiliated with larger families. On the other hand, these investors are more swayed by top performers affiliated with larger families. In the case of countries with more sophisticated investors, the affiliation with a large family should be sufficient for funds with a moderately good performance to obtain more flows. This is because sophisticated investors increase their performance threshold in order to invest in top–performing funds, which leads to a greater sensitivity to middle performers and reduces the sensitivity of flows to superior performance for these investors.

Our tests strongly confirm our second hypothesis regardless of the proxies for investor sophistication used. In countries with less sophisticated investors, affiliation with large families increases the convexity of the flow–performance relationship at the top of the performance scale (*High–Mid*). In these countries, investors buy more top performers affiliated with larger families. Contrarily, the sensitivity to middle–range performers decreases. We observe the opposite results in countries with more sophisticated investors. In these countries, investors become more sensitive to the medium performance range and less sensitive to high performance when funds are part of large families. This decreases the convexity of the flow–performance relationship at the top of the performance scale (*High–Mid*), which is in line with the findings for the US (Huang et al., 2007).

Our third hypothesis posits that family size affects the convexity of the flow–performance

[18] In the robustness tests, we use additional proxies for investor sophistication, including financial literacy, financial openness, and GDP per capita.

relationship between the low– and high–performance ranges (*High–Low*), particularly in countries with less sophisticated investors. We expect funds affiliated with large families to experience fewer outflows if they perform poorly and to obtain a significantly greater flow if they do well in countries with less sophisticated investors. Our results confirm this prediction and show a more convex flow–performance relationship between (*High–Low*) performance ranges for countries where investors are less sophisticated. We also observe that family size decreases (*High–Low*) convexity in countries with more sophisticated investors. This change in convexity is mostly explained by the lower sensitivity of flows to top–performing funds observed in these countries.[19]

The coefficients of the control variables are consistent with the main findings in the literature. Past flows and the number of countries where the fund is sold increase flows, consistent with Ferreira et al. (2012) and Ferreira et al. (2018). Flows are negatively related to the volatility of fund returns (e.g., Sirri & Tufano, 1998; Huang et al., 2007). Larger and older funds get less flow, as in Ferreira et al. (2012), and Cremers et al. (2016), and funds that charge more fees or load more on small–caps also obtain more flows (e.g, Ferreira et al., 2012).

Our results are economically important. For example, when we use the percentage of the population owning shares as a proxy for investor sophistication (in Columns 2–3 of Panel A of Table 2.3), we find that affiliation with larger families increases the convexity of (*High–Mid*) and (*High–Low*) performance ranges by 23% and 40%, respectively for the group of countries

[19] Our results in Panel A of Table 2.3 show a higher flow–performance sensitivity to poor–performing funds that are members of a large family in countries with more sophisticated investors. Given that family size is expected to affect the behavior of the less sophisticated investors, this result indicates a sophisticated behavior from unsophisticated investors. In Panel B of Table 2.3, the coefficient on the interaction between poor–performance and family size is not statistically significant when we use four–factor alpha rather than raw returns as our performance measure. In the robustness tests, we also find that the coefficient on the interaction between poor–performance and family size is no longer statistically significant when we control for other fund–level and country–level characteristics in our model (see Tables B.4, B.5, and B.6). These findings are in line with the results of Huang et al. (2007) for the US fund industry.

with less sophisticated investors.[20] For countries with more sophisticated investors, the convexity of (*High–Mid*) declines by 34%, and (*High–Low*) convexity decreases by 42%.[21]

We next test for the impact of family size on the flow–performance relationship in individual countries. We therefore run identical regressions to those in Equation (2.3) for each country in our sample, except that we use fund–fixed effects rather than country–fixed effects. The results are presented in Table B.3.[22]

We first observe that family size influences the flow–performance sensitivity in many countries in our sample. Consistent with the predictions in our first hypothesis, we also find that there are substantial differences in the way family size affects convexity across countries. In countries where investors are less sophisticated, like Argentina and Indonesia, family size increases the convexity of the flow–performance sensitivity. In contrast, family size decreases convexity in the US, the UK, and Canada, where investors are more sophisticated.

Next, we examine the impact of family size on the convexity of the flow–performance sensitivity of (*High–Mid*) and (*High–Low*) performance ranges. Our results show that in seven countries, namely Australia, Canada, Denmark, France, Sweden, the UK, and the US, family size significantly decreases the convexity of both performance ranges. All these countries belong to the group of countries in our sample with an above–median percentage of the population owning shares – countries with more sophisticated investors. In addition, we also find that most countries where the affiliation with large families contributes to increasing the convexity of the flow–performance sensitivity of (*High–Mid*) and (*High–Low*) performance ranges have a below–median percentage of the population owning shares – countries with less

[20] To compute the economic impact of (*High–Mid*) performance range we divide the change in convexity that is due to a fund's affiliation with large families (*Change in convexity (High–Mid)*) – computed as the difference between the coefficients on the *High x Family size* and *Mid x Family size* interactions variables – by the level of convexity for the funds that are not affiliated with large families (*High–Mid*) – calculated as the difference between the coefficients of *High* and *Mid*. As an example (from Column (2) of Panel A of Table 2.3): 23% = 0.0429/0.1901; where 0.0429 = (0.0351– (–.0078)); and 0.1901 = (0.2307–0.0406). To compute the economic impact of (*High–Low*) we proceed likewise, except that we use the coefficients of *Low* and the coefficients on the *Low x Family size* interaction variable, rather than the coefficients of *Mid* and *Mid x Family size*.

[21] The magnitude of the economic impact is also relevant when investor sophistication is proxied by trading costs or emerging markets. In countries with higher (lower) trading costs, family size increases (decreases) the convexity of (*High–Mid*) and (*High–Low*) by 22% and 42% (39% and 47%), respectively. In the case of emerging markets, affiliation with larger families increases the convexity of (*High–Mid*) and (*High–Low*) performance ranges by 20% and 41%, respectively, while a fund's affiliation with a large family decreases the convexity of (*High–Mid*) and (*High–Low*) performance ranges by 32% and 50%, respectively.

[22] In Table B.3, we measure performance using raw returns. In the untabulated analysis we run the country–by–country regressions with performance measured using four–factor alpha and find similar results.

sophisticated investors. These countries are Argentina, Greece, Indonesia, Italy, Netherlands, Poland, Portugal, and Thailand. These findings support our second and third hypotheses.

Our country–by–country results are also very important economically. In the US, affiliation with larger families decreases the convexity of (*High–Mid)* and *(High–Low)* performance ranges by 64% and 52%, respectively. In the case of Portugal, however, (*High–Mid*) convexity increases by 50%, while (*High–Low*) convexity decreases by 76%.

Overall, our results highlight the importance of investor sophistication when studying the role of family size on the response of flows to past performance in different countries around the world.

2.4. Robustness

We perform a number of robustness checks on the main findings. The results are presented in Appendix B.

Huang et al. (2007) report that larger fund complexes charge lower fees, produce more star funds, and allow investors to have access to a wide range of products.[23] To understand whether our results are affected by these variables, we start by running the regressions in Panel A of Table 2.3 including *Fees*, *Star affiliation*, and *Diversity*, and the interaction of past performance (*Low*, *Mid*, and *High* performance ranges) with theses variables. *Fees* are measured as the expense ratio plus one–seventh of front–end loads; *Star affiliation* is a dummy variable that takes the value of one for funds that are affiliated with star families (i.e., those including a star fund) but are not stars themselves, and zero otherwise; *Diversity* is a dummy variable that is one if the number of different fund categories offered by the affiliated family is larger than the medium number for all families, and zero otherwise. The results are presented in Table B.4 and show the inclusion of these variables does not affect our main conclusions.

Providing investors with more fund choices within the complex, larger fund families may also reduce the transaction costs associated with switching from one fund to another. Additionally, because switching a fund entails a certain level of uncertainty and investors are more likely to know about a larger family and its funds, we might expect this to affect the impact of family size on the flow–performance sensitivity. We test this by adding the costs of switching funds and the number of available investment alternatives to our regressions in Panel A of Table 2.3 and interact each one of these variables with past performance.

[23] Khorana et al. (2009) also find that large families charge lower fees when using an international sample of 18 countries.

We follow Keswani et al. (2020) and proxy for switching costs by using back–end fees and front–end fees. As investors pay front– and back–end fees when buying and selling funds, respectively, we measure the cost of switching funds in a given country–quarter as the average of: (i) the weighted average front–end fee; and (ii) the weighted average back–end fee, where the weights are determined by a fund's assets under management relative to the country's total assets under management in that quarter. We compute the *Number of available investment alternatives* by using the number of funds with similar styles based on their *SMB*– and *HML* loadings. In each quarter, we sort funds into three groups based on *SMB* loadings (low, medium, and high) and also into three groups based on *HML* loadings to obtain nine equal–sized groups. The fund's *Number of investment alternatives* in a given quarter is the total number of funds in the same *SMB/HML* group.[24] The results are presented in Table B.5 and show that the documented effects of family size on the flow–performance sensitivity remain unchanged.

The literature shows conflicts of interests in mutual funds that are owned by banking groups. In the US, this includes Massa and Rehman (2008), and internationally, Gil–Bazo et al. (2020), and Ferreira et al. (2018). Ferreira et al. (2018) show that outside the US (but not in the US), affiliated funds exhibit less flow–performance sensitivity – particularly to poor performing funds – than non–affiliated funds, which the authors find consistent with non–US affiliated fund investors being unsophisticated.[25]

Banks follow cross–selling strategies as this allows them to offer mutual funds jointly with other financial products. We would therefore expect many affiliated fund investors to be clients of other financial products the bank is offering, particularly in less developed countries where most mutual funds are run by asset management divisions of groups whose primary activity is commercial banking. Therefore, captive investors may react differently to the performance of funds managed by large complexes that are part of financial conglomerates. We investigate this possibility by performing the flow–performance tests in Panel A of Table 2.3 separating bank–affiliated and non–affiliated funds.[26]

The results are presented in Table B.6 and confirm that family size has a larger impact on the convexity of the bank–affiliated funds – both *(High–Low)* and *(High–Mid)* – in countries

[24] Hoberg et al. (2018) also sort funds using a similar procedure.

[25] Ferreira et al. (2018) use a worldwide sample to show that commercial bank–affiliated funds underperform unaffiliated funds. This is because affiliated funds do not always invest in a way that maximizes investor returns; instead, they choose to invest in a way that benefits the banking group they are owned by. We thank Pedro Pires for providing us with the data.

[26] For simplicity, we only present the results of reestimating Columns (2) and (3) of Panel A of Table 2.3, where we proxy for investor sophistication using the percentage of population owning shares. We find robust results for all our proxies for investor sophistication.

with less sophisticated investors. In these countries, investors react less to poor– and mid–performing bank–affiliated funds that belong to larger families and react more to the performance of those affiliated funds that are part of larger complexes. This larger impact is also confirmed economically, as family size increases the convexity of (*High–Mid)* and *(High–Low)* performance ranges by 26% and 50% in the case of the bank–affiliated funds, and by 20% and 37% for non–affiliated funds, respectively. Table B.6 also shows that our main conclusions are robust as the effect of family size on convexity remains significant for bank–affiliated and non–affiliated funds.

Our sample includes both domestic funds (those investing primarily in stocks of the country of domicile), and international funds (those that invest primarily in stocks of countries other than the country of domicile, including funds investing in a particular country, regional funds, and global funds). In all our regressions, we include fund type (domestic, foreign, regional, and global) fixed effects to control for differences in these types of funds. To test whether our results hold separately for domestic and international funds, we repeat our regressions in Panel A of Table 2.3 individually for domestic and international funds.

Table B.7 shows that the results are robust in both sub–samples. Table B.7 also shows that family size has a particularly strong impact on the convexity of international funds for the (*High–Mid)* performance range in less sophisticated countries. Family size increases the convexity of (*High–Mid)* performance ranges by 36% in the case of international funds, and by 27% for domestic funds. This is consistent with less sophisticated investors facing higher participation costs when investing in international funds.

We use weighted least squares in our main tests, weighting each fund by the inverse of the number of funds in that country–quarter. This is to avoid giving excessive weight to countries in our sample with a greater fraction of the number of funds.[27] As the US represents nearly 30% of the observations in our sample, one can argue that the US dominance of our sample is driving our results. We therefore run separate regressions where we exclude the US from our sample. Table B.8 presents the results of these tests and shows that excluding the US does not change our main findings.

To address concerns of cross–sectional dependence in our results, we rerun the results in Panel A of Table 2.3 using the Fama–Macbeth estimation procedure. Table B.9 presents the results and demonstrates that our main conclusions are confirmed.

[27] As the average fund size is very different across countries in our sample, we also use weighted least squared weighting in unreported results by the inverse of the average TNA in each country–quarter; the results remain similar.

We use additional proxies for the level of investor sophistication in a country. Panel A of Table B.10 presents the means of these proxies that include the percentage of adults who are financially literate in the country, the KAOPEN index, measuring a country's degree of capital account openness and GDP per capita. Panel B of Table B.10 shows that our main results are confirmed when we use these proxies.

In the untabulated analysis, we run the regressions in Table 2.3 with performance measured using benchmark–adjusted returns. Our results remain similar. The untabulated analysis also addresses concerns that residuals are correlated within country–time and the regressions are estimated in Table 2.3 with *t*–statistics twoway–clustered by country–time. We find that our results remain unchanged.

2.5. Conclusion

In this study, we use data from 33 countries to show substantial differences in the way a fund's affiliation with large families affects the flow–performance sensitivity across countries. We find that family size reduces the convexity of the flow–performance relationship in countries where investors are more sophisticated. On the other hand, family size increases the flow–performance convexity in countries with less sophisticated investors.

Our results are consistent with the literature that shows that the US–based evidence is not a universal truth. We show that the US evidence only holds for countries where investors are more sophisticated. The economic impact of our results is also significant.

Our results are important for investors, mutual fund companies, and regulators. As family size affects investors' allocation decisions, it determines mutual fund industry outcomes such as fees, risk–taking, and performance.

3. The flow-performance sensitivity of quantitative funds

Abstract: In this paper we study differences in the flow-performance sensitivity between quantitative and non–quantitative actively managed US equity funds. We show that quantitative investors buy more top performing funds and sell less poor performers, which is no different from the main findings in the mutual fund literature. When testing for differences in flow-performance convexity between quantitative and non–quantitative funds, we find homogeneity rather than heterogeneity in investors preferences. Our results are important as they suggest that any differences to be found in fees, risk-taking or performance between quantitative and non-quantitative funds originate from fund managers and fund management companies' decisions and strategies rather from investors preferences.

JEL classification: G11, G23, G40

Keywords: Quantitative analysis, Mutual fund flow-performance sensitivity, Mutual fund industry.

3.1. Introduction

The literature shows that mutual fund flows are highly dependent on past performance (Ippolito, 1992; Chevalier & Ellison, 1997; Sirri & Tufano, 1998; Del Guercio & Tkac, 2002; Berk & Tonks, 2007; Del Guercio & Reuter, 2014). There is also evidence that the way investors react to past performance determines how fund managers manage their portfolios, namely the level of fees charged, the level of risk-taking, and the performance delivered to the investor (Chevalier & Ellison, 1997; Berk & Green, 2004).[28,29] Additionally, different studies document a non-linear relation between flows and performance, i.e., the flow-performance relationship is convex as investors tend to buy intensely winners and fail to sell poor performers with the same intensity (e.g., Sirri & Tufano, 1998; Huang et al., 2007; Del Guercio & Tkac, 2002).[30] The literature also shows that chasing winners and not selling losers is an unsophisticated thing to do as fund performance persist for poor performers but not for those funds at the top of the performance scale (Carhart, 1997; Fama & French, 2010). The link between investors sophistication and convexity is also established by Kim (2011) and Ferreira et al. (2012) that show that investor sophistication reduces convexity and that convexity decreases over time.[31,32]

In this paper we study the flow-performance sensitivity of quantitative funds. In the past few years, advances in machine learning and big–data analysis have been used by the mutual

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[28] Seminal papers that show that past fund performance is a critical determinant of decision-making by investors include Spitz (1970) and Smith (1978).

[29] This is also consistent with the findings in recent literature using cross country data that show that the flow-performance sensitivity determines fund performance and how active fund managers are (Ferreira et al., 2012; Cremers et al., 2016; Ferreira et al., 2018).

[30] The literature offers both rational and behavioral explanations for why the flow-performance relationship is convex. In the rational perspective, Ippolito (1992) builds a model to study the relation of flows to recent performance and finds the slope to be steeper in the high region when allowing different slopes in the regions of low and high performance. Lynch and Musto (2003) provide a model where investors expect management companies to abandon only bad strategies or managers. Huang et al. (2007) find that the power of search costs reduces the sensitivity of flows to performance. Liang et al. (2019) show that funds with more onerous restrictions on flows exhibit a convex flow-performance function, due to a less sensitive response of flows in the mid-performance region. In the behavioral perspective, Chevalier and Ellison (1997) find that greater flow sensitivity to performance is associated with greater fund manager risk taking as fund managers will gain significant flow if they perform well but do not lose significantly if they perform poorly. Goetzmann and Peles (1997) show that investors exhibit cognitive dissonance by overestimating the performance of their existing mutual fund investments. Sirri and Tufano (1998) and Evans (2010) find that investors may also buy into past winners and not sell past losers because fund families tend to advertise outperforming funds rather than drawing attention to poor performers.

[31] The work by Getmansky (2012) provides additional evidence that sophisticated and unsophisticated investors react differently to past hedge fund performance.

[32] The results in Kim (2011) show that convexity decreases over time in the United States, which is consistent with the findings in Ferreira et al. (2012) that convexity dissipates as markets develop and investors become more sophisticated.

fund industry on their quest for higher returns. Quantitative funds remove the emotional and cognitive input from the decision process, as they rely on objective mathematical and statistical models to select securities. For this reason, investors expect quantitative funds to overcome the observed inability of human–managed active funds to beat their benchmarks, which has contributed to the growing demand of quantitative funds (D'Acunto et al., 2019). The growing competition of index funds and ETFs has also contributed to the increasing number of quantitative funds, as passive investments have been capitalizing on the lack of skill of active managers by keeping costs low and eliminating the risk of underperforming a benchmark (Cremers et al., 2016).

Despite the rising interest of investors in quantitative funds, very little is known about the impact of quantitative analysis on the mutual fund industry and on the overall market stability. Also, we find virtually no literature on the flow-performance relationship of quantitative funds. Zhao (2006) finds no significant differences in fund flows among quantitative and non-quantitative funds and concludes that there are no different investment preferences among both types of funds. Abis (2020) finds more outflows for quantitative funds in recession periods, which she finds consistent with quantitative investors being more sophisticated investors. However, none of these studies test for differences in the flow-performance sensitivity between quantitative and non-quantitative funds. Zhao (2006) also finds no differences in performance between quantitative and non–quantitative funds, but her results indicate that quantitative funds do better during recession periods, while non–quantitative funds do better during market upturns. There are other studies looking at differences in the performance of quantitative and non-quantitative funds, but the results are not entirely conclusive. Ahmed and Nanda (2005) and Casey, Quirk and Associates (2005) show that quantitative funds outperform non-quantitative funds, while Wermers et al. (2012) find the opposite. Beggs et al. (2021) show that quantitative investing may result in a more unstable market because quantitative funds fire sales have a much larger impact on market instability than fire sales by traditional mutual funds. There is also evidence that quantitative funds charge lower fees than their non–quantitative peers (e.g., Ahmed & Nanda, 2005; Zhao, 2006; Abis, 2020).

Although the use of quantitative techniques has contributed to the increasing popularity of quantitative funds among mutual fund investors, one important question that is yet to be answered is whether the different stock selection approach of quantitative funds influences investor investment decisions. While quantitative strategies select securities based on a predetermined set of rules, which may contribute to deliver to investors a clear and understandable message about their diligence and skills, most quantitative funds rely on proprietary strategies that lack transparency. This explains why many people consider quantitative funds as black-boxes, and makes more difficult for investors to understand what the real strategies adopted by these funds (Zhao, 2006). Therefore, we would expect investors to get more familiar with financial products and to have a better understanding of mutual funds before investing in quantitative funds. As a result, quantitative funds are expected to have a more sophisticated clientele, and, because more sophisticated investors have been shown to sell more poorly performing funds and buy less top performers, we anticipate a less convex flow-performance relationship for quantitative funds. This is our main hypothesis.

We use the classification provided by Lipper Hindsight to identify quantitative funds. According to Lipper Hindsight, quantitative funds are defined as *"funds that use a rules–based mathematical model in order to initiate buy and sell decisions."*; i.e., funds which rely solely on quantitative models to select stocks. We identify 217 quantitative funds in the 2000–2019 period, representing nearly 6% of the funds in our sample.[33]

We use two different approaches to test for differences in the flow-performance sensitivity between quantitative and non-quantitative investors, using both relative and absolute fund flow and measuring performance with raw returns and four-factor alpha. We also run our tests with both quarterly and annual data. In the first approach, we examine flows of funds for bottom and top performance quintiles, like in Berk and Tonks (2007). At the end of each period, we start by sorting funds into quintiles based on their raw returns over the previous year. We then compute the average relative and absolute net flow over the period of the quintile formation and test whether it is statistically different from zero. Our results indicate significant net outflows in the bottom performance quintiles and net inflows into top performance quintiles, for both quantitative and non–quantitative funds, which indicates that investors chase past performance and is consistent with the literature (Berk & Green, 2004; Berk & Tonks, 2007; Del Guercio & Reuter, 2014). However, our results also show no significant differences in the net inflow and net outflow of capital of quantitative and non–quantitative funds. We next follow Berk and Tonks (2007) and Del Guercio and Reuter (2014) and use a regression–based approach that allows to control for different fund characteristics when investigating differences in the flow–performance sensitivity between quantitative and non-quantitative funds. Confirming our prior findings, our results show that past performance determines fund flows. Most importantly, we also find no significant differences on how quantitative and non–quantitative capital flows react to both raw returns and risk–adjusted performance. Our results

[33] See Table 3.1.

hold whether we use relative or absolute fund flow and whether focusing on quarterly or annual flows.

Contrary to our expectations, we find no significant differences in the way quantitative and non-quantitative investors react to past performance. Therefore, our main hypothesis is rejected, as the evidence does not confirm that quantitative funds have a more sophisticated clientele than their non-quantitative counterparts.

We confirm the robustness of our results by looking at net and absolute flows of funds for bottom and top performance terciles rather than quintiles and we find that our results do not change.

Our paper makes important contributions to the literature. We contribute to the literature on the mutual fund flow-performance sensitivity by being the first to study the flow performance relationship for quantitative funds. Additionally, we contribute to the better understanding of quantitative funds, as the literature on this type of funds is rather scarce. By showing no differences in the flow-performance sensitivity of quantitative and non-quantitative investors our results indicate homogeneity rather than heterogeneity in investors preferences. This finding is important for investors and practitioners, as the flow-performance sensitivity determines how fund managers and mutual fund companies run their portfolios and, hence, determines the level of fees charged, the level of risk-taking, and ultimately the performance delivered to the investor. Our findings are also important for future research trying to explain differences among quantitative and non-quantitative funds. This is because our results indicate that any differences that may be found between quantitative and non-quantitative funds originate from mutual fund managers and fund management companies' decisions and strategies and cannot be attributed to differences in investors preferences.

3.2. Data and variables description

3.2.1. Data

We use data for US open–end, and actively managed equity funds from the Lipper Hindsight survivorship–bias free database in the 2000-2019 period.[34] Although Lipper lists multiple share classes as separate funds, they have the same holdings, the same manager, and the same returns before expenses and loads. To prevent double counting of funds, we follow, e.g., Demirci et al. (2021) and Ferreira et al. (2019), and use the primary share class as our unit of observation and

[34] This dataset is used in Demirci et al. (2021), except that we focus on US–domiciled domestic funds only.

aggregate fund–level variables across different share classes. Our sample is restricted to domestic funds, i.e., those funds investing primarily in US stocks.

3.2.2. Quantitative versus non–quantitative funds

We use the classification provided by Lipper Hindsight to identify quantitative and non–quantitative funds, which is done according to the funds' Principal Investment Strategy reported in their prospectus's disclosures. Lipper flags funds which purely rely on quantitative models to select securities as quantitative: *"funds that use a rules–based mathematical model in order to initiate buy and sell decisions."* Although many funds employ quantitative screening to narrow the investment universe, in many cases investment decisions are made at the portfolio manager's discretion, meaning that ultimately their main stock selection criterion remains the human judgment. To our knowledge, Lipper Hindsight is the unique database providing this classification. Zhao (2006), Abis (2020) and Beggs et al. (2021), perform textual analysis of mutual fund prospectuses to identify quantitative funds. The classification criterion in Zhao (2006) is consistent with Lipper Hindsight's classification, as it assumes that quantitative funds are only those funds relying solely on computer models to select securities (*purely quantitative–oriented funds or quant jocks*). Abis (2020) and Beggs et al. (2021) classification process, however, allows the possibility for some hybrid or mixed funds are classified as quantitative funds.

At the end of 2019, the Lipper Hindsight database lists a total of 32,058 US equity mutual funds, of which 1,592 funds are quantitative funds. After removing closed–end funds, index–tracking funds, exchanged–traded funds and funds of funds, we get a total of 27,653 funds, 1,397 of which are quantitative funds. We then eliminate non–primary funds, and end–up with 8,749 funds, including 408 quantitative funds. We impose additional filters to construct our final sample: (1) we exclude non–domestic funds, by removing funds identified by Lipper as international funds (those that invest primarily in stocks domiciled outside the US, including foreign funds, i.e., funds investing in a specific country, regional funds, and global funds); (2) we impose a minimum of 36 continuous monthly observations for each fund, in order to ensure that we have sufficient time series observations to calculate four–factor alphas observations for each fund; and (3) we require mutual funds to have data on all our control variables. This leads to a final sample of 3,915 unique funds, of which 3,698 are non–quantitative funds and 217 are quantitative funds.

Figure 3.1 shows the number of quantitative funds (solid line) and the number of quantitative funds as a percentage of the total number of funds (dashed line) for the 2000–2019 sample period.

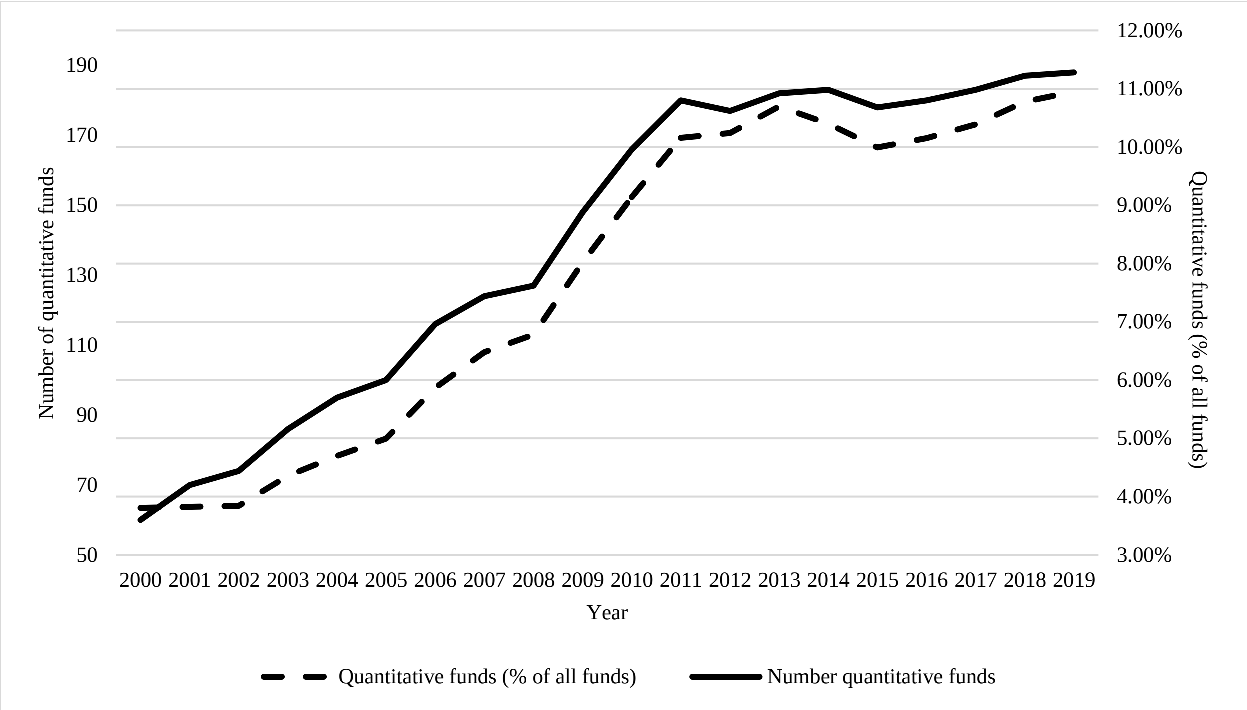

Figure 3.1: Quantitative funds in our sample

This figure shows the number of quantitative funds (solid line) and the number of quantitative funds as a percentage of the total number of funds (dashed line) for the 2000–2019 period. The sample is restricted to US open–end and actively managed domestic equity funds drawn from the Lipper Hindsight database.

The number of quantitative funds has increased steadily over the course of our sample period. In the year 2000, we identify 60 funds classified by Lipper Hindsight as quantitative, representing 4% of the total number of funds in our sample. In 2019, the number of quantitative funds climbs to 188 funds, which represents nearly 10% of the total number of funds.

Table 3.1 presents the number of unique funds in our sample and the total assets under management (TNA) at the end of 2019, for both non–quantitative and quantitative funds.

Table 3.1: Mutual fund industry sample by quantitative and non–quantitative funds

This table presents the number of unique funds in our sample and total net assets (TNA) under management (sum of all share classes in millions of US dollars at the end of 2019) for both quantitative and non–quantitative funds. The sample is restricted to US open–end and actively managed domestic equity funds drawn from the Lipper Hindsight database. The sample period is 2000–2019. See Appendix C for variable definitions.

Funds	Number of funds	TNA ($ million)
Quantitative	217	173,062
Non–quantitative	3,698	4,200,469
Total	3,915	4,373,531

We have a sample of 3,698 non–quantitative funds and 217 quantitative funds, representing a TNA of \$4,200 billion and \$173 billion, respectively.[35]

3.2.3. Variables description

3.2.3.1. Fund flow

We compute both, absolute and net fund flow following the literature (e.g., Chevalier & Ellison, 1997; Sirri & Tufano, 1998; Huang et al., 2007). Absolute fund flow as Absolute flow is calculated as the change in total net assets adjusted for internal growth due to investment returns:

$$Absolute\ Flow_{i,t} = TNA_{i,t} - TNA_{i,t-1}(1+R_{i,t}), \tag{3.1}$$

where $TNA_{i,t}$ is the total net asset value in US dollars of fund *i* at the end of period *t*, and $R_{i,t}$ is fund *i*'s raw return in period *t*. Net fund flow is the new money growth rate that is due to new external money. Net fund flow for fund *i* at quarter *t* is calculated as:

$$Flow_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1}(1+R_{i,t})}{TNA_{i,t-1}}, \tag{3.2}$$

where $TNA_{i,t}$ is the total net asset value in the local currency of fund *i* at the end of quarter *t*, and $R_{i,t}$ is fund *i*'s raw return in quarter *t*. We first compute quarterly fund flows and annual flow is calculated as the sum of quarterly fund flows. Panel A of Table 3.2 presents descriptive statistics of the fund characteristics for quantitative and non-quantitative funds.[36] Panel B of Table 3.2 presents differences in fund characteristics for quantitative and non-quantitative funds.

[35] See Ferreira et al. (2013), and Cremers et al. (2016) for a detailed description of Lipper's data coverage.

[36] To ensure that extreme values do not drive our results, we winsorize fund flow also other fund characteristics, including performance, volatility, and fees, at the bottom and top 1% level of the distribution.

Table 3.2: Mutual fund characteristics for quantitative and non–quantitative funds

This table presents details on mutual fund characteristics for both quantitative and non–quantitative funds. Panel A presents summary statistics for mutual fund characteristics. In Panel B we present differences in means of mutual fund characteristics for quantitative and non–quantitative funds and run a *t*–test, testing whether these differences are statistically significant. Panels C and D present pairwise correlations among fund characteristics for quantitative and non–quantitative funds, respectively. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. The sample is restricted to US open–end and actively managed domestic equity funds drawn from the Lipper Hindsight database. The sample period is 2000–2019. See Appendix C for variable definitions.

Panel A: Summary statistics for mutual funds characteristics for quantitative and non–quantitative funds

Variable	Mean	Median	Standard deviation	Percentile 10	Percentile 90	Observations
Quantitative funds						
Raw return (% quarter)	1.89	2.91	8.87	–11.36	12.39	9,086
Raw return (% year)	7.84	9.67	18.48	–23.90	32.06	2,503
Four–factor alpha (% quarter)	–0.33	–0.29	3.10	–4.47	2.99	9,086
Four–factor alpha (% year)	–1.25	–1.19	7.17	–9.78	3.11	2,503
TNA ($ million)	718	170	1,952	20.8	1,684	9,086
TNA family ($ million)	40,266	6,680	183,698	211.4	69,557	9,086
Flow (% quarter)	0.59	–1.71	18.08	–10.53	12.02	9,086
Flow (% year)	8.18	–7.62	86.09	–34.59	47.68	9,086
Absolute flow ($ million quarter)	–5.96	–1.02	55.94	–178.22	243.25	9,086
Absolute flow ($ million year)	–26.88	–5.62	297.65	–168.28	89.68	9,086
Flow volatility (% quarter)	9.70	4.46	17.28	1.31	21.68	9,086
Age (years)	13.07	11.17	9.61	4.08	23.08	9,086
Total expense ratio (% year)	1.14	1.11	0.42	0.66	1.66	9,086
Loads (% year)	1.08	0.14	1.51	0.00	3.60	9,086
Non–quantitative funds						
Raw return (% quarter)	1.81	2.86	9.54	–11.52	12.60	150,557
Raw return (% year)	7.71	9.78	20.80	–21.50	32.32	34,278
Four–factor alpha (% quarter)	–0.30	–0.27	3.77	–4.30	3.62	150,557
Four–factor alpha (% year)	–1.20	–1.11	8.20	–9.74	6.83	34,278
TNA ($ million)	1,433	241	5,563	17.5	2,917	150,557
TNA family ($ million)	70,501	9,973	195,268	116.6	153,563	150,557
Flow (% quarter)	0.35	–1.69	18.00	–9.83	9.96	150,557
Flow (% year)	5.52	–7.39	79.08	–32.34	38.13	150,557
Absolute flow ($ million quarter)	–7.97	–1.10	78.09	–181.00	226.97	150,557
Absolute flow ($ million year)	–36.59	–5.85	500.43	–208.94	83.57	150,557
Flow volatility (% quarter)	8.45	3.82	16.13	1.08	17.32	150,557
Age (years)	15.18	11.67	12.95	4.17	29.33	150,557
Total expense ratio (% year)	1.24	1.19	0.46	0.76	1.83	150,557
Loads (% year)	1.43	0.72	1.70	0.00	4.23	150,557

Panel B: Differences in mutual funds characteristics: quantitative versus non–quantitative funds

Fund characteristics	Quantitative	Non–quantitative	Quantitative minus Non–quantitative: Difference	(p–value)
Raw return (% quarter)	1.89	1.81	0.08	(0.16)
Raw return (% year)	7.84	7.71	0.13	(0.34)
Four–factor alpha (% quarter)	–0.33	–0.30	–0.03	(0.39)
Four–factor alpha (% year)	–1.25	–1.20	–0.06	(0.28)
TNA ($ million)	718	1,433	–715***	(0.00)
TNA family ($ million)	40,266	70,501	–30,235***	(0.00)
Flow (% quarter)	0.59	0.35	0.24	(0.21)
Flow (% year)	8.18	5.52	2.66	(0.10)
Absolute flow ($ million quarter)	–5.96	–7.97	-2.02**	(0.02)
Absolute flow ($ million year)	–-26.88	–36.70	-9.82*	(0.08)
Flow volatility (% quarter)	9.70	8.45	1.25***	(0.00)
Age (years)	13.07	15.18	–2.11***	(0.00)
Total expense ratio (% year)	1.14	1.24	–0.11***	(0.00)
Loads (% year)	1.08	1.43	–0.35***	(0.00)

Panel C: Pairwise correlations among fund characteristics (annual data) – Quantitative funds

		1	2	3	4	5	6	7	8	9	10
Raw return	1	1									
Four–factor alpha	2	0.194	1								
TNA	3	–0.095	–0.033	1							
TNA family	4	–0.027	0.038	0.601	1						
Flow	5	–0.018	–0.012	0.016	0.016	1					
Absolute flow	6	0.062	0.057	–0.253	–0.095	0.149	1				
Flow volatility	7	0.025	0.029	–0.234	–0.085	0.094	0.113	1			
Age	8	0.013	–0.004	0.325	0.113	–0.185	–0.205	–0.171	1		
Total expense ratio	9	–0.027	–0.074	–0.388	–0.385	–0.036	0.097	0.057	–0.133	1	
Loads	10	–0.002	–0.028	0.025	–0.013	0.026	0.005	–0.092	0.027	0.407	1

Panel D: Pairwise correlations among fund characteristics (annual data) – Non–quantitative funds

		1	2	3	4	5	6	7	8	9	10
Raw return	1	1									
Four–factor alpha	2	0.295	1								
TNA	3	–0.016	–0.030	1							
TNA family	4	0.018	0.054	0.620	1						
Flow	5	–0.036	–0.016	–0.013	0.001	1					
Absolute flow	6	0.032	0.073	–0.230	–0.120	0.147	1				
Flow volatility	7	0.009	0.011	–0.262	–0.060	0.111	0.107	1			
Age	8	0.067	0.035	0.419	0.232	–0.181	–0.204	0.107	1		
Total expense ratio	9	–0.077	–0.087	–0.431	–0.359	–0.015	0.102	–0.204	0.107	1	
Loads	10	–0.035	–0.039	0.019	0.048	0.006	0.003	0.003	0.367	0.107	1

We observe that quantitative funds get on average more net flow than non-quantitative funds, but the differences are not statistically significant. In the case of gross flow, quantitative funds get significantly less gross flow than their non-quantitative counterparts.

3.2.3.2. Fund risk-adjusted performance

We measure fund performance using risk–adjusted returns (i.e., Carhart, 1997, four–factor alpha). To estimate four–factor alpha, we run the following regression:

$$R_{i,t} = \alpha_i + \beta_1 MKT_{i,t} + \beta_2 SMB_{i,t} + \beta_3 HML_{i,t} + \beta_4 MOM_{i,t} + \varepsilon_{i,t}\,, \qquad (3.3)$$

In Equation (3.3), $R_{i,t}$ is the return net of fees of fund *i* in month *t* in excess of the one–month US Treasury bill rate; $MKT_{i,t}$ (*market)* is the excess return on the market in month *t*; $SMB_{i,t}$ (*small minus big*) is the average return on the small–capitalization stock portfolio minus the average return on the large–capitalization stock portfolio; $HML_{i,t}$ (*high minus low*) is the average return on high book–to–market stock portfolio minus the average return on low book–to–market stock portfolio; and $MOM_{i,t}$ (*momentum*) is the average return on past 12–month winners portfolio minus the average return on past 12–month losers portfolio. The previous 36 months of net fund returns are used to estimate the time series regression of monthly excess returns based on the fund's factor portfolios. Next, we to compare the difference between the expected return and realized return of the fund and use this to estimate the fund's abnormal return (or alpha) in each month. We compound monthly alphas to calculate quarterly alphas.

From summary statistics presented in Table 3.2, we conclude that the average quarterly and yearly raw return are higher for quantitative funds, but the differences are not statistically significant. Quantitative funds generate lower alpha, but there are also no significant differences between the alpha produced by quantitative and non–quantitative funds, whether alpha is measured quarterly or yearly. Regarding other mutual fund characteristics, quantitative funds are smaller, younger and belong to smaller families, consistent with the findings in Zhao (2006) and Abis (2020). Consistent with Ahmed and Nanda (2005), Zhao (2006), and Abis (2020), quantitative funds charge significantly lower fees. Quantitative funds charge, on average, a 0.11% lower expense ratio. Additionally, their average loads represent nearly three–quarters of the average loads charged by non–quantitative funds.

Table 3.2, Panels C and D, present pairwise correlations between fund characteristics for quantitative and non–quantitative funds, respectively. From Table 3.2, we conclude that using these fund–level variables together in our tests does not raise concerns of multicollinearity.

3.3. Measuring flow-performance sensitivity for quantitative and non-quantitative funds

We use two different approaches to measure differences in the flow–performance sensitivity of quantitative and non-quantitative funds. We start by examining flows of funds for bottom and top performance quintiles, like in Berk and Tonks (2007). In this approach, at the end of each period, we sort funds into quintiles based on their raw returns over the previous year. Next, we compute the average relative and absolute net flow over the period of the quintile formation and test whether it is statistically different from zero. We do likewise for both quantitative and non-quantitative funds and then calculate the differences between the flows into quantitative and non-quantitative funds and run a *t*–test to find whether these differences are statistically significant.

To further investigate differences in the flow–performance sensitivity between quantitative and non-quantitative funds, we next use a regression–based approach, following Berk and Tonks (2007) and Del Guercio and Reuter (2014). We run the following regression:

$$\begin{aligned} Flows_{i,t} = \; \mu + \; \beta Bottom\, performance_{i,t-1} + \delta\, Performance_{i,t-1} \\ + \; \lambda Top\, performance_{i,t-1} + \theta \alpha_{i,t-1} + \; \eta X_{i,t-1} \; + \varepsilon_{i,t}. \end{aligned} \tag{3.4}$$

We regress the relative flows or absolute flows (computed according to Equations (3.2) and (3.1), respectively) of fund *i* in period *t* on past performance, measured as raw returns. We allow for nonlinearity in the flow–performance sensitivity by including bottom and top relative performance dummies (if fund *i*'s performance is in the bottom or the top quintile of funds in period *t–1*, respectively). Following Berk and Tonks (2007) and Del Guercio and Reuter (2014), we also include past period four–factor alpha ($\alpha_{i,t-1}$), to test for investor's sensitivity to both raw return and four-factor alpha. Additional control variables include fund size, fund family size, flows, age, total expense ratio, and loads (Chevalier & Ellison, 1997; Sirri & Tufano, 1998; Huang et al., 2007; Ferreira et al., 2012). Additionally, we include volatility, measured by the standard deviation of returns (Huang et al., 2007).

To test for differences in the flow–performance sensitivity of quantitative and non–quantitative funds, we follow the procedure in Del Guercio and Reuter (2014), and pool quantitative and non–quantitative funds in a single regression, and present the coefficients separately for: (1) quantitative funds, where the coefficients correspond to independent variables (and fixed effects) interacted with a quantitative dummy variable that takes the value of one if the fund is classified as a quantitative fund; and, (2) non–quantitative funds, where the coefficients correspond to independent variables (and fixed effects) interacted with a non–quantitative dummy variable, which takes the value of one if the fund is not classified as a quantitative fund. We then run a *t*–test to determine the differences in the coefficients on prior–period four–factor alpha (and prior–period control variables) between quantitative and non–quantitative funds. All regressions include time fixed effects and benchmark fixed effects, and we account for cross–sectional correlation and for the time series autocorrelation within funds computing robust standard errors clustered by fund and time.

3.4. Empirical results on differences between the flow-performance sensitivity for quantitative and non-quantitative funds

We first look at flows of funds for bottom and top performance quintiles, following the Berk and Tonks (2007) approach. Table 3.3 presents the results with performance measured using raw returns. We use quarterly data in Panel A and annual data in Panel B. First, at the end of each period, we sort funds into quintiles based on their raw returns over the previous year. We then compute the average relative and absolute net flow over the period of the quintile formation and test whether it is statistically different from zero. Column (1) shows the results for all funds, Columns (2) and (3), present the results for quantitative and non–quantitative funds, respectively. In Column (4) we compute the differences between the two categories of funds and run a *t*–test to find whether these differences are statistically significant.

Table 3.3: Fund flows and performance in the bottom and top performance quintiles – raw returns
This table presents the average relative and absolute net flows (computed according to Equations (3.2) and (3.1), respectively) of the bottom and top performance quintiles, using quarterly data in Panel A and annual data in Panel B. Column (1) reports the results for all funds in our sample, Columns (2) and (3) report the results for quantitative and non–quantitative funds, respectively. At the end of each period, we sort funds into quintiles based on their raw returns over the previous year. We next compute the average relative and absolute net flow over the period of the quintile formation and test whether it is statistically different from zero. Column (4) presents the differences between quantitative and non–quantitative funds, and the results of a *t*–test, testing whether these differences are statistically significant. *p*–values are reported in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. See Appendix C for variable definitions.

Panel A – Quarterly data

	All funds	Quantitative	Non–quantitative	Quantitative minus Non–quantitative (p–value)
	(1)	(2)	(3)	(4)
Bottom performance t–1				
Flow (%)	–3.3912***	–3.1744***	–3.4637***	0.2893
	(0.00)	(0.00)	(0.00)	(0.49)
Absolute flow	–25.0116***	–23.5397***	–25.3186***	1.7789
	(0.00)	(0.00)	(0.00)	(0.41)
Top performance t–1				
Flow (%)	5.3492***	4.9585***	5.4311***	–0.4726
	(0.00)	(0.00)	(0.00)	(0.35)
Absolute flow	15.8794***	13.6457***	16.0646***	–2.4189
	(0.00)	(0.00)	(0.00)	(0.33)
Number of observations	159,643	9,086	150,557	–

Panel B – Annual data

	All funds	Quantitative	Non–quantitative	Quantitative minus Non–quantitative (p–value)
	(1)	(2)	(3)	(4)
Bottom performance t–1				
Flow (%)	–11.7734***	–11.247***	–11.8115***	0.5645
	(0.00)	(0.00)	(0.00)	(0.57)
Absolute flow	–77.9784***	–69.1476***	–78.8504***	9.7028
	(0.00)	(0.00)	(0.00)	(0.68)
Top performance t–1				
Flow (%)	25.7445***	24.7815***	25.8136***	–1.0321
	(0.00)	(0.00)	(0.00)	(0.84)
Absolute flow	40.1879***	39.8405***	41.7914***	–1.9510
	(0.00)	(0.00)	(0.00)	(0.87)
Number of observations	36,781	2,503	34,278	–

Our results show significant net outflows of capital in the bottom performance quintiles and net inflow of capital into top performance quintiles, for both quantitative and non–quantitative funds, which indicates that investors chase past performance and is consistent with the assumptions of the Berk and Green (2004) model. More importantly, the results in Table 3.3 show no significant differences in the net inflow and net outflow of capital of quantitative and non–quantitative funds. We find identical results in Table 3.4, when we use four–factor alpha rather than raw returns as our performance measure.

Table 3.4: Fund flows and performance in the bottom and top performance quintiles – four–factor alpha
This table presents the average relative and absolute net flows of the bottom (computed according to Equations (3.2) and (3.1), respectively) and top performance quintiles, using quarterly data in Panel A and annual data in Panel B. Column (1) reports the results for all funds in our sample, Columns (2) and (3) report the results for quantitative and non–quantitative funds, respectively. At the end of each period, we sort funds into quintiles based on their four–factor alpha over the previous year. We next compute the average relative and absolute net flow over the period of the quintile formation and test whether it is statistically different from zero. Column (4) presents the differences between quantitative and non–quantitative funds, and the results of a *t*–test, testing whether these differences are statistically significant. *p*–values are reported in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. See Appendix C for variable definitions.

Panel A – Quarterly data

	All funds	Quantitative	Non–quantitative	Quantitative minus Non–quantitative (p–value)
	(1)	(2)	(3)	(4)
Bottom performance t–1				
Flow (%)	–3.2201***	–2.6713***	–3.2804***	0.6091
	(0.00)	(0.00)	(0.00)	(0.67)
Absolute flow	–24.3583***	–22.206***	–24.7364***	2.5303
	(0.00)	(0.00)	(0.00)	(0.26)
Top performance t–1				
Flow (%)	4.7643***	4.1631***	4.8223***	–0.6592
	(0.00)	(0.00)	(0.00)	(0.61)
Absolute flow	12.0918***	12.1312***	11.9123***	0.2189
	(0.00)	(0.00)	(0.00)	(0.53)
Number of observations	159,643	9,086	150,557	–

Panel B – Annual data

	All funds	Quantitative	Non–quantitative	Quantitative minus Non–quantitative (p–value)
	(1)	(2)	(3)	(4)
Bottom performance t–1				
Flow (%)	–5.4525***	–6.8791***	–5.0694***	–1.8097
	(0.00)	(0.00)	(0.00)	(0.17)
Absolute flow	–67.7135***	–69.3722***	–66.8994***	–2.4728
	(0.00)	(0.00)	(0.00)	(0.74)
Top performance t–1				
Flow (%)	22.6345***	21.1987***	22.8589***	–1.6602
	(0.00)	(0.00)	(0.00)	(0.41)
Absolute flow	33.9085***	31.674***	34.915***	–3.2410
	(0.00)	(0.00)	(0.00)	(0.69)
Number of observations	36,781	2,503	34,278	–

We next use the regression–based approach, following Berk and Tonks (2007) and Del Guercio and Reuter (2014). Tables 3.5 and 3.6 present the results for relative and absolute flows, respectively.

Table 3.5: Fund flow–performance sensitivity – relative flow

This table presents the estimates of panel regressions measuring the flow–performance sensitivity for funds in our sample, as presented in Equation (3.4). We use quarterly data in Panel A and annual data in Panel B. Relative fund flow (computed according to Equation (3.2)) is regressed on prior–period performance measured using raw returns. We also include dummies for funds in the bottom and top prior–period performance quintiles, and prior–period four–factor alpha. Lagged control variables include fund size, fund family size, flows, flow volatility, age, tracking error, total expense ratio, and loads. Regressions also include time fixed effects, benchmark fixed effects, and style fixed effects. Column (1) reports the results of a pooled regression that contains all funds in our sample, i.e., quantitative and non–quantitative funds. The coefficients in Columns (2) and (3) are from a single regression, where the coefficients in Column (2) correspond to independent variables (and fixed effects) interacted with a quantitative dummy variable, which takes the value of one if the fund is classified by Lipper Hindsight as a quantitative fund, and the coefficients in Column (3) correspond to independent variables (and fixed effects) interacted with a non–quantitative dummy variable, which takes the value of one if the fund is not classified by Lipper Hindsight as a quantitative fund. Robust *t*–statistics clustered by fund and quarter (or by fund and year) are reported in parentheses. Column (4) presents the difference between the coefficients of independent variables for quantitative and non–quantitative funds, from Columns (2) and (3), respectively, and the results of a *t*–test, testing whether these differences are statistically significant (*p*–values are reported in parentheses). *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. See Appendix C for variable definitions.

Panel A – Quarterly data

	All funds	Quantitative	Non–quantitative	Quantitative minus Non–quantitative (p–value)
	(1)	(2)	(3)	(4)
Bottom Performance	–0.0116***	–0.0161***	–0.0117***	–0.0044
	(–8.50)	(–2.63)	(–8.37)	(0.37)
Performance	0.3105***	0.2853**	0.3269***	–0.0416
	(8.93)	(2.43)	(9.14)	(0.59)
Top performance	0.0249***	0.0260***	0.0257***	–0.0003
	(16.35)	(4.51)	(16.25)	(0.64)
Four–factor alpha	0.6447***	0.6949***	0.6400***	0.0549
	(18.81)	(4.05)	(18.26)	(0.75)
TNA (log)	–0.0036***	–0.0081***	–0.0033***	–0.005***
	(–9.75)	(–4.78)	(–8.76)	(0.01)
TNA Family (log)	0.0026***	0.0038***	0.0025***	0.0013
	(10.85)	(3.30)	(10.10)	(0.25)
Flows	0.1413***	0.1359***	0.1404***	–0.0045
	(19.47)	(6.18)	(18.54)	(0.85)
Flow volatility	0.1676***	0.0996***	0.1723***	–0.0727***
	(16.56)	(2.95)	(16.35)	(0.00)
Age	–0.0156***	–0.0121***	–0.0159***	0.0030
	(–22.29)	(–3.57)	(–22.12)	(0.28)
Total expense ratio	–1.4254**	–4.5072**	–1.0943**	–3.413***
	(2.57)	(–2.39)	(2.03)	(0.00)
Loads	2.1201***	3.0212	2.0176***	1.0036
	(3.89)	(1.50)	(3.59)	(0.30)
Adjusted R–squared	0.201			0.203
Number of observations	159,643			159,643

Panel B – Annual data

	All funds	Quantitative	Non–quantitative	Quantitative minus Non–quantitative (p–value)
	(1)	(2)	(3)	(4)
Raw return (Bottom)	–0.0623***	–0.0746**	–0.0602***	–0.0138
	(–5.29)	(–2.42)	(–5.18)	(0.71)
Raw return	0.1753***	0.1995***	0.1698***	0.0297
	(7.74)	(2.01)	(7.41)	(0.84)
Raw return (Top)	0.1198***	0.1114***	0.1148***	–0.0034
	(7.87)	(4.16)	(7.45)	(0.39)
Four–factor alpha	0.4390***	0.4506**	0.4287***	0.0219
	(6.93)	(2.53)	(6.70)	(0.56)
TNA (log)	–0.0271***	–0.0536***	–0.0251***	–0.0286***
	(–8.12)	(–3.40)	(–7.37)	(0.00)
TNA Family (log)	0.0194***	0.0344***	0.0181***	0.0163
	(8.74)	(3.15)	(7.93)	(0.14)
Flow	0.0931***	0.0757*	0.0941***	–0.0184
	(8.85)	(1.79)	(8.74)	(0.67)
Flow volatility	1.0731***	1.1810***	1.0675***	0.1135
	(17.03)	(4.71)	(16.41)	0.9007
Age	–0.0662***	–0.0605**	–0.0663***	0.0060
	(–10.81)	(–2.03)	(–10.64)	(0.01)
Total expense ratio	–1.3083**	–3.9759**	–1.0243**	2.951***
	(–2.12)	(–2.13)	(–1.98)	(0.00)
Loads	1.6035***	1.4500	1.6202***	–0.1702
	(2.95)	(1.17)	(3.01)	(0.60)
Adjusted R–squared	0.175			0.177
Number of observations	36,781			36,781

Table 3.6: Fund flow–performance sensitivity – absolute flow

This table presents the estimates of panel regressions measuring the flow–performance sensitivity for funds in our sample, as presented in Equation (3.4). We use quarterly data in Panel A and annual data in Panel B. Absolute fund flow (computed according to Equation (3.1)) is regressed on prior–period performance measured using raw returns. We also include dummies for funds in the bottom and top prior–period performance quintiles, and prior–period four–factor alpha. Lagged control variables (no reported in panels) include fund size, fund family size, absolute flows, absolute flow volatility, age, tracking error, total expense ratio, and loads. Regressions also include time fixed effects, benchmark fixed effects, and style fixed effects. Column (1) reports the results of a pooled regression that contains all funds in our sample, i.e., quantitative and non–quantitative funds. The coefficients in Columns (2) and (3) are from a single regression, where the coefficients in Column (2) correspond to independent variables (and fixed effects) interacted with a quantitative dummy variable, which takes the value of one if the fund is classified by Lipper Hindsight as a quantitative fund, and the coefficients in Column (3) correspond to independent variables (and fixed effects) interacted with a non–quantitative dummy variable, which takes the value of one if the fund is not classified by Lipper Hindsight as a quantitative fund. Robust *t*–statistics clustered by fund and quarter (or by fund and year) are reported in parentheses. Column (4) presents the difference between the coefficients of independent variables for quantitative and non–quantitative funds, from Columns (2) and (3), respectively, and the results of a *t*–test, testing whether these differences are statistically significant (*p*–values are reported in parentheses). *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. See Appendix C for variable definitions.

Panel A – Quarterly data

	All funds	Quantitative	Non–quantitative	Quantitative minus Non–quantitative (p–value)
	(1)	(2)	(3)	(4)
Bottom Performance	–3.5369***	–4.9497**	–3.3951***	–1.5546
	(–3.56)	(–2.05)	(–3.32)	(0.89)
Performance	135.4260***	154.0587**	134.4411***	19.6177
	(5.04)	(2.33)	(4.82)	(0.26)
Top performance	4.9859***	4.5973**	5.3126***	–0.7153
	(4.10)	(1.98)	(4.15)	(0.85)
Four–factor alpha	206.3724***	196.3715***	210.5493***	–14.1778
	(10.94)	(2.95)	(10.80)	(0.59)
Adjusted R–squared	0.425			0.428
Number of observations	159,643			159,643

Panel B – Annual data

	All funds	Quantitative	Non–quantitative	Quantitative minus Non–quantitative (p–value)
	(1)	(2)	(3)	(4)
Bottom Performance	–15.0493***	–18.3747*	–16.4405***	–1.9340
	(–4.41)	(–1.86)	(–4.58)	(0.74)
Performance	41.8997**	49.4534*	39.3884**	10.0650
	(2.14)	(1.75)	(2.01)	(0.53)
Top performance	20.8795***	19.2798*	22.0410***	–2.7620
	(4.89)	(1.74)	(4.88)	(0.92)
Four–factor alpha	157.3753***	160.6522**	154.4371***	6.2200
	(8.04)	(2.55)	(7.89)	(0.70)
Adjusted R–squared	0.359			0.365
Number of observations	36,781			36,781

We start, in Column (1), by running a pooled regression that includes all funds in our sample taken together. To test for differences between quantitative and non–quantitative funds, we next pool quantitative and non–quantitative funds in a single regression and present the coefficients separately for: (1) quantitative funds, where the coefficients, presented in Column (2), correspond to independent variables (and fixed effects) interacted with a quantitative dummy variable that takes the value of one if the fund is classified as a quantitative fund; and (2) non–quantitative funds, where the coefficients, presented in Column (3), correspond to independent variables (and fixed effects) interacted with a non–quantitative dummy variable, which takes the value of one if the fund is classified as a non–quantitative fund. In Column (4), we run a *t*–test to see if there are differences in the coefficients of quantitative and non–quantitative funds.

We find that flows respond to past performance, which confirms our preliminary results in Tables 3.3 and 3.4 and is consistent with the literature (Chevalier & Ellison, 1997; Sirri & Tufano, 1998; Del Guercio & Tkac, 2002; Berk & Tonks, 2007; Del Guercio & Reuter, 2014). Our results also show that fund flows are sensitive to both raw returns and four–factor alpha as in Del Guercio and Reuter (2014). When looking at the results in Columns (4) of Tables 3.5 and 3.6 we find no significant differences in the way quantitative and non-quantitative investors react to past performance. This is true for bottom performers or top-performing funds, and when performance is measured by raw returns or four-factor alpha. The results also hold whether we use relative or absolute fund flow and whether focusing on quarterly or annual flows.

Additionally, our results in Table 3.5 show that larger quantitative funds get less flow, while flow volatility has less impact on next quarter flow (but not in next year) for quantitative funds. Finally, our results also indicate a stronger flow-fee sensitivity for quantitative investors.

Overall, our results are consistent with no differences in the flow-performance sensitivity of quantitative and non-quantitative funds.

3.5. Robustness tests

In this section we run additional tests to check the robustness of our results. The tables are presented in Appendix D. There may be concerns about the power of our tests when we divide the sample of funds into quintiles. We therefore redo our tests using terciles rather than quintiles. The results of examining flows of funds for bottom and top performance terciles are presented in Tables D.1 and D.2 for performance measured using raw returns and four-factor alpha, respectively. We next rerun the regression–based approach with past performance terciles in Tables D.3 and D.4 for relative and absolute flows, respectively, with performance measured as raw returns and four-factor alphas. These tests show that our main conclusions do not change.

3.6. Conclusion

In this paper we study differences in the flow-performance sensitivity between quantitative and non–quantitative actively managed US equity funds. We find that quantitative investors buy more top performing funds and sell less poor performers, which is no different from the main findings in the mutual fund literature. Our findings also indicate no significant differences in the way quantitative and non-quantitative investors react to past performance, which indicates homogeneity rather than heterogeneity in investors preferences.

Our results are important for investors and practitioners. As the flow-performance sensitivity affects how fund managers and mutual fund companies run their portfolios, it determines the level of fees charged, the level of risk-taking, and ultimately the performance delivered to the investor.

Our results are also important for future research trying to explain differences among quantitative and non-quantitative funds as they suggest that any differences to be found in fees, risk-taking or performance between quantitative and non-quantitative funds originate from fund managers and fund management companies’ decisions and strategies rather from investors preferences.

4. Active share and quantitative funds

Abstract: We study differences in *Active share* between quantitative and non–quantitative actively managed US equity funds. Our results show that the *Active share* is lower for quantitative funds. When testing for differences in the impact of *Active share* on the performance of quantitative and non–quantitative funds we find that, consistent with the literature, *Active share* predicts the performance of non–quantitative funds, but decreases the performance of quantitative funds. This difference remains statistically and economically important for funds with different benchmark types.

JEL classification: G11, G23, G40

Keywords: Quantitative analysis, Active share, Management skill, Mutual fund industry.

4.1. Introduction

The literature shows that, although most individual investors could benefit from stock market participation, the benefits of participation depend on whether investors hold adequately diversified portfolios (e.g., Campbell & Viceira, 2002; Campbell, 2006; D'Acunto et al., 2019).[37] The literature also shows that the large majority of investors do not diversify their portfolios and that most investors who choose to do it, seek for professional advice on their investment decisions (Von Gaudecker, 2015; Badarinza et al., 2016). Of those investors who prefer to gain equity exposure without trading stocks directly, many choose to do it through delegation to mutual funds. In the US, 47% of households own mutual funds, representing 89% of the total mutual fund assets under management (ICI, 2021).

There is however a long debate in the mutual fund literature on whether fund managers have the ability to properly diversify their portfolios and also on whether diversification increases fund performance. The bulk of the literature suggests that, after taking into account fees and controlling for systematic risk exposure, most actively managed mutual funds underperform their benchmarks (e.g., Gruber, 1996; Carhart, 1997), which has contributed to the increasing adoption of passive investment strategies (e.g., Cremers & Petajisto, 2009; Cremers et al., 2016). The shift towards passive investing stands out as one of the key developments in asset management in recent years, as investors prefer to keep costs low and eliminate the risk of underperforming a benchmark, rather than engage in the illusion of the superior performance of actively managed funds.[38]

The objective of active management is to produce a return that exceeds its benchmark return.[39] Therefore, the attempt to outperform a fund's benchmark (i.e., to create value to investors) depends on fund manager's ability to deviate from the benchmark. The influential study by Cremers and Petajisto (2009) introduced a new measure of active portfolio management, which represents *"the fraction of portfolio that is different from the benchmark index"* (Cremers & Petajisto, 2009, p. 3330). Cremers and Petajisto (2009) show that funds with higher *Active share* outperform their reported benchmarks, and find that the risk–adjusted performance of high–active–share funds is significantly higher than that of low–active–share

[37] While a relatively small share of American families' savings (15%) are directly invested in individual stocks, a majority (55%) have some level of investment in the stock market.

[38] At the end of 2020, the share of assets managed by passive funds in the US mutual fund industry is 35% (ICI, 2020).

[39] The distinction between active and passive investing is not always clear–cut; for example, some nominally active investment funds behave passively by following so–called "closet–indexing" strategies (Cremers & Petajisto, 2009).

funds. These results are also consistent with that observed in Petajisto (2013) and Cline and Gilstrap (2021), and in other studies that show that the empirical relation between deviations from the benchmark and fund alpha is reliably positive (Kacperczyk et al., 2005; Kacperczyk et al., 2014).[40]

In this paper, we study differences in *Active share* between quantitative and non–quantitative funds. We specifically start by understanding how active quantitative funds are and whether these funds deviate more or less than non–quantitative funds from their benchmarks. Next, and more important, we look at the impact of *Active share* on the performance of quantitative and non–quantitative funds. The main research question of our study is therefore whether there are differences in the impact of *Active share* on the performance of quantitative and non–quantitative funds.

Quantitative funds have come to play an increasing role in mutual fund industries in recent years. Advances in machine learning and big data analysis together with investor's belief that quantitative models are less susceptible to cognitive errors and biases have contributed to the increasing popularity of quantitative funds. While emotions and cognitive errors, influence individuals' trading decisions, quantitative funds remove the emotional and cognitive input from the decision process, as they rely on objective mathematical and statistical models to select securities. For this reason, investors expect quantitative funds to overcome the inability of human–managed active funds to beat their benchmarks (D'Acunto et al., 2019).

Despite the rising interest of investors in quantitative funds, very little is known about how quantitative analysis affects the mutual fund industry. Ahmed and Nanda (2005) and Casey, Quirk and Associates (2005) find that quantitative funds outperform traditional fund managers, while Wermers et al. (2012) show that fundamental methods of stock selection are superior to quantitative approaches. Zhao (2006) finds no differences in performance between quantitative and non–quantitative funds. Ahmed and Nanda (2005), Zhao (2006) and Abis (2020) find that quantitative funds charge lower fees than non–quantitative funds. Abis (2020) proposes an equilibrium model that predicts that quantitative funds focus on stock picking, hold more stocks and display pro–cycle performance, while non–quantitative funds do both stock picking and market timing and focus on stocks with less available information. Beggs et al. (2021) show that quantitative funds fire sales have a much larger impact on market instability than fire sales by

[40] The evidence that a fund's *Active share* predicts its future risk–adjusted performance also holds internationally, as indicated in Cremers et al. (2016) and Keswani et al. (2020).

traditional mutual funds, which indicates that quantitative investing may result in a more instable market.[41]

We use the classification provided by Lipper Hindsight to identify quantitative funds. According to Lipper Hindsight, quantitative funds are *"funds that use a rules–based mathematical model in order to initiate buy and sell decisions."*, i.e., funds which rely solely on quantitative models to select stocks. Because Lipper Hindsight does not provide data on *Active share*, we follow Cremers et al. (2016) and compute this variable using data from the FactSet database. Our final sample includes 204 quantitative funds in the 2000–2019 period, representing 6% of the funds in our sample.[42]

We start by looking at differences in *Active share* between quantitative and non–quantitative funds. Our results show that the level of *Active share* is lower for quantitative funds than for their non–quantitative peers by around 4%, which is economically important. Because the literature shows differences in *Active share* between different fund benchmark types (e.g., Frazzini et al., 2016), we move on and also test for differences in *Active share* between quantitative and non–quantitative funds by fund benchmark type, namely for large–, all–, mid–, and small–cap funds. Like Frazzini et al. (2016), our results show differences in the average *Active share* across funds with different benchmark types, but, more important for our study, we also find statistically and economically differences between quantitative and non–quantitative funds in the *Active share* of all benchmark types. These differences vary between –9% and –15% for all–cap and small–cap funds, respectively. We next look at the impact of *Active share* on the performance of quantitative and non–quantitative funds. In the case of non–quantitative funds, we find that *Active share* increases future performance, which is consistent with the findings in Cremers and Petajisto (2009). But we find opposite results for quantitative funds as, rather than increasing performance, *Active share* decreases the performance of these funds. The results are both statistically and economically important. A 10% increase in *Active share* leads to an increase of 27 basis points in next year's four–factor alpha of non–quantitative funds, while it is associated with a decrease of 19 basis points in next year's four–factor alpha of quantitative funds. This represents a difference of 46 basis points in the four–factor alpha of quantitative and non–quantitative funds. We also find important differences in the four–factor alpha of funds with different benchmark types, particularly for small and mid–cap funds (–65

[41] Some papers study the impact of quantitative methods on hedge fund performance, including Khandani and Lo (2011), Chincarini (2014), and Harvey et al. (2017). There are also some studies on the impact of quantitative investing on financial markets (Kirilenko & Lo, 2013; Birru et al., 2019; D'Acunto et al., 2019) and fund management (Fabozzi et al., 2007, 2008).

[42] See Table 4.1.

and –89 basis points, respectively). In sum, our results show marked differences not only in the level of *Active share* of quantitative and non–quantitative funds but also in the impact of *Active share* on the performance of these funds.

We conduct a number of tests to confirm the robustness of our results. Because quantitative funds are on average much smaller than non–quantitative funds, we start by looking at whether fund size determines the observed differences. We find that this is not the case, as the difference remains for both smaller and larger quantitative and non–quantitative funds. We next run our main tests using benchmark–adjusted returns rather than four–factor alphas as our performance measure. We find that the results remain unchanged and that the economic impact also remains highly significant. To alleviate concerns that our results are driven by differences in fee levels between quantitative and non–quantitative funds, we run our main tests with gross performance and our main conclusions do not change. We control for fund turnover in our main regressions and conclude that our results remain unchanged. Finally, we also examine alternative ways of clustering the standard errors of our regressions. We cluster by fund family and time and by fund style and time. We find that our results do not change.

Our study makes important contributions. First, we add to the scarce literature on quantitative funds. Second, to the best of our knowledge, we are the first to study *Active share* for quantitative funds. Third, our results have significant implications for both investors and practitioners. *Active share* has become a widely used concept in fund analysis and, consistent with the main findings in the literature, market participants believe that the attempt to outperform a fund's benchmark (i.e., to create value to investor) depends on fund manager's ability to deviate from the benchmark. Our findings indicate that not only quantitative funds deviate less from their benchmarks but that greater benchmark differentiation results in underperformance rather than outperformance for these funds. These conclusions suggest that quantitative funds do not adequately diversify portfolios and, contrary to investors' expectations, quantitative funds do not overcome the inability of human–managed active funds to beat their benchmarks. Moreover, our results in Chapter 3 find no differences in the flow-performance sensitivity of quantitative and non-quantitative investors, which indicates that the observed differences in *Active share* originate from fund managers and fund management companies' decisions and strategies and cannot be attributed to differences in investors preferences.

Finally, our conclusions are also relevant to policy–making. Our study contributes to the understanding of how fund managers add value for their clients. At a time when the fraction of individual investors that delegate their portfolio management to professional investment managers is increasing, they suggest that regulators should keep quantitative funds under close scrutiny.[43]

4.2. Data and variables description

4.2.1 Data

Our study uses data from two primary databases: Lipper Hindsight and FactSet. We obtain individual fund characteristics, such as fund name, returns, benchmark, size, and expenses from the Lipper Hindsight survivorship–bias free database. We focus on US open–end, and actively managed equity funds in the 2000–2019 period. Lipper lists multiple share classes as separate funds, but these funds have the same holdings, the same manager, and the same returns before expenses and loads. Therefore, to prevent double counting of funds, we follow, e.g., Demirci et al. (2021), and use the primary share class as our unit of observation and aggregate fund–level variables across different share classes.

Because Lipper Hindsight does not provide data on *Active share*, we follow Cremers et al. (2016) and compute this variable using data from the FactSet database. The Factset database covers portfolio equity holdings for institutional investors. We match the Lipper (fund characteristics and performance) and Factset (fund holdings) databases by CUSIP (Committee on Uniform Security Identification Procedures), ISIN (International Securities Identification Number) or fund name.[44]

To identify quantitative and non–quantitative funds, we use the classification provided by Lipper Hindsight, which follows the funds' Principal Investment Strategy reported in their prospectus's disclosures. Lipper flags funds which purely rely on quantitative models to select securities as quantitative: *"funds that use a rules–based mathematical model in order to initiate buy and sell decisions."*[45]

Our sample is restricted to domestic funds, i.e., those funds investing primarily in US stocks. We impose a minimum of 36 continuous monthly observations for each fund, in order to ensure that we have sufficient time series observations to calculate four–factor alphas observations for each fund. We also require mutual funds to have data on all our control

[43] In 1980, 48% of U.S. equity was directly held by individuals, as opposed to being held through intermediaries; by 2020, that fraction was down to 15% (ICI, 2021)
[44] See Ferreira and Matos (2008) provide a detailed description of this data source.
[45] Section 3.2.2 presents a detailed explanation on how we proceed to identify our sample of quantitative funds.

variables. Overall, our sample is identical to that described in Section 3.2.2, except that we additionally exclude those funds for which holdings are not available in LionShares.[46]

This leads to a final sample of 3,330 unique funds and a TNA of $4,205 billion. Figure 4.1 shows the number of quantitative funds and the number of quantitative funds as a percentage of the total number of funds for the 2000–2019 sample period.

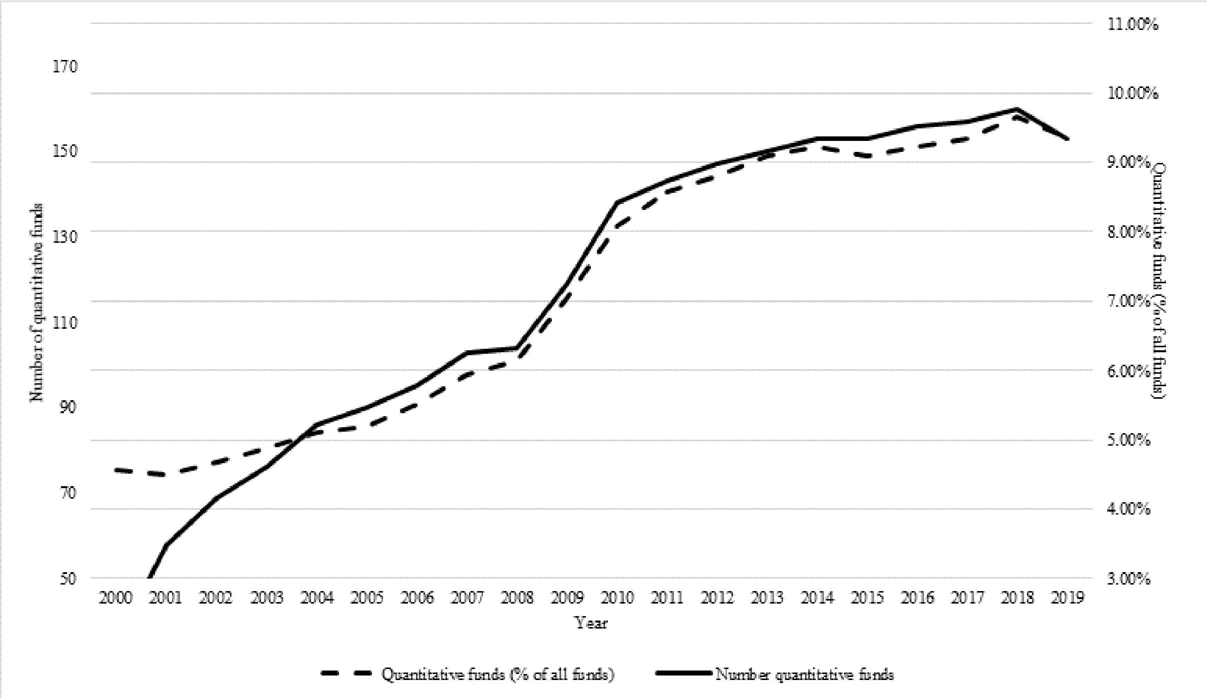

Figure 4.1: Quantitative funds in our sample

This figure shows the number of quantitative funds (solid line) and the number of quantitative funds as a percentage of the total number of funds (dashed line) for the 2000–2019 period. The sample is restricted to US open–end and actively managed domestic equity funds drawn from the Lipper Hindsight database for which holdings are available in Factset.

In the year 2000, the number of quantitative funds represents nearly 4% of the total number of funds in our sample and it goes up to more than 9% at the end of 2019.

Table 4.1 presents the number of unique funds in our sample and the total assets under management (TNA) at the end of 2019, for both non–quantitative and quantitative funds.

[46] See Ferreira et al. (2013), and Cremers et al. (2016) for a detailed description of Lipper's data coverage.

Table 4.1: Mutual fund industry sample by quantitative and non–quantitative funds
This table presents the number of unique funds in our sample and total net assets (TNA) under management (sum of all share classes in millions of US dollars at the end of 2019) for both quantitative and non–quantitative funds. The sample is restricted to US open–end and actively managed domestic equity funds drawn from the Lipper Hindsight database for which holdings are available in Factset. The sample period is 2000–2019. See Appendix E for variable definitions.

Funds	Number of funds	TNA ($ million)
Non–quantitative	3,126	4,037,673
Quantitative	204	167,804
Total	3,330	4,205,477

We have a sample of 3,126 are non–quantitative funds and 204 are quantitative funds, representing a TNA of $4,038 billion and $168 billion, respectively.

4.2.2. Measuring Active share

We follow Cremers and Petajisto (2009) and measure *Active share* as the percentage of fund's portfolio holdings that differ from its benchmark index holdings, calculated as:

$$Active\ share = \frac{1}{2}\sum_{i=1}^{n}\left|w_{i,fund} - w_{i,index}\right|, \tag{4.1}$$

where $w_{i,fund}$ and $w_{i,index}$ are the portfolio weights of stock *i* in the fund and its benchmark index, respectively, and the sum is taken over the universe of all stocks in the fund.

Active share measures the difference between a portfolio's holdings and those of its benchmark, and has an intuitive economic interpretation: *"We can decompose a mutual fund portfolio into a 100% position in the benchmark index, plus a zero–net–investment long–short portfolio. The long–short portfolio represents all the active bets the fund has taken. Active share measures the size of that long–short portfolio as a fraction of the total portfolio of the fund. We divide the sum of portfolio weight differences by 2 so that a fund that has 0 overlap with its benchmark index gets a 100% Active share (i.e., we do not count the long side and the short side of the positions separately)"* (Cremers & Petjisto, 2009, p. 3335).

Table 4.2, Panel A, presents summary statistics for *Active share* for quantitative and non–quantitative funds in our sample. In Panel A, we observe that the average *Active share* for quantitative and non–quantitative funds in our sample is 75.84% and 79.51%, respectively. This means that on average quantitative funds deviate less 4% from their benchmarks than their non–quantitative peers, which is economically relevant. In Panel B of Table 4.2, we conclude that the difference in *Active share* between quantitative and non–quantitative funds is also statistically significant.

Table 4.2: Fund Active share for quantitative and non–quantitative funds

This table presents details on mutual fund *Active share* for both quantitative and non–quantitative funds. Panel A presents summary statistics for fund *Active share*. In Panel B, we compute the average *Active share* by fund benchmark type, namely large–, all–, mid–, and small–cap funds, for quantitative and non–quantitative funds. Panel B also presents the differences in means of *Active share* by fund benchmark type for quantitative and non–quantitative funds and the results of a t–test which show whether these differences are statistically significant. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. The sample is restricted to US open–end and actively managed domestic equity funds drawn from the Lipper Hindsight database for which holdings are available in Factset. The sample period is 2000–2019. See Appendix E for variable definitions.

Panel A: Summary statistics for fund Active share for quantitative and non–quantitative funds

Funds	Mean	Median	Standard deviation	Percentile 10th	Percentile 90th	Number of observations
Quantitative	75.84	77.81	17.40	2.64	100.00	2,345
Non–quantitative	79.51	83.24	16.36	0.31	100.00	29,705
All	79.22	82.85	16.47	0.31	100.00	32,050

Panel B: Average Active share by fund benchmark type

			Quantitative minus Non–quantitative	
Benchmark type	Quantitative	Non–quantitative	Difference	(p–value)
All–cap	68.78	69.32	–0.54	(0.69)
Large–cap	67.63	70.79	–3.16	(0.00)
Mid–cap	87.46	90.20	–2.73	(0.00)
Small–cap	84.48	89.50	–5.02	(0.00)
All	75.84	79.51	–3.67	(0.00)

The literature has shown differences in *Active share* between fund benchmark types (e.g., Frazzini et al., 2016). Therefore, in Panel B of Table 4.2, we compute the average *Active share* by fund benchmark type, namely large–, all–, mid–, and small–cap funds, for quantitative and non–quantitative funds. Panel B also presents the differences in means for quantitative and non–quantitative funds and the results of a *t*–test which show whether these differences are statistically significant. From Panel B, we observe that, for both active quantitative and non–quantitative funds, small– and mid–cap funds have higher average *Active share* and large– and all–cap funds have lower average *Active share*. Like Frazzini et al. (2016) we also find a substantial difference in the average *Active share* between large– and small–cap funds that holds for quantitative and non–quantitative funds. However, and most important for our study, we also find substantial differences in the average *Active share* of quantitative and non–quantitative funds for the different fund benchmark types. The average *Active share* is higher for non–quantitative funds for all fund benchmark types, and we find statistically significant differences for large–, mid–, and small–cap funds. These differences are also economically important as, in the case of small–cap funds, the average *Active share* for quantitative funds is lower than that of non–quantitative funds by more than 5%.

4.2.3. Measuring fund performance

We measure fund performance using both benchmark–adjusted returns and risk–adjusted returns (i.e., Carhart,1997, four–factor alpha). Benchmark–adjusted returns are calculated as the difference between the fund's raw return and the return of its specific benchmark given in the Lipper database.[47] To estimate four–factor alpha, we run the following regression:

$$R_{i,t} - R_f = \alpha_i + \beta_1 MKT_{i,t} + \beta_2 SMB_{i,t} + \beta_3 HML_{i,t} + \beta_4 MOM_{i,t} + \varepsilon_{i,t}\ . \qquad (4.2)$$

In Equation (4.2), $R_{i,t}$ is the return net of fees in US dollars of fund i in month t; R_f is the return on the one–month US Treasury bill rate; $MKT_{i,t}$ (*market)* is the excess return on the market in month t; $SMB_{i,t}$ (*small minus big*) is the average return on the small–capitalization stock portfolio minus the average return on the large–capitalization stock portfolio; $HML_{i,t}$ (*high minus low*) is the average return on high book–to–market stock portfolio minus the average return on low book–to–market stock portfolio; and $MOM_{i,t}$ (*momentum*) is the average return on past 12–month winners portfolio minus the average return on past 12–month losers portfolio.[48] We use the previous 36 months of net fund returns to estimate the time series regression of monthly excess returns based on the fund's factor portfolios. We next compare the difference between the expected return and the realized return of the fund and use this difference to estimate the fund's abnormal return (or alpha) in each month. We compound monthly alphas to calculate annual alphas (e.g., Ferreira et al., 2013).

Table 4.3, Panel A, presents summary statistics for mutual fund characteristics. In Panel B, we present differences in means of mutual fund characteristics for quantitative and non–quantitative funds and run a *t–test*, testing whether these differences are statistically significant.

[47] The Lipper "Technical Indicator Benchmark".
[48] Factors are from AQR Capital Management (https://www.aqr.com/Insights/Datasets). Table F.1 reports means and standard deviations of monthly factor returns.

Table 4.3: Mutual fund characteristics for quantitative and non–quantitative funds
This table presents details on mutual fund characteristics for both quantitative and non–quantitative funds. Panel A presents summary statistics for mutual fund characteristics. In Panel B we present differences in means of mutual fund characteristics for quantitative and non–quantitative funds and run a *t*–test, testing whether these differences are statistically significant. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. The sample is restricted to US open–end and actively managed domestic equity funds drawn from the Lipper Hindsight database for which holdings are available in Factset. The sample period is 2000–2019. See Appendix E for variable definitions.

Panel A: Summary statistics for mutual funds characteristics for quantitative and non–quantitative funds

Variable	Mean	Median	Standard deviation	Percentile 10	Percentile 90	Observations
Quantitative funds						
Raw return (% year)	8.15	10.33	18.29	–12.30	32.04	2,345
Benchmark–adjusted return (% year)	–0.84	–0.73	5.87	–7.18	5.00	2,345
Four–factor alpha (% year)	–1.24	–1.13	6.08	–7.71	5.14	2,345
Tracking error (% year)	4.92	3.98	3.41	1.95	9.43	2,345
TNA ($ million)	836	227	1,906	27	2,074	2,345
Age (years)	13.99	12.25	9.27	5.42	23.42	2,345
Total shareholder costs (%)	1.30	1.19	0.57	0.69	2.14	2,345
Flow (% years)	9.03	–7.39	72.63	–33.96	48.96	2,345
Benchmark return (% year)	10.62	13.34	17.94	–11.08	31.99	2,345
Non–quantitative funds						
Raw return (% year)	8.24	10.18	20.35	–12.86	32.22	29,705
Benchmark–adjusted return (% year)	–0.77	–1.06	7.07	–8.06	6.68	29,705
Four–factor alpha (% year)	–1.26	–1.11	7.52	–9.09	6.13	29,705
Tracking error (% year)	5.99	4.79	4.29	2.46	10.93	29,705
TNA ($ million)	1,674	304	6,242	23	3,456	29,705
Age (years)	16.99	13.42	13.34	5.50	31.75	29,705
Total shareholder costs (%)	1.45	1.31	0.62	0.79	2.32	29,705
Flow (% years)	5.34	–7.50	60.06	–32.25	37.49	29,705
Benchmark return (% year)	8.99	12.03	19.47	–20.42	32.53	29,705

Panel B: Differences in mutual funds characteristics: quantitative versus non–quantitative funds

			Quantitative minus Non–quantitative	
Fund characteristics	Quantitative	Non–quantitative	Difference	(p–value)
Raw return (% year)	8.15	8.24	0.09	(0.41)
Benchmark–adjusted return (% year)	–0.84	–0.77	–0.06	(0.68)
Four–factor alpha (% year)	–1.24	–1.26	0.02	(0.76)
Tracking error (% year)	4.92	5.99	–1.07***	(0.00)
TNA ($ million)	836	1,674	–839***	(0.00)
Age (years)	13.99	16.99	–3.00***	(0.00)
Total shareholder costs (%)	1.30	1.45	–0.16***	(0.00)
Flow (% years)	9.03	5.34	3.69**	(0.03)
Benchmark return (% year)	10.62	8.99	1.62***	(0.00)

We find no statistically significant differences in performance between quantitative and non–quantitative funds.

4.2.4. Control Variables description

Regarding other mutual fund characteristics, quantitative funds are smaller, younger and belong to smaller families, consistent with the findings in Zhao (2006) and Abis (2020). Consistent with Ahmed and Nanda (2005), Zhao (2006), and Abis (2020), quantitative funds charge significantly lower fees. Compared to non–quantitative funds, quantitative funds charge, on average, a 0.16% lower total shareholder costs.

4.3. Active share for quantitative and non–quantitative funds

To study differences in *Active share* between quantitative and non–quantitative funds, we start by running a panel regression of *Active share* on a quantitative dummy variable, as follows:

$$Active\ share_{i,t} = a + \beta Quantitative_i + \varepsilon_{i,t}, \tag{4.3}$$

where *Active share* is the percentage of a fund's portfolio holdings that differ from its benchmark index holdings calculated as in Equation (4.1), and $Quantitative_i$ is a dummy variable that takes the value of one if the fund is classified by Lipper Hindsight as a quantitative fund and zero otherwise. We add time fixed affects to our regression and, because it is important to control for differences in fund benchmarks across *Active share* levels (e.g., Cremers & Petajisto, 2009), we also introduce benchmark fixed effects in our tests.[49,50] To account for cross–sectional correlation and for the time series autocorrelation within funds, we compute robust standard errors clustered by fund and time.

We next add to the regression in Equation (4.3) a number of lagged controls known to influence fund *Active share*:

$$Active\ share_{i,t} \ = \ a + \ \beta Quantitative_i + \gamma X_{i,t-1} + \varepsilon_{i,t}, \tag{4.4}$$

where $Quantitative_i$ is a dummy variable that takes the value of one if the fund is classified as a quantitative fund, and $X_{i,t-1}$ is a set of lagged control variables that the literature has shown to determine *Active share* (e.g., Cremers & Petajisto, 2009; Frazzini et al., 2016). We start by adding tracking error, which represents the annualized volatility of the difference between a

[49] We follow Cremers et al. (2016) and use the Lipper Technical Indicator Benchmark instead of the self–declared Fund Manager Benchmark. This is to avoid concerns that the fund may strategically choose its benchmark. In untabulated results we find similar using the Fund Manager Benchmark.

[50] To make sure that the results are not driven by the introduction of benchmark fixed effects in our tests, we also run some specifications where we exclude these fixed effects from the regressions.

portfolio return and its benchmark index return. Next, we control for different fund characteristics, including fund size and fund size squared, fund age, total shareholder costs, measured as total expense ratio plus one–fifth of loads. We also add prior year and prior one to three years fund flows and fund benchmark–adjusted returns, and control for the level of fund's benchmark returns by including, both prior year and prior one to three years benchmark returns. Finally, we follow Cremers et al. (2016) and use the Herfindahl index to proxy for industry competitiveness, and, following Petajisto (2013), we also add to our regressions the Chicago Board Options Exchange (CBOE) market volatility index (VIX). Like in the regression in Equation (4.3), we include time and benchmark fixed effects, and we compute robust standard errors clustered by fund and time.

Next, to understand whether fund and market characteristics affect mutual fund *Active share* differently for quantitative and non–quantitative funds and test for the significance of these differences, we rerun the regression in Equation (4.4), removing the quantitative dummy variable from the regression. We start by presenting the results of a pooled regression that contains all funds in our sample taken together. To test for differences in *Active share* between quantitative and non–quantitative funds, we follow Del Guercio and Reuter (2014), and pool quantitative and non–quantitative funds in a single regression, and present the coefficients separately for: (1) quantitative funds, where the coefficients correspond to independent variables (and fixed effects) interacted with a quantitative dummy variable that takes the value of one if the fund is classified as a quantitative fund; and, (2) non–quantitative funds, where the coefficients correspond to independent variables (and fixed effects) interacted with a non–quantitative dummy variable, which takes the value of one if the fund is not classified as a quantitative fund. We then run a *t*–test to determine the differences in the coefficients on prior–period four–factor alpha (and prior–period control variables) between quantitative and non–quantitative funds. As in the regressions in Equation (4.4), these regressions also include time fixed effects and benchmark fixed effects, and we account for cross–sectional correlation and for the time series autocorrelation within funds computing robust standard errors clustered by fund and time.

Finally, because the literature has shown differences in *Active share* between fund benchmark types (e.g., Frazzini et al., 2016), we run additional tests, where we add to our previous regressions dummy variables for the different benchmark types. Therefore, large–, mid– and small–cap variables are dummy variables that equal one if the fund benchmark types are large–, mid–, and small–cap, respectively and zero otherwise. We also present the results for all–cap funds.

4.4. Empirical results on fund Active share

Table 4.4 shows the results for our *Active share* tests. Column (1) presents the results for the regression presented in Equation (4.3), where we regress *Active share* in a dummy variable that takes the value of one if the fund is classified by Lipper Hindsight as a quantitative fund and zero otherwise.

Table 4.4: Fund Active share

This table presents panel regressions to study differences in *Active share* between quantitative and non–quantitative funds. In Column (1) we regress *Active share* on a quantitative dummy variable ($Quantitative_i$) that takes the value of one if a fund i is classified by Lipper Hindsight as a quantitative fund and zero otherwise, according to Equation (4.3), where *Active share* is the percentage of a fund's portfolio holdings that differ from its benchmark index holdings calculated as in Equation (4.1). In Column (2) we add tracking error to the regression in Equation (4.3), as indicated in Equation (4.4). Tracking error represents the annualized volatility of the difference between a portfolio return and its benchmark index return. In Column (3) we control for different fund characteristics, including fund size and fund size squared, fund age, total shareholder costs, measured as estimated as total expense ratio plus one–fifth of loads. We also add prior year and prior one to three years fund flows and fund benchmark–adjusted returns, and control for the level of fund's benchmark returns by including, both prior year and prior one to three years benchmark returns, according to Equation (4.4). In Column (4) we use the Herfindahl index to proxy for industry competitiveness, and add to our regressions the Chicago Board Options Exchange (CBOE) market volatility index (VIX), as indicated in Equation (4.4). Regressions also include time fixed effects and benchmark fixed effects. Robust *t*–statistics clustered by fund and year are reported in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. See Appendix E for variable definitions.

	(1)	(2)	(3)	(4)
Quantitative	–0.0314***	–0.0296***	–0.0317***	–0.0323***
	(–8.43)	(–7.74)	(–8.48)	(–8.55)
Tracking error		2.1055***	1.9244***	1.9639***
		(68.87)	(63.71)	(65.38)
TNA (log)			0.0025	0.0018
			(1.31)	(0.95)
(TNA (log))^2			–0.0010***	–0.0010***
			(–6.40)	(–6.36)
Age			–0.0097***	–0.0087***
			(–7.57)	(–6.80)
Total shareholder costs			2.3886***	2.3261***
			(16.49)	(16.17)
Flow, t–1 to t			–0.0010	–0.0015*
			(–1.11)	(–1.68)
Flow, t–3 to t–1			0.0003	–0.0008
			(0.34)	(–1.02)
Benchmark adjusted return, t–1 to t			0.0415***	0.0469***
			(3.78)	(4.22)
Benchmark adjusted return, t–3 to t–1			0.0405***	0.0403***
			(2.83)	(2.76)
Benchmark return, t–1 to t			0.2234***	0.2495***
			(14.86)	(16.55)
Benchmark return, t–3 to t–1			0.3105***	0.3228***
			(17.98)	(18.29)
Fund industry Herfindahl				3.5145***
				(3.50)
VIX				–0.0069***
				(–3.98)
Adjusted R–squared	0.125	0.225	0.274	0.279
Number of observations	32,050	32,050	32,050	32,050

Column (1) presents the results controlling for benchmark fixed effects. We next add to the regression in Column (1) a number of controls known to influence fund *Active share*, as indicated in Equation (4.4): tracking error in Column (2); In Column (3), we add fund characteristics, including fund size and fund size squared, age, fees, measured as total shareholder costs and prior year and prior one to three years fund flows. We also add fund benchmark–adjusted returns (both prior year and prior one to three years fund benchmark–adjusted returns), and prior year and prior one to three years fund's benchmark returns, which are variables that are beyond the manager's direct control; Finally, Column (4) also includes the Herfindahl index to proxy for industry competitiveness, and VIX, the Chicago Board Options Exchange (CBOE) market volatility index, to control for stock market volatility. All specifications include time fixed effects and standard errors clustered by fund and year.

Our results show that, whatever specification we use, the coefficient on our *Quantitative* dummy variable is always negative and statistically significant. This confirms our initial results which show that the level of *Active share* is lower for quantitative funds when compared to their non–quantitative counterparts. Economically, the coefficient of –0.0323 (Column (4) of Table 4.4) shows that on average the level of *Active share* for quantitative funds is lower than that of non–quantitative funds by around 4%.

Looking at the different control variables in our regressions, we observe that tracking error is positively related to *Active share*. Economically, its coefficient of 1.9639, in Column (4) of Table 4.4, means that a 5% increase in the annualized tracking error increases *Active share* by about 10%, which is line with the findings in Cremers and Petajisto (2009). Fees also increase *Active share*, meaning that funds that charge more fees are more active. Past returns, measured as prior year and prior one to three years benchmark–adjusted returns also increase *Active share*, and the results are similar for prior year and prior one to three years fund's benchmark returns. We find no significant results for past one year and past one to three years flows, and as well for fund size. All these results are consistent with the findings in Cremers and Petajisto (2009). Confirming the results in Cremers et al. (2016), we find a positive relation between the Herfindahl index and *Active share*, meaning that less competition in the mutual fund industry leads to higher *Active share*. Lastly, we show that stock market volatility decreases *Active share*, which is in line with the findings in Petajisto (2013), and indicates that funds managers deviate less from fund's benchmark in periods of market turmoil.

Next, we aim to explain differences in *Active share* between quantitative and non–quantitative funds. Table 4.5, Panel A, presents the results of our tests for all market capitalization groups, while Panel B shows the results when from regressions in which we add dummy variables for large– mid– and small–cap funds.

Table 4.5: Active share for quantitative and non–quantitative funds

This table presents differences in *Active share* between quantitative and non–quantitative funds. Panel A presents the results of our tests for all market capitalization groups, while Panel B reports the results of our tests when we look at differences in *Active share* for quantitative and non–quantitative funds within market capitalization groups. We add dummy variables to our previous regressions for the different benchmark types, respectively large– mid– and small–cap funds. Column (1) in Panel A and Panel B, reports the results of a pooled regression, relating *Active share* to control variables, containing all funds in our sample, i.e., quantitative and non–quantitative funds. The coefficients in Columns (2) and (3) are estimated in a single regression. The coefficients in Column (2) correspond to independent variables (and fixed effects) interacted with a quantitative dummy variable, which takes the value of one if the fund is classified by Lipper Hindsight as a quantitative fund. Similarly, the coefficients in Column (3) correspond to independent variables (and fixed effects) interacted with a non–quantitative dummy variable, which takes the value of one if the fund is classified as a non–quantitative fund. The coefficients in Columns (2) and (3) are therefore identical to those obtained when estimating a separate regression for quantitative and for non–quantitative funds. Regressions also include time fixed effects and benchmark fixed effects. Robust *t*–statistics clustered by fund and year are reported in parentheses. Column (4) presents differences between the coefficients on prior–period fund characteristics for quantitative and non–quantitative funds, from Columns (2) and (3), respectively, and the results of a *t*–test, testing whether this difference is statistically significant (*p*–values are reported in parentheses). *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. See Appendix E for variable definitions.

Panel A: Explaining differences in Active share for all market capitalization groups

	All funds	Quantitative	Non–quantitative	Quantitative minus non–quantitative (p–value)
	(1)	(2)	(3)	(4)
Tracking error	1.9709***	2.9631***	1.9168***	1.0463***
	(65.66)	(21.77)	(63.20)	(0.00)
TNA (log)	0.0013	0.0057	0.0019	0.6762
	(0.67)	(0.64)	(1.02)	(0.74)
(TNA (log))^2	–0.0010***	–0.0016**	–0.0010***	–0.0006
	(–6.00)	(–2.00)	(–6.18)	(0.48)
Age (log)	–0.0082***	0.0123**	–0.0098***	0.0213***
	(–6.48)	(2.36)	(–7.50)	(0.00)
Total shareholder costs	2.3739***	3.5211***	2.2565***	1.2646**
	(16.51)	(6.27)	(15.23)	(0.03)
Flow, t–1 to t	–0.0016*	–0.0017	–0.0014	–0.0007
	(–1.74)	(–0.64)	(–1.42)	(0.91)
Flow, t–3 to t–1	–0.0008	0.0015	–0.0010	0.0025
	(–1.06)	(0.74)	(–1.19)	(0.25)
Benchmark adjusted return, t–1 to t	0.0471***	0.0127	0.0471***	–0.0344
	(4.24)	(0.26)	(4.16)	(0.50)
Benchmark adjusted return, t–3 to t–1	0.0405***	–0.0932	0.0466***	–0.1396**
	(2.78)	(–1.35)	(3.13)	(0.05)
Benchmark return, t–1 to t	0.2490***	0.2015***	0.2506***	–0.0491
	(16.53)	(3.37)	(16.07)	(0.43)
Benchmark return, t–3 to t–1	0.3224***	0.3794***	0.3189***	0.0605
	(18.30)	(4.92)	(17.53)	(0.45)
Fund industry Herfindahl	3.5126***	–0.7510	3.7632***	–4.5142***
	(3.49)	(–0.28)	(3.59)	(0.00)
VIX	–0.0069***	–0.0012	–0.0070***	0.0058**
	(–3.98)	(–0.24)	(–3.90)	(0.05)
Adjusted R–squared	0.273			0.276
Number of observations	32,050			32,050

Panel B: Explaining differences in Active share within market capitalization groups

	All funds	Quantitative	Non–quantitative	Quantitative minus Non–quantitative (p–value)
	(1)	(2)	(3)	(4)
All–cap	0.6573***	0.5699***	0.6632***	–0.0933***
	(85.21)	(17.69)	(83.04)	(0.00)
Large–cap	0.666***	0.5529***	0.6739***	–0.121***
	(97.22)	(18.15)	(99.14)	(0.00)
Mid–cap	0.8288***	0.709***	0.8368***	–0.1278***
	(118.12)	(22.23)	(119.79)	(0.00)
Small–cap	0.8188***	0.6785***	0.8297***	–0.1512***
	(116.32)	(21.86)	(118.96)	(0.00)
Tracking error	1.4972***	2.5091***	1.4419***	1.0672***
	(61.75)	(20.60)	(59.43)	(0.00)
Adjusted R–squared	0.472			0.4870
Number of observations	32,050			32,050

Column (1) in Panel A and Panel B, reports the results of a pooled regression, relating *Active share* to control variables, containing all funds in our sample, i.e., quantitative and non–quantitative funds. The coefficients in Columns (2) and (3) are estimated in a single regression. The coefficients in Column (2) correspond to independent variables (and fixed effects) interacted with a quantitative dummy variable, which takes the value of one if the fund is classified by Lipper Hindsight as a quantitative fund. Similarly, the coefficients in Column (3) correspond to independent variables (and fixed effects) interacted with a non–quantitative dummy variable, which takes the value of one if the fund is classified as a non–quantitative fund. The coefficients in Columns (2) and (3) are therefore identical to those obtained when estimating a separate regression for quantitative and for non–quantitative funds. In Column (4) we test the differences in the coefficients on prior period four–factor alpha between quantitative and non–quantitative funds, obtained in Columns (2) and (3).

The results in Table 4.5, Panel A, Columns (2) and (3) show that tracking error increases the *Active share* for both quantitative and non–quantitative funds. However, we observe that the impact of tracking error in *Active share* is much higher for quantitative funds than for their non–quantitative counterparts. A 5% increase in the annualized tracking error increases *Active share* by about 10% for non–quantitative funds, while *Active share* goes up by 15% (1.5 times more) in the case of quantitative funds. While fund age decreases *Active share* for non–quantitative funds, it significantly increases the level of *Active share* for quantitative funds. The level of fees funds charge to investor increases *Active share* for both types of funds, but the impact is considerably larger for quantitative funds. Although, prior benchmark–adjusted returns have a significant impact on *Active share* for non–quantitative funds, we find no impact for quantitative funds. Finally, it is also interesting to observe that, while mutual fund industry competition and market volatility contribute to decrease the *Active share* of non–quantitative funds, these variables have no significant impact on the level of *Active share* of quantitative funds.

Table 4.5, Panel B, reports the results of our tests when we look at differences in *Active share* for quantitative and non–quantitative funds within market capitalization groups. We do this by adding to our previous regressions dummy variables for the different benchmark types. Our results show that the level of *Active share* for quantitative funds is lower across all benchmark types. By looking at the differences between quantitative and non–quantitative funds, the results in Column (4) show that the differences are not only statistically significant but also economically important as these differences vary from 9% for all–cap funds to 15% in the case of small–cap funds.

4.5. The impact of Active share on the performance of quantitative and non–quantitative funds

In the previous section we conclude that quantitative funds have lower *Active share* than their non–quantitative peers. In this section we aim to explain the impact of *Active share* on quantitative and non–quantitative funds. The literature is not entirely conclusive to this aspect. Cremers and Petajisto (2009) and Petajisto (2013) show that *Active share* increases fund performance and that, while funds with the lowest *Active share* underperform theirs benchmarks, funds with the highest *Active share* significantly outperform their benchmarks. Frazzini et al. (2016) argue that, contrary to the findings in Cremers and Petajisto (2009) and Petajisto (2013), *Active share* does not predict future returns. However, a recent study by Cline and Gilstrap (2021) confirms the findings in Cremers and Petajisto (2009) and Petajisto (2013). These results are also confirmed by Kacperczyk et al. (2005), and Kacperczyk et al. (2014), showing a positive relation between fund four–factor alpha and deviations from the benchmark. Cremers et al. (2016) and Keswani et al. (2020) also find that *Active share* increase performance when using international samples of mutual funds.

To test for differences in the impact of *Active share* on the performance of quantitative and non–quantitative funds, we start by running a panel regression where we regress fund performance on *Active share*, tracking error and a number of control variables, as indicated in Equation (4.5):

$$Performance_{i,t} \; = \; a + \; \beta Active\ share_{i,t} + \delta X_{i,t-1} + \varepsilon_{i,t}, \tag{4.5}$$

where *Performance* is measured using four–factor alpha or benchmark–adjusted returns, and *Active share* is the percentage of a fund's portfolio holdings that differ from its benchmark index holdings calculated as in Equation (4.1).[51] $X_{i,t-1}$ represents a set of lagged control variables used by Cremers and Petajisto (2009), Petajisto (2013), and Cremers et al. (2016), that we also include in Equation (4.4). These variables include, tracking error, fund size and fund size squared, fund age, total shareholder costs, prior year and prior one to three years fund flows and fund benchmark–adjusted returns, and prior year and prior one to three years fund's benchmark returns. Finally, we also control for the Herfindahl index and the market volatility index (VIX). We start by presenting the results of a pooled regression that contains all funds in our sample taken together. Next, we test for differences in *Active share* between quantitative and non–quantitative funds by pooling quantitative and non–quantitative funds in a single regression, and present the coefficients separately for: (1) quantitative funds, where the coefficients correspond to independent variables (and fixed effects) interacted with a quantitative dummy variable that takes the value of one if the fund is classified as a quantitative fund; and, (2) non–quantitative funds, where the coefficients correspond to independent variables (and fixed effects) interacted with a non–quantitative dummy variable, which takes the value of one if the fund is not classified as a quantitative fund. Finally, we run a *t*–test to determine the differences in the coefficients on prior–period four–factor alpha (and prior–period control variables) between quantitative and non–quantitative funds. As in the regressions in Equation (4.4), we employ time and benchmark fixed effects and allow for cross–sectional correlation and for the time series autocorrelation within funds computing robust standard errors clustered by fund and time.

The next step is to understand whether the predictive power of *Active share* is different for funds with different levels of *Active share* and for quantitative and non–quantitative funds. To do so, we rerun the regression in Equation (4.5), except that we now add to the regression the interaction of *Active share* with dummy variables indicating the prior year quintile for a fund's *Active share*. We therefore run the following regression:

$$Performance_{i,t} = a + \beta Active\ share_{i,t} + \beta_1 Active\ share_{i,t} \text{x}\ Dummy\ Active\ share_{q,i,t} + \delta X_{i,t-1} + \varepsilon_{i,t}, \tag{4.6}$$

[51] The results for benchmark–adjusted returns are presented in Appendix F and discussed in the robustness section.

where, $Dummy\ Active\ share_{q,i,t}$ is equal to 1 if the fund's level of *Active share* in the prior year is in the 2nd, 3rd, 4th or 5th quintiles of *Active share* ($q = 2, 3, 4, or\ 5$), and zero otherwise. The coefficient on *Active share* (β) represents the coefficient for funds with lowest prior year *Active share*, i.e., those funds classified in the first quintile.

Finally, to analyze whether the impact of *Active share* in mutual fund performance is different for funds with different benchmark types, we add to the regression in Equation (4.5) dummy variables for the different benchmark types, as follows:

$$Performance_{i,t} = a + \lambda Active\ share_{i,t} + \lambda_1 Active\ share_{i,t} \text{x}\ Dummy\ Active\ share_{b,i,t} + \delta X_{i,t-1} + \varepsilon_{i,t}. \quad (4.7)$$

In Equation (4.7), we include one dummy variable for each fund benchmark type, i.e., one dummy variable for large–, mid– and small–cap funds. This means that we have three dummy variables, the $Dummy\ Active\ share_{b,i,t}$ takes the value of 1 if the fund benchmark type (b) is large–, mid– or small–cap, and zero otherwise. The coefficient on *Active share* (λ) represents the coefficient for all–cap funds.

The results of our tests are presented in Section 4.6.

4.6. Empirical results on the impact of Active share on the performance of quantitative and non–quantitative funds

Table 4.6 presents the results for our tests on the impact of *Active share* on the performance of quantitative and non–quantitative funds, with performance measured using four–factor alpha.

Table 4.6: Fund performance and Active share

This table presents panel regressions to study differences in the impact of *Active share* on the performance of quantitative and non–quantitative funds, with performance measured using four–factor alpha. We regress fund performance on *Active share*, and a number of control variables that we also include in Equation (4.4), as indicated in Equation (4.5). *Active share* is the percentage of a fund's portfolio holdings that differ from its benchmark index holdings calculated as in Equation (4.1). The set of lagged control variables include, tracking error, fund size and fund size squared, fund age, total shareholder costs, prior year and prior one to three years fund flows and fund benchmark–adjusted returns, and prior year and prior one to three years fund's benchmark returns. We also control for the Herfindahl index and the market volatility index (VIX). In Column (1) we present the results of a pooled regression that contains all funds in our sample taken together, i.e., quantitative and non–quantitative funds. In Column (2) the coefficients correspond to independent variables (and fixed effects) interacted with a quantitative dummy variable that takes the value of one if the fund is classified as a quantitative fund. In Column (3) the coefficients correspond to independent variables (and fixed effects) interacted with a non–quantitative dummy variable, which takes the value of one if the fund is not classified as a quantitative fund. Column (4) presents the difference in coefficients between quantitative and non–quantitative funds, and the results of a t–test testing whether these differences are statistically significant. Regressions also include time fixed effects and benchmark fixed effects. Robust *t*–statistics clustered by fund and year are reported in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. See Appendix E for variable definitions.

	All funds	Quantitative	Non–quantitative	Quantitative minus Non–quantitative (p–value)
	(1)	(2)	(3)	(4)
Active share	0.0242***	–0.0186*	0.0272***	–0.0452***
	(5.97)	(–1.78)	(6.31)	(0.00)
Tracking error	–0.2311***	–0.2531***	–0.2289***	–0.0251
	(–9.27)	(–3.40)	(–8.90)	(0.76)
TNA (log)	0.0005	–0.0089**	0.0012	–0.0101**
	(0.41)	(–1.99)	(0.95)	(0.03)
(TNA (log))^2	–0.0001	0.0005	–0.0001	0.0005
	(–0.54)	(1.28)	(–0.97)	(0.14)
Age (log)	0.0019***	0.0017	0.0020***	–0.0003
	(2.71)	(0.69)	(2.77)	(0.89)
Total shareholder costs	–0.5555***	–0.5162**	–0.5490***	0.0330
	(–7.30)	(–2.26)	(–6.88)	(0.89)
Flow, t–1 to t	0.0004	0.0011	0.0003	0.0008
	(0.70)	(0.81)	(0.48)	(0.59)
Flow, t–3 to t–1	0.0002	–0.0010	0.0004	–0.0014
	(0.47)	(–0.71)	(0.71)	(0.36)
Performance, t–1 to t	0.0245**	–0.0223*	0.0263***	–0.0486***
	(2.48)	(–1.86)	(2.81)	(0.00)
Performance, t–3 to t–1	–0.0384***	–0.0291	–0.0407***	0.0110
	(–3.51)	(–0.79)	(–3.61)	(0.76)
Benchmark return, t–1 to t	–0.0337***	–0.0452	–0.0344***	–0.0108
	(–3.47)	(–1.61)	(–3.37)	(0.72)
Benchmark return, t–3 to t–1	–0.0158	0.0960**	–0.0216*	0.1176**
	(–1.31)	(2.13)	(–1.73)	(0.01)
Fund industry Herfindahl	0.2983	–4.1172***	0.5499	–4.6671***
	(0.60)	(–2.73)	(1.06)	(0.00)
VIX	–0.0013	0.0035	–0.0015*	0.0035**
	(–1.54)	(1.52)	(–1.78)	(0.04)
Adjusted R–squared	0.076			0.0780
Number of observations	32,050			32,050

As indicated in Section 4.5, we present first (in Column 1) the coefficients separately for all funds taken together, i.e., quantitative and non–quantitative funds, and then, in Columns (2) and (3), separately for quantitative and non–quantitative funds, respectively. In Column (2) the coefficients correspond to independent variables (and fixed effects) interacted with a quantitative dummy variable that takes the value of one if the fund is classified as a quantitative fund. In Column (3) the coefficients correspond to independent variables (and fixed effects) interacted with a non–quantitative dummy variable, which takes the value of one if the fund is not classified as a quantitative fund. Column (4) presents the difference in coefficients between quantitative and non–quantitative funds, and the results of a *t*–test testing whether these differences are statistically significant.

The results for non–quantitative funds, in Column (3) of Table 4.6, indicate that *Active share* is a significant predictor of future performance for these funds, which is consistent with the findings in Cremers and Petajisto (2009). However, we find opposite results for quantitative funds. In Column (2), we observe that rather than increasing performance, *Active share* decreases the future performance of quantitative funds. The results are not only statistically significant but also economically important. A 10% increase in *Active share* is associated with an increase of 27 basis points in the four–factor alpha of non–quantitative funds over the next year, while, in the case of quantitative funds, the same 10% increase in *Active share* leads to a decrease in next year's four–factor alpha of quantitative funds of 19 basis points. Even more important for our study is the difference in *Active share* coefficients between quantitative and non–quantitative funds, observed in Column (4). Controlling for the other fund characteristics, the difference in coefficients is –0.0452, indicating that a 10% increase in *Active share* results in a difference in next year's four–factor alpha between quantitative and non–quantitative funds of –45 basis points. This difference is economic relevant as the average annual four factor alpha for funds in our sample is –124 and –126 basis points for quantitative and non–quantitative funds, respectively, as indicated in Table 4.3).

We next look at the results for the control variables in our regressions. We observe that, although tracking error decreases four–factor alpha for both quantitative and non–quantitative funds, we find no statistically significant differences on how tracking error affects quantitative and non–quantitative funds. Fund size affects significantly more negatively the performance of quantitative funds as well as past performance, while prior one to three years fund's benchmark returns have a more positive impact on next year four–factor alpha. Overall, the results for non–quantitative funds are in line with those observed in Cremers and Petajisto (2009). Additionally, we find a significant difference in how the Herfindahl index and VIX affect the performance of quantitative and non–quantitative funds. Our results indicate that the performance of quantitative funds react more positively to the competition in the mutual fund industry and to higher stock market volatility.

We next aim to understand whether the predictive power of *Active share* is different for quantitative and non–quantitative funds with different levels of *Active share*. Table 4.7 presents the results of running the regressions in Equation (4.6), where we add to the regression in Equation (4.5) the interaction of *Active share* with dummy variables indicating the prior year quintile for a fund's *Active share*.

Table 4.7: Fund performance and Active share for funds with different levels of Active share

This table presents panel regressions to study differences in the predictive power of *Active share* for quantitative and non–quantitative funds with different levels of *Active share*, with performance measured using four–factor alpha. In Equation (4.6) we add the interaction of *Active share* with dummy variables indicating the prior year quintile for a fund's *Active share* to the regression in Equation (4.5), where we regress fund performance on *Active share*, and a number of control variables (not reported). $Dummy\ Active\ share_{q,i,t}$ is equal to 1 if the fund's level of *Active share* in the prior year is in the 2nd, 3rd, 4th or 5th quintiles of *Active share* ($q = 2, 3, 4, or\ 5$), and zero otherwise. The coefficient on *Active share* represents the coefficient for funds with lowest prior year *Active share*, i.e., those funds classified in the first quintile. In Column (1) we present the results of a pooled regression that contains all funds in our sample taken together, i.e., quantitative and non–quantitative funds. In Column (2) the coefficients correspond to independent variables (and fixed effects) interacted with a quantitative dummy variable that takes the value of one if the fund is classified as a quantitative fund. In Column (3) the coefficients correspond to independent variables (and fixed effects) interacted with a non–quantitative dummy variable, which takes the value of one if the fund is not classified as a quantitative fund. Column (4) presents the difference in coefficients between quantitative and non–quantitative funds, and the results of a t–test testing whether these differences are statistically significant. Regressions also include time fixed effects and benchmark fixed effects. Robust t–statistics clustered by fund and year are reported in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. See Appendix E for variable definitions.

	All funds	Quantitative	Non–quantitative	Quantitative minus Non–quantitative (p–value)
	(1)	(2)	(3)	(4)
Active share (Q1)	0.0106	0.0118	0.0107	0.0011
	(1.18)	(0.59)	(1.09)	(0.96)
Active share (Q2)	–0.0003	–0.0018	–0.0005	–0.0007
	(–0.12)	(–0.28)	(–0.20)	(0.99)
Active share (Q3)	0.0049	–0.0094	0.0058	–0.0141*
	(1.48)	(–1.03)	(1.53)	(0.10)
Active share (Q4)	0.0075**	–0.0079	0.0081**	–0.0149*
	(1.97)	(–0.85)	(2.02)	(0.08)
Active share (Q5)	0.0087**	–0.0177*	0.0105**	–0.0271***
	(2.15)	(–1.71)	(2.41)	(0.00)
Tracking error	–0.2420***	–0.1716**	–0.2419***	0.0700
	(–9.51)	(–2.38)	(–9.23)	(0.42)
Adjusted R–squared	0.077			0.080
Number of observations	32,050			32,050

From Table 4.7, we observe that non–quantitative funds with higher *Active share* perform better, and we also find a significant difference in the future performance of those funds in the top and bottom quintiles of *Active share*. These results are consistent with the findings of Cremers and Petajisto (2009), Petajisto (2013), and Cline and Gilstrap (2021). We also find that the effect of *Active share* on fund performance is concentrated in those funds with the highest levels of *Active share*. Although this is true for both quantitative and non–quantitative funds, our results show that *Active share* affects performance in a different way. While *Active share* increases the performance of non–quantitative funds with highest *Active share*, it has a negative impact on the performance of those quantitative funds classified at the top of the *Active share* scale. Additionally, our results also show that these differences are statistically significant for those funds classified in the three top quintiles of *Active share*.

Finally, we also analyze whether the impact of *Active share* in mutual fund performance is different for funds with different benchmark types. We therefore run the repression in Equation (4.7), which corresponds to that in Equation (4.5) with dummy variables for funds with different benchmark types: large–, mid– and small–cap funds.[52]

The results are presented in Table 4.8 and show substantial differences in how *Active share* affects the performance of quantitative and non–quantitative funds with different benchmark types.

Table 4.8: Fund performance and Active share for funds with different benchmark types

This table presents panel regressions to study differences in how *Active share* affects the performance of quantitative and non–quantitative funds with different benchmark types, with performance measured using four–factor alpha. In Equation (4.7) we add dummy variables for the different benchmark types to the regression in Equation (4.5), where we regress fund performance on *Active share*, and a number of control variables (not reported). $Dummy\ Active\ share_{b,i,t}$ takes the value of 1 if the fund benchmark type is large–, mid– or small–cap, and zero otherwise. The coefficient on *Active share* represents the coefficient for all–cap funds. In Column (1) we present the results of a pooled regression that contains all funds in our sample taken together, i.e., quantitative and non–quantitative funds. In Column (2) the coefficients correspond to independent variables (and fixed effects) interacted with a quantitative dummy variable that takes the value of one if the fund is classified as a quantitative fund. In Column (3) the coefficients correspond to independent variables (and fixed effects) interacted with a non–quantitative dummy variable, which takes the value of one if the fund is not classified as a quantitative fund. Column (4) presents the difference in coefficients between quantitative and non–quantitative funds, and the results of a t–test testing whether these differences are statistically significant. Regressions also include time fixed effects and benchmark fixed effects. Robust t–statistics clustered by fund and year are reported in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. See Appendix E for variable definitions.

	All funds	Quantitative	Non–quantitative	Quantitative minus Non–quantitative (p–value)
	(1)	(2)	(3)	(4)
Active share x All–cap	0.0131	–0.0013	0.0141	–0.0151
	(1.25)	(–0.04)	(1.28)	(0.64)
Active share x Large–cap	0.0209***	–0.0081	0.0228***	–0.0298**
	(4.51)	(–0.58)	(4.68)	(0.02)
Active share x Mid–cap	0.0481***	–0.0345***	0.0543***	–0.0888***
	(5.02)	(–2.52)	(5.45)	(0.00)
Active share x Small–cap	0.031***	–0.0235*	0.042***	–0.065***
	(3.66)	(–1.75)	(4.04)	(0.00)
Tracking error	–0.2343***	–0.2411***	–0.2333***	–0.0080
	(–9.40)	(–3.21)	(–9.07)	(0.92)
Adjusted R–squared	0.077			0.0790
Number of observations	32,050			32,050

[52] In this regression, the coefficient on *Active share* (λ) represents the coefficient for all–cap funds. The coefficients for large–, mid– and small–cap funds reflect the total impact of *Active share* on performance (and not the difference to all–cap).

We find that *Active share* increases the future performance of non–quantitative funds across all benchmark types, but it has a negative impact on the performance of quantitative funds. These differences in future performance are statistically significant for all benchmark types, except for all–cap funds. The economic impact of these differences is also important. A 10% increase in *Active share* leads to a difference between the future performance of large–cap quantitative and non–quantitative funds of –30 basis points. This difference is even higher for small–cap and mid–cap funds as it goes up to –65 and –89 basis points, respectively.

Overall, our results are consistent with the findings that *Active share* has predictive power on the future performance of non–quantitative funds, but it decreases the future performance of quantitative funds. We also find evidence that these differences in performance between quantitative and non–quantitative funds are not only statistically significant but are also economically important.

4.7. Robustness tests

In this section we run additional tests to check the robustness of our results. The tables are presented in Appendix F.

Our initial tests show that the size of non–quantitative funds is much larger than that of their quantitative counterparts. Our results in Table 4.6 also show significant differences in how fund size affect the performance of quantitative and non–quantitative funds. To understand whether fund size determines the observed differences on the impact of *Active share* for quantitative and non–quantitative funds, we follow Cremers and Petajisto (2009), and run a regression similar to that in Equation (4.5), except that we add to the regression the interaction of *Active share* with a dummy variable indicating below–median fund size for that year. The results of these tests are presented in Table F.1 and show that the observed differences in the impact of *Active share* on the performance of quantitative and non–quantitative funds remain for both smaller and larger funds.

We next run our main regressions where we test for differences on the impact of *Active share* on the performance of quantitative and non–quantitative funds using benchmark–adjusted returns (computed as the difference between the fund's return and the return on its benchmark) rather than four–factor alphas as our performance measure. The results for those tests in Tables 4.6, 4.7, and 4.8, are presented in Tables F.2, F.3, and F.4, respectively. Table F.2 presents the results of regressing this performance on last year *Active share*. Consistent with our previous findings when measuring performance with four–factor alphas, we observe that *Active share* increases the benchmark–adjusted returns of non–quantitative funds, but it decreases the benchmark–adjusted returns of their non–quantitative peers. The results are also economically important, as a 10% increase in *Active share* is associated with a difference in next year's benchmark–adjusted return between quantitative and non–quantitative funds of –51 basis points. (the average benchmark–adjusted return for funds in our sample is –78 basis points: –84 and –77 basis points for quantitative and non–quantitative funds, respectively, as indicated in Table 4.3). Next, we run the tests in Table 4.7, testing the predictive power of *Active share* is different for funds with different levels of *Active share* for quantitative and non–quantitative funds. The results in Table F.3, confirm our main results. *Active share* increases the performance of non–quantitative funds and decreases the performance of quantitative funds. The differences are statistically significant across all quintiles of *Active share*. Table F.4 tests whether the impact of *Active share* in mutual fund performance is different for funds with different benchmark types. The results confirm those in Table 4.8 that show significant differences in how *Active share* affects the performance of quantitative and non–quantitative funds with different benchmark types.

To alleviate concerns that our results are driven by differences in fee levels between quantitative and non–quantitative funds, we run our main tests with gross performance. We compute gross four–factor alpha performance by adding back total expense ratio to net four–factor alpha. Tables F.5, F.6, and F.7 present the results for our main tests in Tables 4.6, 4.7, and 4.8. These tests show that our main conclusions do not change.

Different studies, including Cremers and Petajisto (2009), Kacperczyk et al. (2005), Pastor et al. (2017), and Hoberg et al. (2018), show that a fund's turnover is related to its alpha. Therefore, it is important to understand whether our results are affected by the inclusion of turnover in our regressions. We compute turnover using data from the FactSet/LionShares database. We follow Pastor et al. (2017) and measure fund turnover using the minimum of a fund's total purchases and sales over a year scaled by the average fund NAV over the same period. The turnover data only covers around 80% of the observations in our sample, which explains why we do not include this variable in our main analysis. Tables F.8, F.9, and F.10 show that our main results, in Tables 4.6, 4.7, and 4.8, respectively, remain unchanged even after controlling for turnover in our regressions.

Additionally, we examine alternative ways of clustering standard errors. To allow for the possibility that fund performance is correlated both within mutual fund family and within time, in untabulated results, we also cluster on family and time. We find that our results are robust.

We follow Hoberg et al. (2018) and we cluster standard errors by fund style and time. Fund style is computed based on SMB and HML loadings. In each period, we double sort funds into three groups based on SMB loadings (low, medium, and high) and, independently, into three groups based on HML loadings. This gives us a 3–by–3 size–by–value grid. In untabulated results we find that our results do not change.

4.8. Conclusion

We study differences in *Active share* between quantitative and non–quantitative actively managed US equity funds. We find that the level of *Active share* is lower for quantitative funds than for their non–quantitative peers. By looking at the impact of *Active share* on the performance of quantitative and non–quantitative funds, we find that *Active share* increases future performance of non–quantitative funds, but *Active share* decreases the performance of quantitative funds. Our results also show statistically and economically differences between quantitative and non–quantitative funds in the *Active share* of all benchmark types.

Our results are important for investors, practitioners, and regulators. *Active share* has become a widely used concept in fund analysis. We show that not only quantitative funds deviate less from their benchmarks but that greater benchmark differentiation results in underperformance rather than outperformance for these funds. Our study contributes to the understanding of how managers add value for their clients

5. Conclusion

This thesis presents three studies on actively managed equity mutual funds. We start by studying differences in the way a fund's affiliation with large families affects the flow–performance sensitivity internationally. Next, we study differences in the flow-performance sensitivity between quantitative and non–quantitative actively managed US equity funds. Finally, we also look at differences in *Active share* between quantitative and non–quantitative US funds.

In the first paper, we find that family size reduces the convexity of the flow–performance relationship in countries where investors are more sophisticated. On the other hand, family size increases the flow–performance convexity in countries with less sophisticated investors. Our results are consistent with the literature that shows that the US–based evidence is not a universal truth. We show that the US evidence only holds for countries where investors are more sophisticated. The economic impact of our results is also significant. Our results are important for investors, mutual fund companies, and regulators. As family size affects investors' allocation decisions, it determines mutual fund industry outcomes such as the level of fees charged, the level of risk-taking, and ultimately the performance delivered to the investor.

The second paper shows that quantitative investors buy more top performing funds and sell less poor performers, which is no different from the main findings in the mutual fund literature. Our findings also indicate no significant differences in the way quantitative and non-quantitative investors react to past performance, which indicates homogeneity rather than heterogeneity in investors preferences. Our findings are significant for investors and practitioners. The flow-performance sensitivity determines mutual fund industry outcomes such as fees, risk–taking, and performance by influencing how fund managers and mutual fund companies run their portfolios. Our results are also important for future research trying to explain differences among quantitative and non-quantitative funds as they suggest that any differences to be found in fees, risk-taking or performance between quantitative and non-quantitative funds originate from fund managers and fund management companies' decisions and strategies rather from investors preferences.

In the third paper, our findings conclude that the level of *Active share* is lower for quantitative funds than for their non–quantitative peers. By looking at the impact of *Active share* on the performance of quantitative and non–quantitative funds, we find that *Active share* increases future performance of non–quantitative funds, but *Active share* decreases the performance of quantitative funds. We show that not only quantitative funds deviate less from their benchmarks but that greater benchmark differentiation results in underperformance rather than outperformance for these funds. Our results also show statistically and economically differences between quantitative and non–quantitative funds in the *Active share* of all benchmark types. Our results are essential for investors, practitioners, and regulators. As *Active share* has become a widely used concept in fund analysis, our study contributes to the understanding of how managers add value for their clients. Our findings are also relevant to policy–making. At a time when the fraction of individual investors that delegate their portfolio management to professional investment managers is increasing, they suggest that regulators should keep quantitative funds under close scrutiny.

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Appendix A. Variable definitions

Variable	Definition
Panel A: Fund characteristics	
Raw return	Fund's net return in local currency (percentage per quarter) (Lipper).
Four–factor alpha	Four–factor alpha (percentage per quarter) is estimated with three years of past monthly fund excess returns in US dollars, and regional factors (Asia–Pacific, Europe, North America, or Emerging or markets) or world factors in the case of global funds. The classification is based on the fund´s investment region using data on the fund's domicile country and geographic investment style provided by the Lipper database.
Flow	Percentage growth in TNA (in local currency) in a quarter, net of internal growth (assuming reinvestment of dividends and distributions). See equation (2.1).
Flow category	Average percentage growth in TNA (in local currency) in a quarter, net of internal growth (assuming reinvestment of dividends and distributions) into funds with the same investment style, i.e., geographical focus.
Size	Total net assets in millions of US dollars (Lipper).
Family size	Family total net assets in millions of US dollars of other equity funds in the same management company excluding the own fund TNA (Lipper).
Large fund family	Dummy variable that takes the value of one if the fund family size is above the median fund family size in the country, quarter, and investment region concerned, and zero otherwise.
Star affiliation	Dummy variable that takes the value of one for funds that are affiliated with star families (i.e., those including a star fund) but are not stars themselves, and zero otherwise.
Age	Number of years since the fund launch date (Lipper).
Expense ratio	Total expense ratio (Lipper).
Loads	Sum of front–end plus back–end loads (Lipper).
SMB	Loadings on the small–minus–big size factor (SMB) from four–factor alpha regressions.
HML	Loadings on the high–minus–low factor (HML) from four–factor alpha regressions.

Countries sold	Number of countries where a fund is registered to sell (Lipper).
Volatility	Standard deviation of monthly fund returns in the prior 36 months.
Panel B: Country characteristics	
Population owning shares	Percentage of the population owning shares in a country (Grout et al., 2009).
Trading costs	The annual average stock market transaction costs in basis points (including commissions, fees, and price impact) (Global Universe Data–ElkinsMcSherry).
Emerging markets	Emerging market dummy that equals one if the country is an emerging market (MSCI Emerging Markets Index, https://www.msci.com/market–classification).
Market share of top five management companies	Market share (percentage of TNA sum) of the top five management companies (equity funds) in each country (computed using Lipper data).
Financial literacy	Percentage of adults who are financially literate (Klapper et al., 2015).
Financial openness	KAOPEN index (Chinn & Ito, 2006) is an index measuring a country's degree of capital account openness. The index is based on the binary dummy variables that codify the tabulation of restrictions on cross–border financial transactions reported in the IMF's Annual Report on Exchange Arrangements and Exchange Restrictions (AREAER).
GDP per country	Gross Domestic Product per capita in US dollars in the fund’s country (World Development Indicators).

Appendix B

This appendix contains tables that supplement the analysis in Chapter 2 “Does mutual fund family size matter? International Evidence”.

Table B.1: Mutual fund industry sample by country – Domestic and international mutual funds
This table presents the number of unique funds in our sample and total net assets (TNA) under management (sum of all share classes in millions of US dollars at the end of 2015), splitting the sample in Table 2.1 into domestic and international mutual funds.

	Domestic Funds		International Funds	
Country	Number of Funds	TNA ($ million)	Number of Funds	TNA ($ million)
Argentina	30	19.81	35	1.21
Australia	662	132.66	681	196.58
Austria	15	101.02	217	56.82
Belgium	30	92.32	784	86.45
Brazil	927	34.07	8	2.36
Canada	529	399.39	856	239.74
China	18	241.02	9	172.74
Denmark	29	184.69	232	169.50
Finland	33	165.57	177	178.75
France	298	212.94	1,211	170.18
Germany	68	819.71	408	336.91
Greece	25	32.15	21	14.15
Hong Kong	14	741.78	93	312.72
India	302	167.04	18	8.86
Indonesia	66	84.78		
Italy	57	221.94	292	225.72
Japan	672	125.43	596	190.15
Malaysia	152	99.02	116	23.60
Netherlands	21	305.76	137	305.50
New Zealand	12	53.11	36	60.64
Norway	57	231.97	135	407.34
Poland	62	95.45	49	49.46
Portugal	19	20.99	53	35.68
Singapore	11	119.54	155	88.96
South Africa	149	161.78	29	139.01
South Korea	597	58.54	248	24.56
Spain	86	127.60	274	101.11
Sweden	126	662.07	193	521.06
Switzerland	113	439.74	236	366.49
Taiwan	194	47.04	176	46.49
Thailand	161	73.71	49	17.10
UK	501	855.02	789	564.38
US	3,401	2,644.33	977	2,362.21
All countries	9,437	6,201.3	9,290	4,530.35

Table B.2: Summary statistics by country

This table presents the means and the total number of observations of fund–level characteristics by country. Panel B presents means of country–level characteristics by country. The sample is restricted to open–end and actively managed equity funds drawn from the Lipper database. The sample period is 2000–2015. See Appendix A for variable definitions.

Panel A– Fund–level characteristics by country

Country	N	Raw return (% quarter)	Four–factor alpha (% quarter)	Flows (% quarter)	Size ($ million)	Family size ($ million)	Age (years)	Expense ratio (%)	Loads (%)	SMB	HML	Countries sold	Volatility
Argentina	1,717	1.57	–1.35	–0.76	10	45	12	2.93	0.17	0.32	0.07	1.00	0.57
Australia	34,224	1.75	–0.38	–1.04	159	4,868	10	1.53	0.99	–0.09	–0.05	1.14	0.44
Austria	7,472	1.44	–0.73	–0.27	82	1,540	12	1.82	4.50	0.16	–0.10	2.44	0.41
Belgium	16,967	1.36	–0.51	–3.55	64	11,225	8	1.33	4.80	–0.11	–0.10	2.62	0.32
Brazil	18,628	–1.83	–3.10	–1.79	86	4,233	8	1.77	0.21	0.22	–0.23	1.00	0.62
Canada	42,259	1.54	–0.65	0.60	287	13,071	13	2.24	5.71	0.05	–0.01	1.00	0.38
China	544	3.40	1.40	–3.16	579	3,062	7	1.82	2.24	0.29	–0.19	1.00	0.46
Denmark	8,634	2.20	0.03	0.45	144	2,385	12	1.55	1.87	0.09	–0.15	1.80	0.42
Finland	6,894	1.92	–0.20	1.80	142	3,124	9	1.73	1.90	0.21	–0.13	1.58	0.45
France	43,242	1.57	–0.63	–0.33	188	6,864	13	1.73	3.21	0.07	–0.06	1.54	0.40
Germany	15,266	1.95	–0.66	–1.76	378	14,360	15	1.53	4.18	0.02	–0.12	2.00	0.40
Greece	1,405	–0.05	–1.83	0.73	61	246	12	2.77	5.94	0.15	0.38	1.02	0.55
Hong Kong	3,071	1.93	0.35	0.56	280	3,480	13	1.45	4.74	0.04	–0.12	2.49	0.42
India	8,539	3.15	1.65	–0.41	123	1,858	8	2.31	0.91	0.08	–0.66	1.25	0.60
Indonesia	1,601	1.82	0.02	3.60	93	401	8	2.89	3.17	0.34	–0.03	1.01	0.57
Italy	8,766	1.68	–0.81	–1.67	246	3,816	12	2.09	2.93	–0.08	–0.05	1.01	0.32
Japan	37,861	1.55	–0.55	–2.28	112	15,383	9	1.59	2.54	0.18	–0.01	1.00	0.38
Malaysia	7,545	1.55	0.16	–1.76	58	1,913	10	1.70	5.61	0.22	0.12	1.08	0.35
Netherlands	4,730	2.02	–0.29	–0.92	357	4,474	14	1.25	0.81	0.07	–0.10	1.24	0.40
New Zealand	953	2.52	0.12	–0.32	48	444	12	1.32	2.01	0.16	–0.11	1.21	0.44
Norway	7,632	3.07	–0.12	0.69	202	3,111	12	1.48	1.27	0.17	0.00	1.71	0.47
Poland	2,677	0.79	–1.60	4.06	129	510	8	3.32	4.63	–0.05	0.38	1.00	0.55
Portugal	2,843	1.07	–0.74	–1.07	43	326	11	1.87	2.00	0.10	–0.09	1.09	0.42
Singapore	5,638	2.12	0.06	–1.37	68	950	11	1.99	4.84	0.09	–0.18	1.23	0.40
South Africa	4,837	1.17	–0.60	0.71	160	1,619	11	1.59	1.92	0.00	–0.28	1.00	0.48
South Korea	16,491	2.58	–0.88	–7.47	67	3,423	7	1.84	0.34	0.33	–0.01	1.00	0.53
Spain	11,654	1.61	–0.83	0.68	71	1,456	11	2.06	0.81	–0.21	0.10	1.02	0.41
Sweden	13,070	2.49	0.50	1.15	378	13,779	14	1.41	0.32	0.02	–0.17	1.56	0.45
Switzerland	10,187	2.08	–0.39	–1.33	188	13,858	13	1.27	3.07	0.12	–0.11	1.34	0.38
Taiwan	11,593	2.02	0.34	–1.57	57	1,124	10	2.96	3.15	0.49	–0.41	1.00	0.47
Thailand	6,495	2.65	–0.32	–1.03	37	714	10	1.67	0.82	0.34	–0.16	1.00	0.49
UK	39,939	2.12	–0.02	–0.07	510	11,475	16	1.46	3.71	0.22	–0.10	2.28	0.37
US	169,816	1.83	–0.27	0.61	1,420	60,539	14	1.33	1.64	0.19	–0.01	1.05	0.37
All countries	573,190	1.73	–0.43	–0.48	563	23,429	12	1.63	2.47	0.13	–0.06	1.31	0.41

Panel B– Country–level characteristics by country

Country	Population owning shares (%)	Trading costs (basis points)	Emerging market dummy
Argentina	0.52	63.72	1
Australia	35.11	32.27	0
Austria	7.11	30.23	0
Belgium	17.30	29.61	0
Brazil	1.62	50.22	1
Canada	37.52	32.51	0
China	5.90	43.63	1
Denmark	23.50	33.91	0
Finland	14.50	41.37	0
France	14.70	25.96	0
Germany	12.50	24.17	0
Greece	8.36	54.09	0
Hong Kong	22.98	41.60	0
India	2.00	67.49	1
Indonesia	0.15	72.11	1
Italy	7.98	30.61	0
Japan	30.75	21.07	0
Malaysia	6.27	53.76	1
Netherlands	17.05	26.99	0
New Zealand	28.10	38.34	0
Norway	7.30	32.13	0
Poland	2.70	33.16	1
Portugal	3.07	32.32	0
Singapore	11.97	40.37	0
South Africa	2.63	51.30	1
South Korea	9.30	54.56	1
Spain	5.00	28.24	0
Sweden	19.70	30.51	0
Switzerland	20.22	29.66	0
Taiwan	34.78	49.24	1
Thailand	5.30	58.55	1
UK	15.09	50.10	0
US	21.20	23.94	0
All countries	13.70	31.28	

Table B.3: Flow–performance sensitivity and fund’s affiliation with large families – country level regressions

In this table we run the identical analysis to Table 2.3– Panel A, except that the results are estimated country by country. We, therefore, run identical regressions to those of Equation (2.3) for each country in our sample, except that fund–fixed effects are used rather than country–fixed effects. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. See Appendix A for variable definitions.

	Argentina	Australia	Austria	Belgium	Brazil	Canada	China	Denmark	Finland	France	Germany	Greece	Hong Kong	India	Indonesia	Italy	Japan
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
Low	0.1421**	0.0749**	0.1060*	0.0326	0.0932**	0.0501***	0.0341	0.1061**	0.1433*	0.1228***	0.0833**	0.1449*	0.0960	0.0232	0.1079	0.0603**	0.0353**
	(2.19)	(2.38)	(1.94)	(1.11)	(2.51)	(2.72)	(0.46)	(1.99)	(1.66)	(4.14)	(2.25)	(1.65)	(1.23)	(0.54)	(0.56)	(2.35)	(2.22)
Low x Large fund family	–0.0807*	0.0433*	–0.0802*	0.0531*	–0.0303	0.0454**	0.0121	0.0575*	0.0845	–0.0395*	0.0342	–0.0736	0.1099	0.0041	–0.1210	–0.0396**	–0.0079
	(–1.72)	(1.87)	(–1.78)	(1.95)	(–1.07)	(2.17)	(0.42)	(1.83)	(1.23)	(–1.75)	(1.28)	(–1.01)	(1.11)	(0.15)	(–0.71)	(–2.16)	(–0.89)
Mid	0.0231	0.0215***	0.0400**	0.0099	0.0423***	0.0574***	0.1017	0.0153	0.0631***	0.0309***	0.0189*	0.0472*	0.0335	0.0626***	0.2012***	0.0207	0.0142***
	(0.74)	(3.58)	(2.27)	(1.50)	(3.54)	(9.37)	(1.21)	(1.10)	(3.35)	(4.37)	(1.87)	(1.66)	(0.58)	(4.14)	(2.79)	(1.63)	(2.76)
Mid x Large fund family	–0.0560*	0.0137**	–0.0331	0.0310*	0.0037	0.0225**	–0.0017	0.0341	–0.0380*	0.0192**	0.0004	–0.0655*	0.0133	0.0325	0.0384	0.0146	–0.0014
	(–1.65)	(2.29)	(–1.26)	(1.67)	(0.27)	(2.29)	(–0.09)	(1.58)	(–1.71)	(2.14)	(0.04)	(–1.89)	(0.22)	(1.20)	(0.42)	(1.16)	(–0.18)
High	0.2404**	0.1540***	0.1580**	0.1217***	0.2084***	0.1551***	0.2689	0.2118***	0.2060**	0.1964***	0.1760***	0.2980*	0.2998**	0.4822***	0.5473*	0.0982**	0.0640***
	(2.17)	(5.46)	(2.47)	(3.05)	(3.38)	(3.81)	(1.02)	(3.08)	(2.24)	(5.06)	(3.18)	(1.95)	(1.98)	(5.85)	(1.87)	(2.21)	(2.61)
High x Large fund family	0.0836	–0.0602**	–0.1072**	–0.0657	0.0851	–0.0634*	0.0618	–0.1281*	–0.1319	–0.1002**	–0.0900*	0.1251	–0.0922	–0.1156	0.4518*	0.0637**	0.0422**
	(1.08)	(–2.01)	(–2.04)	(–1.61)	(–1.11)	(–1.92)	(0.14)	(1.95)	(–1.59)	(–2.36)	(–1.74)	(1.29)	(–1.03)	(–1.33)	(1.67)	(1.97)	(2.17)
Large fund family	0.0043	0.0038	0.0074	–0.0000	0.0010	0.0082***	0.0318**	0.0004	0.0316***	0.0069***	0.0049	0.0300***	–0.0133	0.0062	0.0061	0.0243***	0.0016
	(0.31)	(1.62)	(1.12)	(–0.01)	(0.38)	(2.95)	(2.11)	(0.06)	(4.18)	(3.03)	(1.16)	(2.84)	(–1.45)	(0.98)	(0.23)	(4.67)	(0.80)
Flows category	–0.4588	–0.0850	–0.1959	0.5855***	0.5177	0.0912	1.6145	0.0409	0.1424	–0.0841	0.0808	–0.8026	0.1760	1.6901*	–0.8438	0.1998	0.0795
	(–1.59)	(–0.57)	(–0.83)	(3.52)	(0.72)	(1.12)	(0.81)	(0.18)	(0.60)	(–0.66)	(0.51)	(–1.60)	(0.57)	(1.76)	(–1.43)	(1.06)	(0.98)
Star affiliation	–0.0484***	–0.0088***	0.0064	0.0053*	0.0016	0.0022	–0.0872**	–0.0030	–0.0030	0.0015	–0.0006	–0.0397**	0.0239***	–0.0042	–0.0992***	–0.0074	0.0011
	(–2.87)	(–6.99)	(1.24)	(1.67)	(0.65)	(0.80)	(–2.01)	(–0.50)	(–0.37)	(0.66)	(–0.24)	(–2.22)	(2.73)	(–0.88)	(–3.97)	(–1.61)	(0.59)
Age (log)	–0.0093	–0.0343***	0.0030	0.0294***	–0.0050	–0.0157***	0.0018	–0.0071*	0.0049	–0.0101***	–0.0085***	–0.0207**	–0.0163**	0.0031	–0.0194	0.0051	–0.0061**
	(–1.12)	(–12.91)	(0.41)	(5.53)	(–1.56)	(–5.60)	(0.06)	(–1.66)	(0.63)	(–5.29)	(–2.90)	(–2.52)	(–2.21)	(0.47)	(–0.96)	(1.03)	(–2.47)
Age x Performance	–0.0203	0.0257***	0.0371*	0.0344*	0.0371***	0.0381***	–0.0852	0.0820***	0.0377	0.0625***	0.0301***	0.0074	0.0566**	0.1659***	0.2788***	0.0722***	0.0458***
	(–0.77)	(3.85)	(1.88)	(1.83)	(3.90)	(4.48)	(–0.59)	(4.54)	(1.12)	(4.79)	(2.67)	(0.29)	(2.08)	(4.65)	(3.44)	(2.77)	(6.57)
Volatility	0.0068	–0.0097	–0.0194	–0.0367*	0.0375*	–0.0891***	0.1111	0.0133	0.0344	–0.0158	–0.0197	0.0533	0.0127	–0.0364	0.3174**	–0.0012	0.0215
	(0.10)	(–0.50)	(–0.54)	(–1.94)	(1.86)	(–5.85)	(0.41)	(0.38)	(0.96)	(–0.86)	(–0.96)	(1.12)	(0.21)	(–1.16)	(2.49)	(–0.03)	(1.56)
Size (log)	–0.0126**	–0.0037***	–0.0190***	–0.0095***	–0.0073***	–0.0077***	–0.0174**	–0.0163***	–0.0265***	–0.0063***	–0.0025**	–0.0175***	–0.0005	–0.0076***	–0.0221**	–0.0124***	–0.0042***
	(–2.39)	(–4.64)	(–4.99)	(–5.56)	(–8.06)	(–8.39)	(–2.24)	(–7.06)	(–5.97)	(–9.45)	(–2.13)	(–4.71)	(–0.15)	(–4.24)	(–2.59)	(–5.57)	(–5.83)
Flows	0.1654***	0.1901***	–0.0080	0.1414***	0.1779***	0.0905***	0.1356**	0.0724***	0.0461***	0.1647***	0.1744***	–0.0169	0.1406***	0.2463***	0.0303	0.1523***	0.2862***
	(4.51)	(11.04)	(–0.29)	(5.04)	(10.04)	(6.38)	(2.08)	(3.73)	(3.09)	(17.62)	(8.39)	(–0.29)	(4.41)	(8.13)	(0.68)	(5.97)	(17.37)
Expense ratio	0.8186	–0.4512**	–1.4459*	0.4294	–0.3878***	0.2576	1.7211	–1.2435*	–0.2881	–0.1625	–0.5317	1.0031	–1.9796***	–0.1672	–1.8688	–0.2363	0.5839**
	(1.21)	(–2.56)	(–1.79)	(1.00)	(–3.56)	(1.51)	(0.32)	(–1.88)	(–0.52)	(–1.14)	(–1.25)	(1.65)	(–2.62)	(–0.28)	(–1.07)	(–0.47)	(2.23)
Loads	–0.0778	–0.2098**	–0.3885	–0.0474	0.1196	–0.0004	–0.1353	–0.8079***	–0.8796**	–0.1136**	0.0519	–0.5391**	0.0092	–0.3248	0.3614	–0.0311	–1.0032***
	(–0.16)	(–2.43)	(–1.00)	(–0.50)	(1.09)	(–0.01)	(–0.16)	(–3.17)	(–2.11)	(–2.11)	(0.65)	(–2.25)	(0.08)	(–0.85)	(0.35)	(–0.45)	(–8.27)
SMB	0.0082	–0.0057*	0.0085	0.0184***	0.0032	–0.0048	0.0136	–0.0084	–0.0088	–0.0012	–0.0045	–0.0184	–0.0054	–0.0010	–0.0585*	0.0181	0.0002
	(0.90)	(–1.88)	(1.18)	(3.98)	(0.64)	(–1.34)	(0.55)	(–1.35)	(–1.13)	(–0.34)	(–0.91)	(–1.40)	(–0.93)	(–0.15)	(–1.81)	(1.61)	(0.09)
HML	–0.0113	–0.0005	0.0005	0.0074*	–0.0016	0.0041*	0.0353	–0.0057	0.0081	0.0006	0.0050	–0.0159*	0.0039	0.0052	0.0390*	0.0034	0.0029*
	(–1.46)	(–0.21)	(0.10)	(1.84)	(–0.32)	(1.96)	(1.26)	(–0.96)	(1.23)	(0.19)	(1.58)	(–1.74)	(0.50)	(0.72)	(1.79)	(0.59)	(1.72)
Countries sold	0.0001	0.0137***	0.0054***	0.0041***	0.0011	–0.0051	0.0002	–0.0021	0.0035	0.0024***	0.0057***	0.0014	0.0024	–0.0042	–0.0329	–0.0081**	0.0207***
	(0.02)	(3.56)	(3.61)	(4.74)	(0.74)	(–0.61)	(0.04)	(–1.48)	(0.93)	(5.12)	(3.94)	(0.52)	(0.73)	(–0.94)	(–0.62)	(–2.08)	(5.45)
Change in convexity *(High–Mid)*	0.1396*	–0.0739***	–0.0741	–0.0967	0.0814	–0.0855***	0.0628	–0.1622***	–0.0939	–0.1192***	–0.0904	0.1906*	–0.1055	–0.1475	0.4134**	0.0491**	0.0436***
Wald test (*p*–value)	(0.08)	(0.00)	(0.74)	(0.12)	(0.47)	(0.00)	(0.61)	(0.01)	(0.12)	(0.00)	(0.39)	(0.09)	(0.32)	(0.11)	(0.03)	(0.02)	(0.00)
Change in convexity *(High–Low)*	0.1643**	–0.1035***	–0.0270	–0.1188	0.1154	–0.1084***	0.0497	–0.1856***	–0.2164**	–0.061***	–0.1242	0.1987**	–0.2021	–0.1191	0.5728**	0.1027***	0.0492***
Wald test (*p*–value)	(0.03)	(0.00)	(0.53)	(0.11)	(0.49)	(0.00)	(0.86)	(0.01)	(0.04)	(0.00)	(0.13)	(0.05)	(0.14)	(0.34)	(0.02)	(0.00)	(0.00)
Adjusted R–squared	0.147	0.088	0.038	0.088	0.087	0.063	0.196	0.069	0.052	0.072	0.075	0.210	0.083	0.236	0.252	0.089	0.136
Number of observations	1,717	34,200	7,472	16,794	18,271	42,228	544	8,634	6,863	42,472	15,202	1,375	3,071	8,531	1,576	8,686	37,737

Table B.3 –Flow–performance sensitivity and fund's affiliation with large families – country level regressions (Continued)

	Malaysia	Netherlands	New Zealand	Norway	Poland	Portugal	Singapore	South Africa	South Korea	Spain	Sweden	Switzerland	Taiwan	Thailand	UK	US
	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)	(29)	(30)	(31)	(32)	(33)
Low	0.0702**	0.0512	0.0218	0.1641**	0.1101***	0.0473**	0.0138	0.0390	0.1358***	0.0659	0.0165	0.0124	0.0533	0.0570*	0.0819***	0.0391***
	(1.97)	(1.18)	(0.14)	(2.05)	(2.83)	(2.19)	(0.28)	(0.41)	(3.45)	(0.85)	(0.43)	(0.21)	(1.52)	(1.73)	(3.97)	(4.30)
Low x Large fund family	–0.0731*	–0.0225	–0.0092	–0.0406	0.0088	–0.0261**	–0.0209	0.0174	–0.0412	–0.0032	0.0185	0.0402	–0.0065	–0.0329	0.0371**	0.0157*
	(–1.85)	(–0.52)	(–0.09)	(–1.25)	(0.48)	(–2.01)	(–0.66)	(0.26)	(0.90)	(–0.03)	(0.53)	(0.93)	(–0.40)	(–1.39)	(2.12)	(1.73)
Mid	0.0255***	0.0298**	0.0415	0.0454*	0.0828***	0.0486***	0.0106	0.0256**	0.0282**	0.0591***	0.0237**	0.0063	0.0327***	0.0284**	0.0385***	0.0650***
	(2.94)	(2.28)	(0.73)	(1.78)	(2.92)	(2.60)	(0.74)	(2.23)	(2.33)	(4.02)	(2.23)	(0.87)	(2.89)	(2.21)	(4.59)	(13.64)
Mid x Large fund family	–0.0158	–0.0087	0.0254	0.0222	–0.0454**	–0.0013	0.0224	0.0181	0.0199	–0.0235	–0.0178	0.0027	–0.0254	–0.0397**	0.0213**	0.0160*
	(–0.86)	(–0.46)	(0.74)	(0.75)	(–2.34)	(–0.15)	(0.87)	(1.08)	(1.18)	(–0.95)	(–1.18)	(0.17)	(–1.46)	(–2.31)	(2.22)	(1.88)
High	0.1487***	0.0991*	0.4006*	0.0362	0.1292***	0.1405***	0.1401	0.1876**	0.2686***	0.1617**	0.1725**	0.0484	0.3302***	0.1965**	0.2370***	0.1762***
	(3.19)	(1.79)	(1.92)	(0.61)	(2.89)	(5.38)	(1.52)	(2.04)	(3.47)	(2.06)	(2.28)	(0.81)	(4.04)	(2.36)	(4.56)	(7.23)
High x Large fund family	0.0841**	0.0269	–0.2835	0.0284	0.0402**	0.0451**	–0.0448	0.0490	–0.1020*	–0.0478	–0.1667**	0.0501	–0.0566	0.1541*	–0.1084**	–0.0547**
	(2.11)	(0.66)	(–0.79)	(0.57)	(2.01)	(2.31)	(–0.41)	(0.61)	(–1.65)	(–1.37)	(–2.21)	(0.89)	(–0.56)	(1.94)	(–2.29)	(–2.00)
Large fund family	0.0023	–0.0026	–0.0145	0.0109*	0.0190**	0.0187	0.0066	0.0157**	–0.0022	0.0164***	–0.0013	0.0042***	0.0091**	0.0138***	0.0109***	0.0071***
	(0.51)	(–0.39)	(–1.14)	(1.81)	(2.06)	(1.59)	(1.35)	(2.23)	(–0.66)	(2.92)	(–0.40)	(2.89)	(2.40)	(2.69)	(5.26)	(6.69)
Flows category	–0.5242	0.0556	1.0810*	–0.2135	0.5004	0.2420	0.0050	0.5622	0.3020	0.6730***	0.1438	0.0884	0.8594**	–0.1889	0.2084*	0.1952***
	(–1.35)	(0.33)	(1.68)	(–0.68)	(0.79)	(0.70)	(0.03)	(1.29)	(1.46)	(2.74)	(0.87)	(0.56)	(2.40)	(–0.43)	(1.92)	(3.59)
Star affiliation	–0.0045	–0.0007	–0.0018	–0.0017	–0.0329***	0.0022	–0.0029	–0.0054	–0.0077**	–0.0046	–0.0012	0.0072**	–0.0010	–0.0048	0.0006	0.0022*
	(–0.98)	(–0.13)	(–0.09)	(–0.40)	(–3.16)	(0.28)	(–0.46)	(0.96)	(–2.33)	(–0.66)	(–0.28)	(2.25)	(–0.20)	(–1.09)	(0.29)	(1.93)
Age (log)	–0.0129**	–0.0069	0.0200*	–0.0321***	–0.0148	–0.0215*	–0.0070	–0.0117*	0.0026	–0.0242***	–0.0078	–0.0137***	0.0119**	–0.0306***	–0.0069***	–0.0163***
	(–2.56)	(–1.23)	(1.94)	(–3.68)	(–0.71)	(–1.79)	(–1.07)	(–1.96)	(0.46)	(–2.84)	(–1.62)	(–4.11)	(2.45)	(–3.65)	(–4.02)	(–17.59)
Age x Performance	0.0279	0.0108	0.0339	0.0581***	0.2818***	0.0490**	0.0919***	0.0632***	0.0046	0.0886***	0.0366**	0.0409***	0.0998***	0.1037***	0.0470***	–0.0519***
	(1.52)	(0.63)	(0.61)	(3.22)	(3.97)	(2.07)	(5.02)	(2.68)	(0.23)	(3.17)	(2.56)	(2.88)	(4.11)	(3.42)	(4.98)	(–14.15)
Volatility	–0.0204	–0.0328	–0.2025***	0.0279	0.1795*	–0.0672	0.0073	0.0023	0.0644**	0.0694*	0.0086	0.0521**	0.0550	–0.0004	–0.0190	–0.0430***
	(–0.62)	(–1.10)	(–2.66)	(0.73)	(1.75)	(–1.39)	(0.26)	(0.08)	(2.18)	(1.69)	(0.35)	(2.11)	(1.08)	(–0.01)	(–0.98)	(–5.30)
Size (log)	–0.0034*	–0.0093***	–0.0091	–0.0063***	–0.0164***	–0.0110**	–0.0041	–0.0126***	–0.0012	–0.0204***	–0.0075***	–0.0073***	–0.0162***	–0.0012	–0.0079***	–0.0055***
	(–1.70)	(–3.77)	(–1.31)	(–3.02)	(–3.63)	(–2.14)	(–1.55)	(–4.43)	(–1.21)	(–6.99)	(–4.77)	(–3.82)	(–5.88)	(–1.25)	(–7.52)	(–14.95)
Flows	0.2138***	0.1307***	0.2979***	0.0867***	0.1783***	0.1756***	0.2750***	0.0869**	0.2146***	0.0764***	0.0297	0.1098***	0.1074***	0.2319***	0.1414***	0.2644***
	(7.78)	(3.04)	(2.79)	(4.93)	(3.97)	(4.30)	(6.87)	(2.54)	(8.83)	(2.63)	(1.59)	(5.22)	(3.42)	(8.68)	(9.38)	(21.98)
Expense ratio	0.6607	–0.3713	0.6436	0.0500	–0.0646	–0.6948	–0.7119	–0.2841	–0.8887***	–0.4834	–1.6497***	–0.3658	–0.5790*	0.5793	0.1832	–0.5350***
	(1.18)	(–0.70)	(0.85)	(0.07)	(–0.12)	(–0.92)	(–1.04)	(–0.49)	(–3.35)	(–0.97)	(–4.45)	(–1.10)	(–1.67)	(1.21)	(0.75)	(–4.31)
Loads	0.0906	–0.8915**	–0.7095***	–0.3785**	0.6341**	–0.4947*	0.9917*	0.0835	0.1867	0.0222	0.0115	–0.1485**	0.2181	0.2865*	–0.1448***	–0.1141***
	(0.73)	(–2.44)	(–2.96)	(–2.07)	(2.32)	(–1.95)	(1.76)	(0.59)	(0.34)	(0.10)	(0.09)	(–1.97)	(1.10)	(1.71)	(–3.07)	(–5.43)
SMB	–0.0258***	0.0092	–0.0064	–0.0008	–0.0054	–0.0214*	0.0021	–0.0053	–0.0112**	0.0156*	0.0000	–0.0064	–0.0203**	–0.0197**	0.0024	0.0014
	(–4.53)	(1.42)	(–0.58)	(–0.08)	(–0.35)	(–1.76)	(0.48)	(–0.69)	(–2.38)	(1.95)	(0.00)	(–1.47)	(–2.26)	(–2.13)	(0.65)	(0.69)
HML	–0.0095	0.0001	0.0013	0.0068	0.0160	0.0249***	0.0092*	0.0072	–0.0061	0.0101	0.0080**	0.0001	0.0005	–0.0033	–0.0027	–0.0015
	(–1.31)	(0.02)	(0.09)	(1.04)	(0.95)	(3.32)	(1.93)	(1.08)	(–1.45)	(1.44)	(1.99)	(0.04)	(0.10)	(–0.37)	(–1.01)	(–0.96)
Countries sold	0.0034	0.0002	–0.0317	0.0023*	0.0011	0.0197*	0.0116**	0.0186	0.0085	0.0301**	0.0049***	0.0012	–0.0411***	0.0007	0.0011***	0.0099***
	(0.37)	(0.11)	(–1.58)	(1.84)	(0.44)	(1.76)	(2.10)	(0.35)	(0.89)	(2.31)	(2.78)	(0.45)	(–3.23)	(0.12)	(3.61)	(6.40)
Change in convexity (*High–Mid*)	0.0991*	0.0356**	–0.3084	0.0062	0.0856*	0.0461**	–0.0664	0.0309	–0.1219	–0.0240	–0.1489**	0.0474	–0.0306	0.1931**	–0.1293***	–0.0707***
Wald–test (*p*–value)	(0.07)	(0.03)	(0.19)	(0.23)	(0.07)	(0.04)	(0.85)	(0.81)	(0.19)	(0.23)	(0.03)	(0.43)	(0.64)	(0.02)	(0.00)	(0.00)
Change in convexity (*High–Low*)	0.1572***	0.0494***	–0.2738	0.0690	0.0314**	0.0712**	–0.0231	0.0316	–0.0608	–0.0438	–0.1852**	0.0099	–0.0495	0.1861***	–0.1451***	–0.0704***
Wald–test (*p*–value)	(0.01)	(0.01)	(0.34)	(0.17)	(0.05)	(0.02)	(0.62)	(0.31)	(0.11)	(0.15)	(0.04)	(0.86)	(0.73)	(0.01)	(0.00)	(0.00)
Adjusted R–squared	0.155	0.078	0.141	0.045	0.232	0.154	0.141	0.061	0.254	0.112	0.050	0.038	0.142	0.176	0.058	0.138
Number of observations	7,531	4,730	953	7,632	2,644	2,843	5,638	4,616	16,491	11,654	12,907	10,116	11,593	6,495	39,849	169,367

Table B.4: Flow–performance sensitivity and fund's affiliation with large families across countries – Investor sophistication – The joint effect of Fees, Star affiliation, and Diversity

In this table, we run the identical analysis to Table 2.3 – Panel A, Columns (2–7), except that *Fee*s, *Star affiliation*, and *Diversity*, and the interaction of past performance (*Low*, *Mid*, and *High* performance ranges) with theses variables are add to the regression. Fees are measured as the expense ratio plus one–seventh front–end loads; Star affiliation is a dummy variable that takes the value of one for funds that are affiliated with star families (i.e., those including a star fund) but are not stars themselves, and zero otherwise; Diversity is a dummy variable that is one if the number of different fund categories offered by the affiliated family is larger than the median number for all families, and zero otherwise. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. See Appendix A for variable definitions.

	Population owning shares		Trading Costs		Emerging markets	
	Below	Above	Above	Below	Yes	No
	(1)	(2)	(3)	(4)	(5)	(6)
Low	0.0573***	0.0512***	0.0598***	0.0504***	0.0620***	0.0462***
	(3.48)	(4.21)	(3.54)	(4.14)	(3.69)	(3.80)
Low x Large fund family	–0.0333**	0.0146	–0.0342**	0.0159	–0.0214*	0.0139
	(2.08)	(1.32)	(–2.01)	(1.48)	(–1.88)	(1.43)
Low x Fees	–0.6234	–0.8645	–0.7094	–0.6363	–0.7612	–0.5849
	(0.37)	(–1.14)	(–0.43)	(–0.84)	(–0.45)	(–0.73)
Low x Star affiliation	–0.0503*	–0.0116	–0.0937***	–0.0145	–0.0706*	–0.0155
	(–1.71)	(–0.95)	(–3.21)	(–1.25)	(–1.83)	(–1.38)
Low x Diversity	–0.0112	0.0059	–0.0107	0.0036	–0.0033	0.0013
	(–0.98)	(1.62)	(–0.90)	(0.92)	(–0.41)	(0.34)
Mid	0.0479***	0.0173***	0.0473***	0.0164***	0.0259**	0.0154***
	(3.37)	(3.77)	(3.64)	(3.73)	(2.31)	(3.65)
Mid x Large fund family	–0.0151*	0.0046	–0.0160*	0.0065*	–0.0119	0.0053
	(–1.66)	(1.35)	(–1.78)	(1.85)	(–0.96)	(1.27)
Mid x Fees	–0.6589	0.6423***	–0.2909	0.7192***	–0.0204	0.7155***
	(–1.54)	(3.50)	(–0.83)	(3.71)	(–0.05)	(4.11)
Mid x Star affiliation	–0.0009	0.0137***	–0.0119	0.0092**	–0.0070	0.0118***
	(–0.11)	(3.62)	(–1.60)	(2.20)	(–0.76)	(3.33)
Mid x Diversity	–0.0098***	0.0018	–0.0090**	0.0028***	–0.0112**	0.0023**
	(–2.80)	(1.48)	(–2.50)	(2.73)	(–2.22)	(2.36)
High	0.2028***	0.1618***	0.1985***	0.1638***	0.1963***	0.1572***
	(10.26)	(12.10)	(9.89)	(12.37)	(9.03)	(12.70)
High x Large fund family	0.0495**	–0.0477***	0.0440**	–0.0458***	0.0364*	–0.0415**
	(2.27)	(–3.29)	(2.14)	(–3.01)	(1.91)	(–2.57)
High x Fees	3.4719	–1.5576*	0.6548	–0.6281	1.8080	–1.2514
	(1.54)	(–1.69)	(0.50)	(–0.65)	(0.86)	(–1.36)
High x Star affiliation	–0.0161	–0.0282	–0.0134	–0.0306*	0.0079	–0.0400**
	(–0.52)	(–1.34)	(–0.44)	(–1.70)	(0.20)	(–2.23)
High x Diversity	0.0071	–0.0098	0.0264	–0.0229***	0.0342	–0.0206***
	(0.52)	(–1.46)	(1.29)	(–3.86)	(1.27)	(–3.54)
Large fund family	0.0090***	0.0067***	0.0086***	0.0067***	0.0071***	0.0072***
	(6.27)	(8.51)	(6.55)	(9.49)	(4.47)	(10.45)
Fees	–0.6422*	–0.1512	–0.3632	–0.1379	–0.3581	–0.1919
	(–1.84)	(–1.18)	(–1.37)	(–1.08)	(–1.28)	(–1.51)
Star affiliation	0.0072	0.0029	0.0091**	0.0040*	0.0032	0.0030
	(1.44)	(1.38)	(2.22)	(1.92)	(0.57)	(1.58)
Diversity	0.0037**	0.0029***	0.0034**	0.0030***	0.0065***	0.0026***
	(2.15)	(4.63)	(2.27)	(4.39)	(2.83)	(4.01)
Age (log)	–0.0067***	–0.0140***	–0.0058***	–0.0144***	–0.0055***	–0.0133***
	(–6.32)	(–22.98)	(–6.55)	(–18.74)	(–4.96)	(–21.21)
Age x Performance	0.0389***	0.0395***	0.0430***	0.0403***	0.0470***	0.0414***
	(4.27)	(8.38)	(6.15)	(9.04)	(4.41)	(9.16)
Volatility	0.0002	–0.0235***	0.0121	–0.0249***	0.0211	–0.0224**
	(0.02)	(–2.67)	(0.82)	(–2.83)	(1.22)	(–2.54)
Size (log)	–0.0071***	–0.0055***	–0.0060***	–0.0057***	–0.0049***	–0.0058***
	(–10.32)	(–15.92)	(–9.93)	(–20.25)	(–7.96)	(–19.61)
Flows	0.1559***	0.2031***	0.1677***	0.2019***	0.1915***	0.1903***
	(14.87)	(30.40)	(18.85)	(27.87)	(19.80)	(28.80)

Table B.4 (Continued)

Flows category	0.3370***	0.0792	0.1583*	0.0378	0.3664*	0.0313
	(3.31)	(1.58)	(1.88)	(0.68)	(1.79)	(0.55)
SMB	–0.0110***	–0.0037**	–0.0132***	–0.0001	–0.0156***	0.0002
	(–4.24)	(–2.21)	(–5.08)	(–0.04)	(–5.44)	(0.10)
HML	–0.0016	–0.0005	–0.0061***	0.0029**	–0.0069**	0.0027**
	(–0.73)	(–0.43)	(–3.51)	(2.31)	(–2.55)	(2.24)
Countries sold	0.0049***	0.0015***	0.0009***	0.0040***	–0.0001	0.0023***
	(7.76)	(5.75)	(3.03)	(9.69)	(–0.04)	(8.74)
Change in convexity *(High–Mid)*	0.0646***	–0.0516**	0.0600**	–0.0515**	0.0474*	–0.0463**
Wald test (p–value)	(0.01)	(0.02)	(0.03)	(0.02)	(0.06)	(0.03)
Change in convexity *(High–Low)*	0.0825***	–0.0616***	0.0782***	–0.0609***	0.574**	–0.0549***
Wald test (p–value)	(0.00)	(0.00)	(0.00)	(0.00)	(0.05)	(0.01)
Adjusted R–squared	0.068	0.093	0.083	0.089	0.119	0.081
Number of observations	108,078	462,354	143,579	426,853	79,997	490,435

Table B.5: Flow–performance sensitivity and fund's affiliation with large families across countries – Switching costs and the Number of investment opportunities

In this table, we run the identical analysis to Table 2.3 – Panel A, Columns (2–7), except that we add to the regression *Switching costs*, the *Number of available investment alternatives*, and the interaction of past performance (*Low*, *Mid*, and *High* performance ranges) with these variables. We measure the cost of switching funds (*Switching costs*) in a given country–quarter as the average of (i) the weighted average front–end fee and (ii) the weighted average back–end fee, where the weights are determined by a fund's assets under management relative to the country's total assets under management in that quarter. To compute the *Number of available investment alternatives*, we use the number of funds with similar styles based on their *SMB*– and *HML* loadings. In each quarter, we sort funds into three groups based on *SMB* loadings (low, medium, and high) and also into three groups based on *HML* loadings, to obtain nine equal–sized groups. The fund's *number of investment alternatives* in a given quarter is the total number of funds in the same *SMB/HML* group. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. See Appendix A for variable definitions.

	Population owning shares		Trading Costs		Emerging market	
	Below	Above	Above	Below	Yes	No
	(1)	(2)	(3)	(4)	(5)	(6)
Low	0.0869***	0.0887***	0.0884***	0.0948***	0.0899***	0.0944***
	(3.18)	(5.82)	(3.31)	(6.40)	(3.18)	(6.26)
Low x Large fund family	–0.0345***	0.0133	–0.0362***	0.0149	–0.0342***	0.0153
	(–2.94)	(1.16)	(–3.24)	(1.34)	(2.78)	(1.46)
Low x Switching costs	–0.5552	–0.1408	–0.6625	–0.1356	–0.4376	–0.2179
	(–1.27)	(–0.64)	(–1.32)	(–0.62)	(–1.06)	(–0.96)
Low x Number of investment opportunities	–0.0024	–0.0051	–0.0058	–0.0043	–0.0093	–0.0030
	(–0.42)	(–1.47)	(–0.97)	(–1.34)	(–1.12)	(–1.21)
Mid	0.0419***	0.0199***	0.0295***	0.0268***	0.0346***	0.0267***
	(4.76)	(6.74)	(3.05)	(9.39)	(3.04)	(9.23)
Mid x Large fund family	–0.0196***	0.0088***	–0.0045	0.0038	–0.0144*	0.0048*
	(–3.26)	(3.38)	(–0.83)	(1.30)	(–1.78)	(1.83)
Mid x Switching costs	–0.4796***	0.2240***	–0.1654	0.0237	–0.1210	0.0393
	(–3.76)	(4.23)	(–1.60)	(0.55)	(–0.62)	(0.92)
Mid x Number of investment opportunities	0.0023**	0.0026***	0.0007	0.0026***	0.0011	0.0022***
	(1.98)	(5.00)	(0.41)	(4.91)	(0.56)	(5.12)
High	0.2010***	0.1607***	0.2362***	0.1624***	0.2280***	0.1635***
	(8.93)	(14.26)	(10.65)	(14.01)	(9.43)	(14.71)
High x Large fund family	0.0572***	–0.0443***	0.0612***	–0.0459***	0.0568***	–0.0448***
	(3.01)	(–4.06)	(3.34)	(–4.14)	(2.63)	(–4.41)
High x Switching costs	0.8919*	0.3313	0.8487	0.3563	1.5350*	0.5184*
	(1.71)	(1.00)	(1.29)	(1.13)	(1.91)	(1.69)
High x Number of investment opportunities	–0.0061	0.0004	0.0037	–0.0038	–0.0165	0.0006
	(–1.18)	(0.10)	(0.49)	(–1.04)	(–1.55)	(0.17)
Large fund family	0.0086***	0.0067***	0.0084***	0.0067***	0.0067***	0.0072***
	(6.01)	(8.62)	(6.34)	(9.67)	(4.24)	(10.67)
Switching costs	0.0097	–0.0578	0.0054	–0.0969**	0.0185	–0.0973*
	(0.14)	(–1.30)	(0.08)	(–2.13)	(0.14)	(–1.94)
Number of investment opportunities	0.0036***	0.0007	0.0019*	0.0008	0.0027*	0.0005
	(3.06)	(1.18)	(1.82)	(1.40)	(1.91)	(0.92)
Expense ratio	–0.0954	–0.3928***	–0.3423***	–0.2294***	–0.2225**	–0.2490***
	(–1.04)	(–7.35)	(–3.25)	(–3.58)	(–2.12)	(–4.28)
Star affiliation	–0.0019*	–0.0012**	–0.0042***	–0.0004	–0.0073***	–0.0002
	(–1.66)	(–2.11)	(–3.39)	(–0.80)	(–3.95)	(–0.37)
Diversity	–0.0027***	–0.0012***	–0.0030***	–0.0011***	–0.0028***	–0.0013***
	(–4.03)	(–3.85)	(–3.75)	(–3.40)	(–2.66)	(–4.20)
Age (log)	–0.0060***	–0.0140***	–0.0056***	–0.0144***	–0.0054***	–0.0134***
	(–5.82)	(–23.16)	(–6.34)	(–18.88)	(–4.89)	(–21.61)
Age x Performance	0.0399***	0.0395***	0.0435***	0.0405***	0.0474***	0.0415***
	(4.39)	(8.34)	(6.05)	(9.04)	(4.40)	(9.18)
Volatility	0.0038	–0.0232***	0.0147	–0.0243***	0.0259	–0.0219**
	(0.34)	(–2.64)	(0.98)	(–2.76)	(1.47)	(–2.48)
Size (log)	–0.0070***	–0.0056***	–0.0059***	–0.0057***	–0.0048***	–0.0059***
	(–10.26)	(–15.55)	(–9.90)	(–19.97)	(–7.83)	(–19.29)
Flows	0.1565***	0.2033***	0.1685***	0.2023***	0.1928***	0.1907***
	(14.90)	(30.45)	(18.91)	(27.96)	(19.84)	(28.91)
Flows category	0.3450***	0.0772	0.1457*	0.0370	0.3457*	0.0304
	(3.39)	(1.54)	(1.75)	(0.67)	(1.68)	(0.53)
SMB	–0.0157***	–0.0051*	–0.0162***	–0.0011	–0.0176***	–0.0004
	(–5.01)	(–1.87)	(–5.31)	(–0.64)	(–5.70)	(–0.26)
HML	–0.0030	–0.0010	–0.0070***	0.0026**	–0.0076***	0.0026**
	(–1.39)	(–0.74)	(–3.82)	(2.13)	(–2.72)	(2.13)
Countries sold	0.0049***	0.0015***	0.0009***	0.0039***	–0.0003	0.0023***
	(7.66)	(5.73)	(2.81)	(9.58)	(–0.07)	(8.70)
Change in convexity *(High–Mid)*	0.0762***	–0.0531**	0.0657**	–0.0497***	0.0712**	–0.0496*
Wald test (p–value)	(0.00)	(0.02)	(0.02)	(0.01)	(0.04)	(0.05)
Change in convexity *(High–Low)*	0.0912***	–0.0576***	0.0972***	–0.0608***	0.0908**	–0.0601**
Wald test (p–value)	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.04)
Adjusted R–squared	0.068	0.093	0.083	0.089	0.119	0.081
Number of observations	108,078	462,354	143,579	426,853	79,997	490,435

Table B.6: Flow–performance sensitivity and fund's affiliation with large families across countries – Bank–affiliated versus unaffiliated funds

In this table, we run the identical analysis to Table 2.3 – Panel A, Columns (2–3), except that we run our tests separately for bank–affiliated and unaffiliated funds sub–samples. Bank–affiliated funds are mutual funds for which the ultimate owner of the fund's management company is a commercial banking group. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. See Appendix A for variable definitions.

	Affiliated funds		Unaffiliated funds	
	Below	Above	Below	Above
	(1)	(2)	(3)	(4)
Low	0.0305*	0.0498***	0.0404**	0.0314**
	(1.91)	(3.41)	(2.20)	(2.41)
Low x Large fund family	–0.0549**	0.0152	–0.0411*	0.0390**
	(–2.12)	(1.45)	(–1.89)	(2.43)
Mid	0.0268***	0.0384***	0.0420***	0.0431***
	(4.17)	(9.22)	(8.13)	(13.57)
Mid x Large fund family	–0.0041	0.0043	–0.0076	0.0078**
	(–0.46)	(0.95)	(–1.05)	(2.38)
High	0.2421***	0.1690***	0.2398***	0.1810***
	(9.17)	(10.86)	(9.60)	(11.14)
High x Large fund family	0.0515**	–0.0463**	0.0331*	–0.0418**
	(1.98)	(–2.29)	(1.87)	(–2.15)
Large fund family	0.0120***	0.0073***	0.0040	0.0061***
	(6.11)	(6.60)	(0.46)	(6.12)
Flows category	0.2219**	0.0924	0.0937	–0.0144
	(2.45)	(1.11)	(0.94)	(–0.32)
Star affiliation	–0.0026	–0.0021**	–0.0052***	–0.0013
	(–1.31)	(–2.48)	(–3.41)	(–1.61)
Diversity	–0.0042	0.0006	0.0141***	–0.0134***
	(–0.69)	(0.20)	(2.67)	(–4.19)
Age (log)	–0.0009	–0.0122***	–0.0084***	–0.0162***
	(–0.54)	(–10.31)	(–6.66)	(–18.56)
Age x Performance	0.0420***	0.0360***	0.0428***	0.0432***
	(5.21)	(6.24)	(5.45)	(9.12)
Volatility	0.0241*	–0.0060	0.0051	–0.0362***
	(1.81)	(–0.64)	(0.28)	(–3.75)
Size (log)	–0.0071***	–0.0062***	–0.0055***	–0.0055***
	(–7.32)	(–11.90)	(–8.24)	(–19.17)
Flows	0.1605***	0.1876***	0.1744***	0.2098***
	(14.70)	(21.83)	(16.51)	(23.50)
TER	–0.5740***	–0.2140**	–0.0487	–0.2935***
	(–4.22)	(–2.05)	(–0.38)	(–3.97)
Loads	–0.1460***	–0.0756***	0.0102	0.0053
	(–2.62)	(–3.07)	(0.24)	(0.22)
SMB	–0.0159***	–0.0024	–0.0112***	0.0014
	(–5.47)	(–1.51)	(–3.94)	(0.74)
HML	–0.0080***	0.0019	–0.0044**	0.0032**
	(–4.09)	(1.22)	(–2.17)	(2.30)
Countries sold	0.0009	0.0054***	0.0012***	0.0032***
	(1.10)	(8.55)	(3.53)	(7.23)
Change in convexity *(High–Mid)*	0.0556**	–0.0506**	0.0401*	–0.0496***
Wald test (*p*–value)	(0.04)	(0.02)	(0.06)	(0.01)
Change in convexity *(High–Low)*	0.1064***	–0.0615**	0.0741**	–0.0808***
Wald test (*p*–value)	(0.00)	(0.02)	(0.04)	(0.00)
Adjusted R–squared	0.085	0.080	0.087	0.097
Number of observations	47,790	197,666	60,288	264,688

Table B.7: Flow–performance sensitivity and fund's affiliation with large families across countries – Domestic versus international funds

In this table, we run the identical analysis to Table 2.3 – Panel A, Columns (2–3), except that we run our tests separately for domestic and international funds sub–samples. Domestic funds are those investing primarily in stocks of the country of domicile, while international funds invest primarily in stocks of countries other than the country of domicile, including funds investing in a particular country, regional funds, and global funds. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. See Appendix A for variable definitions.

	Domestic		International	
	Below	Above	Below	Above
	(1)	(2)	(3)	(4)
Low	0.0422**	0.0410***	0.0503**	0.0350***
	(2.03)	(3.75)	(2.36)	(3.17)
Low x Large fund family	–0.0372*	0.0168	–0.0443**	0.0175
	(–1.82)	(1.35)	(–2.01)	(1.53)
Mid	0.0549***	0.0470***	0.0147**	0.0369***
	(8.98)	(14.79)	(2.35)	(8.95)
Mid x Large fund family	–0.0063	0.0016	–0.0058	0.0027
	(–1.06)	(0.31)	(–1.12)	(0.58)
High	0.2130***	0.2117***	0.2399***	0.1730***
	(8.98)	(10.43)	(9.96)	(8.08)
High x Large fund family	0.0489**	–0.0543**	0.0546**	–0.0416**
	(2.01)	(–2.31)	(2.23)	(–2.09)
Large fund family (log)	0.0249***	0.0078***	0.0107**	0.0135***
	(3.31)	(2.97)	(1.97)	(4.54)
Flows category	0.4806***	0.2794*	0.2610*	0.0873
	(4.48)	(1.82)	(1.77)	(1.45)
Star affiliation	–0.0047***	–0.0026***	0.0007	–0.0004
	(–2.99)	(–2.87)	(0.39)	(–0.53)
Age (log)	–0.0076***	–0.0139***	–0.0026	–0.0140***
	(–5.98)	(–20.23)	(–1.18)	(–14.98)
Age x Performance	0.0421***	0.0388***	0.0452***	0.0431***
	(3.92)	(10.40)	(5.38)	(5.47)
Volatility	0.0211	–0.0139*	–0.0172	–0.0304**
	(1.46)	(–1.69)	(–1.33)	(–2.38)
Size (log)	–0.0059***	–0.0048***	–0.0090***	–0.0065***
	(–7.21)	(–12.40)	(–11.18)	(–14.35)
Flows	0.1780***	0.2148***	0.1310***	0.1869***
	(14.61)	(24.06)	(9.83)	(23.58)
TER	–0.0083	–0.4486***	–0.3164*	–0.2646***
	(–0.08)	(–4.79)	(–1.72)	(–3.04)
Loads	0.0058	0.0369	–0.1103**	–0.0544**
	(0.10)	(1.44)	(–2.37)	(–2.14)
SMB	–0.0170***	–0.0061**	0.0041	–0.0018
	(–5.20)	(–2.10)	(1.49)	(–0.94)
HML	–0.0028	0.0003	0.0057**	0.0004
	(–1.00)	(0.21)	(2.45)	(0.23)
Countries sold	0.0037***	0.0008*	0.0050***	0.0017***
	(2.72)	(1.82)	(7.27)	(5.97)
Change in convexity *(High–Mid)*	0.0552**	–0.0559***	0.0604*	–0.0443**
Wald test (*p*–value)	(0.04)	(0.01)	(0.06)	(0.02)
Change in convexity *(High–Low)*	0.0861**	–0.0711***	0.0989**	–0.0591***
Wald test (*p*–value)	(0.03)	(0.00)	(0.04)	(0.00)
Adjusted R–squared	0.078	0.109	0.069	0.081
Number of observations	63,620	225,224	44,458	237,130

Table B.8: Flow–performance sensitivity and fund's affiliation with large families across countries – Excluding the US
In this table, we run the identical analysis to Table 2.3 – Panel A, Columns (2–7), except that we exclude the US from our regressions. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. See Appendix A for variable definitions.

	Population owning shares		Trading Costs		Emerging markets	
	Below	Above	Above	Below	Yes	No
	(1)	(2)	(3)	(4)	(5)	(6)
Low	0.0302**	0.0479***	0.0335**	0.0564***	0.0646***	0.0455***
	(2.09)	(4.54)	(2.44)	(5.13)	(2.70)	(3.11)
Low x Family size	–0.0456**	0.0178*	–0.0474**	0.0169	–0.0432**	0.0252**
	(–2.16)	(1.68)	(–2.34)	(1.56)	(–2.47)	(2.35)
Mid	0.0406***	0.0302***	0.0349***	0.0325***	0.0401***	0.0311***
	(9.12)	(11.17)	(8.85)	(10.04)	(8.38)	(10.76)
Mid x Family size	–0.0078*	0.0049*	–0.0056*	0.0057*	–0.0084	0.0023
	(–1.73)	(1.90)	(–1.68)	(1.88)	(–1.17)	(0.78)
High	0.2307***	0.1773***	0.2395***	0.1760***	0.2545***	0.1712***
	(10.06)	(8.25)	(11.30)	(7.85)	(9.12)	(8.34)
High x Family size	0.0351**	–0.0373**	0.0387**	–0.0467***	0.0341*	–0.0363**
	(2.09)	(–2.38)	(2.27)	(–2.63)	(1.72)	(–2.34)
Large fund family	0.0073***	0.0058***	0.0069***	0.0057***	0.0056***	0.0064***
	(5.16)	(6.10)	(5.41)	(6.53)	(3.80)	(8.21)
Flows category	0.3482***	0.1887**	0.1579*	0.1586**	0.3679*	0.1197
	(3.36)	(2.32)	(1.88)	(2.07)	(1.79)	(1.61)
Star affiliation	–0.0031***	–0.0024***	–0.0051***	–0.0011	–0.0084***	–0.0010
	(–2.68)	(–3.38)	(–4.14)	(–1.39)	(–4.41)	(–1.54)
Age (log)	–0.0067***	–0.0118***	–0.0058***	–0.0126***	–0.0058***	–0.0111***
	(–6.41)	(–15.58)	(–6.65)	(–11.95)	(–5.36)	(–14.96)
Age x Performance	0.0392***	0.0326***	0.0433***	0.0313***	0.0469***	0.0344***
	(4.31)	(6.44)	(6.16)	(7.17)	(4.40)	(7.88)
Volatility	0.0040	–0.0094	0.0153	–0.0097	0.0255	–0.0074
	(0.37)	(–0.89)	(1.03)	(–1.01)	(1.47)	(–0.76)
Size (log)	–0.0070***	–0.0057***	–0.0059***	–0.0061***	–0.0048***	–0.0061***
	(–10.21)	(–12.60)	(–9.82)	(–14.86)	(–7.86)	(–15.67)
Flows	0.1574***	0.1655***	0.1690***	0.1602***	0.1932***	0.1516***
	(15.01)	(22.52)	(18.97)	(20.12)	(19.90)	(20.46)
TER	–0.0847	–0.3467***	–0.3311***	–0.1452**	–0.2138**	–0.1713***
	(–0.92)	(–7.54)	(–3.16)	(–2.13)	(–2.02)	(–2.97)
Loads	–0.0659**	–0.0472**	–0.0265	–0.0645***	0.1023*	–0.0704***
	(–2.36)	(–2.12)	(–0.76)	(–3.21)	(1.87)	(–3.75)
SMB	–0.0106***	–0.0048**	–0.0131***	–0.0056**	–0.0155***	–0.0002
	(–4.07)	(–2.29)	(–5.07)	(–2.41)	(–5.40)	(–0.11)
HML	–0.0052**	0.0037***	–0.0060***	0.0045***	–0.0068**	0.0039***
	(–2.32)	(3.07)	(–3.47)	(3.42)	(–2.52)	(3.09)
Countries sold	0.0050***	0.0014***	0.0007**	0.0041***	–0.0007	0.0023***
	(8.02)	(5.12)	(2.28)	(9.49)	(–0.19)	(8.52)
Change in convexity *(High–Mid)*	0.0429*	–0.0419*	0.0443**	–0.0517**	0.0421*	–0.0383**
Wald test (*p*–value)	(0.06)	(0.07)	(0.04)	(0.04)	(0.08)	(0.02)
Change in convexity *(High–Low)*	0.0807***	–0.0548**	0.0857***	–0.0629***	0.0771***	–0.0612***
Wald test (*p*–value)	(0.00)	(0.03)	(0.00)	(0.01)	(0.01)	(0.01)
Adjusted R–squared	0.067	0.071	0.082	0.063	0.118	0.057
Number of observations	108,078	292,987	143,579	257,486	79,997	321,068

Table B.9: Flow–performance sensitivity and fund's affiliation with large families across countries – Fama–Macbeth
In this table, we run the identical analysis to Table 2.3 – Panel A, Columns (2–7), except that we use Fama–Macbeth cross–sectional regressions. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. See Appendix A for variable definitions.

	Population owning shares		Trading Costs		Emerging market	
	Below	Above	Above	Below	Yes	No
	(1)	(2)	(3)	(4)	(5)	(6)
Low	0.0531**	0.0286*	0.0492**	0.0443***	0.0618***	0.0476***
	(2.21)	(1.95)	(2.14)	(2.96)	(2.58)	(3.20)
Low x Large fund family	–0.0408**	0.0204	–0.0385**	0.0217	–0.0481**	0.0245*
	(–2.14)	(1.56)	(–1.97)	(1.61)	(–2.38)	(1.66)
Mid	0.0418***	0.0589***	0.0477***	0.0583***	0.0514**	0.0568***
	(5.10)	(9.29)	(3.85)	(9.06)	(–2.30)	(9.04)
Mid x Large fund family	–0.0194*	0.0054*	–0.0096	0.0065*	–0.0191	0.0099**
	(–1.72)	(1.84)	(–0.71)	(1.91)	(–1.27)	(2.43)
High	0.1858***	0.1946***	0.1797***	0.1568***	0.2537***	0.1669***
	(5.09)	(7.89)	(5.06)	(6.02)	(3.62)	(6.74)
High x Large fund family	0.0703**	–0.0603***	0.0683**	–0.0624***	0.1136**	–0.0664**
	(2.09)	(–2.68)	(1.99)	(–2.61)	(2.37)	(–2.51)
Large fund family	0.0073***	0.0052***	0.0043**	0.0072***	0.0227	0.0074***
	(2.93)	(5.08)	(2.19)	(7.18)	(0.73)	(7.44)
Flows category	–0.0081***	–0.0041***	–0.0099*	–0.0048***	–0.0265	–0.0049***
	(–4.78)	(–8.42)	(–1.85)	(–9.79)	(–1.27)	(–9.89)
Star affiliation	0.3169	0.0287	0.3210	0.0594	0.0453	–0.0006
	(1.04)	(0.21)	(0.98)	(0.47)	(0.11)	(–0.01)
Age (log)	0.0016	–0.0090***	–0.0039	–0.0109***	0.0073	–0.0096***
	(0.31)	(–3.75)	(–0.57)	(–4.65)	(0.48)	(–4.10)
Age x Performance	–0.0027	–0.0110***	0.0010	–0.0122***	–0.0022	–0.0113***
	(–1.31)	(–13.86)	(0.52)	(–13.80)	(–0.07)	(–14.89)
Volatility	0.0018	–0.0033*	–0.0098	0.0014	–0.0230	0.0012
	(0.35)	(–1.78)	(–1.67)	(0.66)	(–0.52)	(0.57)
Size (log)	0.0584***	0.0389***	0.0768***	0.0378***	0.0872	0.0390***
	(3.38)	(3.77)	(4.39)	(5.62)	(1.17)	(5.85)
Flows	0.0357*	–0.0421***	–0.0115	–0.0084	0.2742*	–0.0112
	(1.78)	(–3.63)	(–0.61)	(–0.88)	(1.96)	(–1.13)
TER	0.1240***	0.2211***	0.1368***	0.2194***	0.1547*	0.2099***
	(6.48)	(18.61)	(7.14)	(18.05)	(1.87)	(17.27)
Loads	0.7208**	–0.3107***	–0.1048	0.0402	0.3278**	–0.0848
	(2.23)	(–2.74)	(–0.62)	(0.31)	(2.01)	(–0.70)
SMB	–0.0433	0.0335	0.1853*	–0.0290	0.5146***	–0.0434**
	(–0.56)	(1.65)	(1.83)	(–1.44)	(3.20)	(–2.08)
HML	–0.0102**	–0.0039**	–0.0167*	–0.0033*	–0.0824**	–0.0026
	(–2.31)	(–2.11)	(–1.81)	(–1.87)	(–2.39)	(–1.48)
Countries sold	0.0048***	0.0021***	0.0080	0.0028***	0.0133	0.0020***
	(6.60)	(3.90)	(1.10)	(4.14)	(0.64)	(3.72)
Change in convexity *(High–Mid)*	0.0897**	–0.0657**	0.0779**	–0.0689**	0.1327*	–0.0759**
Wald test (p–value)	(0.04)	(0.05)	(0.05)	(0.02)	(0.07)	(0.02)
Change in convexity *(High–Low)*	0.1111***	–0.0807***	0.1068***	–0.0841***	0.1617**	–0.0905***
Wald test (p–value)	(0.00)	(0.00)	(0.00)	(0.00)	(0.04)	(0.00)
Number of observations	108,078	462,354	143,579	426,853	79,997	490,435

Table B.10: Flow–performance sensitivity and fund's affiliation with large families across countries – Additional proxies for investor sophistication

This table presents in Panel A means of additional proxies for investor sophistication by country, including the percentage of adults who are financially literate in the country, the KAOPEN index, a measure of a country's degree of capital account openness, and GDP per capita. In Panel B, we run the identical analysis to Table 2.3– Panel A, Columns (2–7), except that we proxy for investor sophistication using additional proxies for investor sophistication. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. See Appendix A for variable definitions.

Panel A– Additional country–level characteristics by country

Country	Financial literacy (%)	Financial openness (%)	GDP per capita ($)
Argentina	28.00	0.14	10,987
Australia	64.00	0.77	55,082
Austria	53.00	1.00	46,657
Belgium	55.00	1.00	43,497
Brazil	35.00	0.40	11,022
Canada	68.00	1.00	45,261
China	28.00	0.17	6,326
Denmark	71.00	1.00	55,894
Finland	63.00	1.00	45,883
France	52.00	1.00	39,859
Germany	66.00	1.00	41,416
Greece	45.00	0.97	23,902
Hong Kong		1.00	34,672
India	24.00	0.17	1,307
Indonesia	32.00	0.51	3,106
Italy	37.00	1.00	34,716
Japan	43.00	1.00	40,019
Malaysia	36.00	0.33	9,217
Netherlands	66.00	1.00	48,736
New Zealand	61.00	1.00	39,470
Norway	71.00	1.00	80,765
Poland	42.00	0.48	12,404
Portugal	26.00	1.00	21,046
Singapore	59.00	1.00	43,343
South Africa	42.00	0.17	6,608
South Korea	33.00	0.61	23,355
Spain	49.00	1.00	29,699
Sweden	71.00	1.00	49,252
Switzerland	57.00	1.00	75,443
Taiwan	37.00		19,464
Thailand	27.00	0.22	5,058
UK	67.00	1.00	42,856
US	57.00	1.00	46,124
All countries	54.68	0.91	41,020

Panel B– Regressions with additional country–level characteristics

	Financial Literacy		Financial openness		GDP per capita	
	Below	Above	Below	Above	Below	Above
	(1)	(2)	(3)	(4)	(5)	(6)
Low	0.0374**	0.0412***	0.0382**	0.0471***	0.0424***	0.0315***
	(2.11)	(4.17)	(2.36)	(4.19)	(3.27)	(2.86)
Low x Family size	–0.0323**	0.0287***	–0.0300**	0.0227**	–0.0376***	0.0234**
	(–2.17)	(2.64)	(–2.03)	(2.29)	(–2.66)	(2.48)
Mid	0.0363***	0.0400***	0.0348***	0.0406***	0.0212***	0.0464***
	(6.91)	(14.88)	(8.15)	(13.98)	(6.15)	(17.43)
Mid x Family size	–0.0106*	0.0097**	–0.0082	0.0060*	–0.0027	0.0043*
	(–1.65)	(2.19)	(–1.32)	(1.88)	(–0.69)	(1.93)
High	0.2116***	0.1740***	0.2087***	0.1787***	0.2190***	0.1731***
	(8.21)	(11.36)	(7.75)	(11.29)	(9.36)	(10.09)
High x Family size	0.0361*	–0.0429**	0.0591***	–0.0416**	0.0553***	–0.0467***
	(1.81)	(–2.39)	(2.63)	(–2.37)	(3.85)	(–2.96)
Large fund family	0.0041**	0.0072***	0.0054***	0.0072***	0.0045***	0.0072***
	(2.24)	(10.21)	(4.41)	(10.07)	(3.46)	(9.37)
Flows category	0.0862	0.1317**	0.2813***	0.0251	–0.0141	0.1824***
	(0.57)	(2.13)	(4.70)	(0.43)	(–0.33)	(3.16)
Star affiliation	–0.0085***	–0.0019***	–0.0093***	–0.0008	–0.0001	–0.0026***
	(–3.69)	(–4.37)	(–6.17)	(–1.49)	(–0.09)	(–3.77)
Age (log)	–0.0085***	–0.0130***	–0.0178***	–0.0121***	–0.0078***	–0.0140***
	(–12.22)	(–19.25)	(–13.11)	(–17.78)	(–7.19)	(–21.53)
Age x Performance	0.0439***	0.0422***	0.0365***	0.0459***	0.0306***	0.0430***
	(3.91)	(9.11)	(3.98)	(9.63)	(4.02)	(8.68)
Volatility	0.0130	–0.0171**	0.0030	–0.0216**	0.0042	–0.0134
	(0.65)	(–2.02)	(0.23)	(–2.42)	(0.36)	(–1.64)
Size (log)	–0.0036***	–0.0059***	–0.0039***	–0.0061***	–0.0055***	–0.0059***
	(–4.54)	(–20.46)	(–8.13)	(–19.86)	(–10.10)	(–16.90)
Flows	0.1958***	0.1910***	0.2034***	0.1906***	0.1773***	0.1953***
	(18.00)	(31.15)	(21.68)	(28.82)	(21.84)	(29.85)
TER	–0.5327***	–0.1917***	–0.3165***	–0.2140***	–0.1878*	–0.3098***
	(–2.78)	(–3.60)	(–3.06)	(–3.29)	(–1.68)	(–6.81)
Loads	0.0036	–0.0313*	–0.0531	–0.0211	–0.2059***	0.0115
	(0.07)	(–1.73)	(–0.93)	(–1.22)	(–8.45)	(0.56)
SMB	–0.0151***	–0.0005	–0.0111***	0.0004	–0.0021	–0.0076***
	(–4.57)	(–0.36)	(–4.90)	(0.24)	(–1.35)	(–4.51)
HML	–0.0038	0.0017	–0.0052**	0.0028**	0.0013	–0.0009
	(–1.38)	(1.12)	(–2.24)	(2.25)	(0.86)	(–0.59)
Countries sold	0.0035***	0.0023***	0.0080***	0.0022***	0.0050***	0.0014***
	(2.69)	(8.73)	(3.14)	(8.14)	(6.94)	(5.64)
Change in convexity *(High–Mid)*	0.0461**	–0.0517**	0.0671**	–0.0476**	0.0573***	–0.0503***
Wald test (*p*–value)	(0.04)	(0.02)	(0.04)	(0.03)	(0.00)	(0.00)
Change in convexity *(High–Low)*	0.0681**	–0.0707***	0.0891***	–0.0643***	0.0923***	–0.0694***
Wald test (*p*–value)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)
Adjusted R–squared	0.116	0.081	0.110	0.082	0.068	0.091
Number of observations	145,375	421,986	103,991	454,847	184,776	385,656

Appendix C. Variable definitions

Variable	Definition
Raw return	Fund net return in UD dollars (percentage per quarter or year) (Lipper).
Four–factor alpha	Net four–factor alpha (percentage per quarter or year) estimated as indicated in Equation (3.3).
TNA	Total net assets in millions of US dollars (Lipper).
TNA family	Family total net assets in millions of US dollars of other equity funds in the same management company excluding the own fund TNA (Lipper).
Flow	Net fund flow computed as indicated in Equation (3.2). Net annual fund flow is the sum of net quarterly fund flows.
Absolute flow	Absolute fund flow computed as indicated in Equation (3.1). Absolute annual fund flow is the sum of absolute quarterly fund flows.
Flows volatility	Standard deviation of fund flows, computed using monthly fund flows over the past 12 months.
Age	Number of years since the fund launch date (Lipper).
Total expense ratio	Total annual expenses as a fraction of TNA (Lipper).
Loads	Sum of front–end and back–end loads (Lipper).

Appendix D

This appendix contains tables that supplement the analysis in Chapter 3 “The flow-performance sensitivity of quantitative funds”.

Table D.1: Fund flows and performance in the bottom and top performance terciles – Raw returns
This table reports the results from estimating our tests in Table 3.3 using prior–year bottom and top performance terciles. *p*–values are reported in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. See Appendix C for variable definitions.

Panel A –Quarterly data

	All funds	Quantitative	Non-quantitative	Quantitative minus Non-quantitative (p-value)
	(1)	(2)	(3)	(4)
Bottom performance t-1				
Flow (%)	-2.6637***	-2.3971***	-2.7289***	0.3318
	(0.00)	(0.00)	(0.00)	(0.35)
Absolute flow	-23.8373***	-21.0907***	-24.2179***	3.1272
	(0.00)	(0.00)	(0.00)	(0.17)
Top performance t-1				
Flow (%)	3.9124***	2.8895***	3.9735***	-1.0840
	(0.00)	(0.00)	(-0.00)	(0.18)
Absolute flow	11.3537***	10.4446***	11.6479***	-1.2033
	(0.00)	(0.00)	(0.00)	(0.36)
Number of observations	159,643	9,086	150,557	-

Panel B – Annual data

	All funds	Quantitative	Non-quantitative	Quantitative minus Non-quantitative (p-value)
	(1)	(2)	(3)	(4)
Bottom performance t-1				
Flow (%)	-11.5815***	-11.2327***	-11.6123***	0.3796
	(0.00)	(0.00)	(0.00)	(0.65)
Absolute flow	-80.1727***	-75.6349***	-81.0209***	5.3860
	(0.00)	(0.00)	(0.00)	(0.48)
Top performance t-1				
Flow (%)	17.2602***	13.9704***	17.4901***	-3.5197
	(0.00)	(0.00)	(0.00)	(0.28)
Absolute flow	19.1609***	19.0298***	16.9528***	2.0770
	(0.00)	(0.00)	(0.00)	(0.92)
Number of observations	36,781	2,503	34,278	-

Table D.2: Fund flows and performance in the bottom and top performance terciles – Four-factor alpha

This table reports the results from estimating our tests in Table 3.4 using prior–year bottom and top performance terciles. *p*–values are reported in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. See Appendix C for variable definitions.

Panel A – Quarterly data

	All funds	Quantitative	Non-quantitative	Quantitative minus Non-quantitative (p-value)
	(1)	(2)	(3)	(4)
Bottom performance t-1				
Flow (%)	-2.4724***	-2.1423***	-2.5275***	0.3852
	(0.00)	(0.00)	(0.00)	(0.57)
Absolute flow	-22.4268***	-20.0656***	-23.0606***	2.9950
	(0.00)	(0.00)	(0.00)	(0.15)
Top performance t-1				
Flow (%)	3.7487***	3.5537***	3.7621***	-0.2084
	(0.00)	(0.00)	(0.00)	(0.59)
Absolute flow	10.8179***	11.9004***	10.3331***	1.5673
	(0.00)	(0.00)	(0.00)	(0.29)
Number of observations	159,643	9,086	150,557	-

Panel B – Four–factor alpha (Annual data)

	All funds	Quantitative	Non-quantitative	Quantitative minus Non-quantitative (p-value)
	(1)	(2)	(3)	(4)
Bottom performance t-1				
Flow (%)	-11.5212***	-10.7119***	-11.6921***	0.9802
	(0.00)	(0.00)	(0.00)	(0.51)
Absolute flow	-84.442***	-81.0982***	-86.3906***	5.2924
	(0.00)	(0.00)	(0.00)	(0.23)
Top performance t-1				
Flow (%)	18.8501***	23.1145***	18.5467***	4.5678
	(0.00)	(0.00)	(0.00)	(0.18)
Absolute flow	15.4517***	14.5631***	16.1447***	-1.5816
	(0.00)	(0.00)	(0.00)	(0.94)
Number of observations	36,781	2,503	34,278	-

Table D.3: Fund flow–performance sensitivity – performance terciles

This table reports the results from estimating our tests in Table 3.5 using prior–year bottom and top performance terciles. *p*–values are reported in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. See Appendix C for variable definitions.

Panel A – Quarterly data

	All funds	Quantitative	Non-quantitative	Quantitative minus Non-quantitative (p-value)
	(1)	(2)	(3)	(4)
Bottom Performance	-0.0086***	-0.0113***	-0.0087***	-0.0026
	(-10.40)	(-2.86)	(-10.21)	(0.85)
Performance	0.1885***	0.2085*	0.1828***	0.0257
	(8.10)	(1.78)	(7.68)	(-0.83)
Top performance	0.0168***	0.0143***	0.0170***	-0.0027
	(19.37)	(3.62)	(19.23)	(0.84)
Four-factor alpha	0.5076***	0.4107***	0.5119***	-0.1012
	(25.54)	(4.01)	(25.25)	(0.33)
Adjusted R-squared	0.192			0.194
Number of observations	39,226			39,226

Panel B – Annual data

	All funds	Quantitative	Non-quantitative	Quantitative minus Non-quantitative (p-value)
	(1)	(2)	(3)	(4)
Bottom performance	-0.0439***	-0.0345**	-0.0265***	-0.0080
	(-11.61)	(-2.14)	(-5.71)	(0.34)
Performance	-0.0167	0.0877	-0.0328	0.1197
	(-0.66)	(0.70)	(-1.26)	(-0.35)
Top performance	0.0422***	0.0288*	0.0437***	-0.0149
	(10.27)	(1.68)	(10.35)	(-0.38)
Four-factor alpha	0.2636***	0.2840***	0.2611***	0.0229
	(11.45)	(3.02)	(11.14)	(0.43)
Adjusted R-squared	0.115			0.119
Number of observations	36,781			36,781

Table D.4: Fund flow–performance sensitivity – gross flow – performance terciles

This table reports the results from estimating our tests in Table 3.6 using prior–year bottom and top performance terciles. *p*–values are reported in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. See Appendix C for variable definitions.

Panel A – Quarterly data

	All funds	Quantitative	Non-quantitative	Quantitative minus Non-quantitative (p-value)
	(1)	(2)	(3)	(4)
Bottom Performance	-4.9974***	-6.2793**	-5.0046***	-1.2747
	(-6.01)	(-2.02)	(-5.80)	(0.63)
Performance	10.1561	66.4458	6.5036	59.9422
	(0.41)	(0.57)	(0.25)	(0.62)
Top performance	7.8016***	1.2649	8.1657***	-6.9008
	(8.45)	(0.54)	(8.39)	(0.65)
Performance squared	-450.8806**	-842.7623	-447.7853**	-394.9773
	(-2.30)	(-1.36)	(-2.23)	(0.54)
Four-factor alpha	180.1705***	187.0155***	182.1832***	4.8323
	(10.96)	(3.29)	(10.70)	(0.94)
Adjusted R-squared	0.438			0.441
Number of observations	159,643			159,643

Panel B – Annual data

	All funds	Quantitative	Non-quantitative	Quantitative minus Non-quantitative (p-value)
	(1)	(2)	(3)	(4)
Bottom Performance	-19.8785***	-39.3377***	-18.7805***	-20.5570
	(-4.99)	(-3.28)	(-4.49)	(0.48)
Performance	54.8775**	4.2442	54.0739**	-49.8288
	(2.35)	(0.05)	(2.24)	(0.59)
Top performance	26.1290***	3.6877	28.3720***	-24.6843
	(5.79)	(0.31)	(5.95)	(0.40)
Four-factor alpha	149.2716***	167.0750*	147.6877***	19.3900
	(7.39)	(1.90)	(7.15)	(-0.37)
Adjusted R-squared	0.106			0.108
Number of observations	36,781			36,781

Appendix E. Variable definitions

Variable	Definition
Raw return	Fund net return in US dollars (percentage per quarter or year) (Lipper).
Benchmark return	Fund's benchmark return (percentage per year)
Benchmark–adjusted return	Difference between the fund's net return and its benchmark return (percentage per year).
Four–factor alpha	Net four–factor alpha (percentage per quarter or year) estimated as indicated in Equation (4.2).
Tracking error	Standard deviation (annualized) estimated with three–year of past monthly benchmark adjusted return.
Active share	Percentage of a fund's portfolio holdings that differ from its benchmark index holdings calculated as in Equation (4.1).
Quantitative	Dummy variable that takes the value of one if the fund is classified by Lipper Hindsight as a quantitative fund and zero otherwise.
TNA	Total net assets in millions of US dollars (Lipper).
TNA family	Family total net assets in millions of US dollars of other equity funds in the same management company excluding the own fund TNA (Lipper).
Total shareholder costs	Fund's annual total expense ratio plus one–fifth of front–end load.
Flow	Percentage growth in TNA in each quarter or year, net of internal growth (assuming reinvestment of dividends and distributions). We follow Chevalier and Ellison (1997) and Sirri and Tufano (1998) and fund flow for fund *i* at period *t* is calculated as: $$Flow_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1}(1+R_{i,t})}{TNA_{i,t-1}},$$ where $TNA_{i,t}$ is the total net asset value in US dollars of fund *i* at the end of quarter *t*, and $R_{i,t}$ is fund *i*'s raw return from in quarter *t*. Net annual fund flow is the sum of net quarterly fund flows.
Absolute flow	Change in total net assets adjusted for internal growth due to investment returns: $$Absolute\ Flow_{i,t} = TNA_{i,t} - TNA_{i,t-1}(1+R_{i,t}),$$

	where $TNA_{i,t}$ is the total net asset value in US dollars of fund *i* at the end of period *t*, and $R_{i,t}$ is fund *i*'s raw return from in period *t*.
Flows volatility	Standard deviation of fund flows, computed using monthly fund flows over the past 12 months.
Age	Number of years since the fund launch date (Lipper).
Total expense ratio	Total annual expenses as a fraction of TNA (Lipper).
Loads	Sum of front–end and back–end loads (Lipper).
Flow, t–1 to t	Prior year fund flow.
Flow, t–3 to t–1	Prior one to three years fund flow.
Benchmark adjusted return, t–1 to t	Prior year fund benchmark–adjusted return.
Benchmark adjusted return, t–3 to t–1	Prior one to three years fund benchmark–adjusted return.
Benchmark return, t–1 to t	Prior year benchmark return.
Benchmark return, t–3 to t–1	Prior one to three years benchmark return.
Fund industry Herfindahl	Sum of squared market shares of fund management companies for open–end equity mutual funds in the fund's country.
VIX	Chicago Board Options Exchange (CBOE) market volatility index.
Large–cap	Dummy variable that equals one if the fund benchmark type is large–cap and zero otherwise.
All–cap	Dummy variable that equals one if the fund benchmark type is all–cap and zero otherwise.
Mid–cap	Dummy variable that equals one if the fund benchmark type is mid–cap and zero otherwise.
Small–cap	Dummy variable that equals one if the fund benchmark type is small–cap and zero otherwise.

Appendix F

This appendix contains tables that supplement the analysis in Chapter 4 “Active share and quantitative funds”.

Table F.1: Performance and Active share below and above fund median size

This table reports the results from estimating our tests in Table 4.6, where we explain differences in the impact of *Active share* on the performance of quantitative and non–quantitative funds, except that we add to the these tests the interaction of *Active share* with a dummy variable indicating below–median fund size for that year. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. See Appendix E for variable definitions.

	All funds	Quantitative	Non–quantitative	Quantitative minus Non–quantitative (p–value)
	(1)	(2)	(3)	(4)
Active share	0.0190***	–0.0208**	0.0213***	–0.0413***
	(4.66)	(–2.05)	(4.90)	0.0000
Active share (below median size)	0.0204***	0.0105*	0.0211***	–0.0106*
	(10.70)	(1.71)	(10.54)	0.0930
Tracking error	–0.2285***	–0.2501***	–0.2262***	–0.0241
	(–9.20)	(–3.35)	(–8.83)	0.7624
Adjusted R–squared	0.080			0.084
Number of observations	32,050			32,050

Table F.2: Fund performance and Active share: Benchmark–adjusted returns

This table reports the results from estimating our tests in Table 4.6, where we test for differences on the impact of *Active share* on the performance of quantitative and non–quantitative funds, except that we use benchmark–adjusted returns as our performance measure. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. See Appendix E for variable definitions.

	All funds	Quantitative	Non–quantitative	Quantitative minus Non–quantitative (p–value)
	(1)	(2)	(3)	(4)
Active share	0.0352***	–0.0136*	0.0382***	–0.0512***
	(9.62)	(–1.78)	(9.83)	(0.00)
Tracking error	–0.0830***	0.0536	–0.0852***	0.1386***
	(–3.55)	(0.83)	(–3.53)	(0.00)
Adjusted R–squared	0.079			0.082
Number of observations	32,050			32,050

Table F.3: Fund performance and Active share for funds with different levels of Active share: Benchmark–adjusted returns

This table reports the results from estimating our tests in Table 4.7, where we explain differences in the predictive power of *Active share* for quantitative and non–quantitative funds with different levels of *Active share*, except that we use benchmark–adjusted returns as our performance measure. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. See Appendix E for variable definitions.

	All funds	Quantitative	Non–quantitative	Quantitative minus Non–quantitative (p–value)
	(1)	(2)	(3)	(4)
Active share (Q1)	0.0077*	0.0011	0.0314***	–0.0303**
	(1.75)	(0.09)	(5.63)	(0.03)
Active share (Q2)	0.0001	0.0012	0.0015	–0.0306***
	(0.06)	(0.23)	(0.81)	(0.01)
Active share (Q3)	0.0012	–0.0006	0.0043*	–0.0352***
	(0.61)	(–0.10)	(1.93)	(0.00)
Active share (Q4)	–0.0024	–0.0040	0.0034	–0.0377***
	(–1.07)	(–0.58)	(1.32)	(0.00)
Active share (Q5)	–0.0053**	–0.0141*	0.0024	–0.0468***
	(–2.19)	(–1.74)	(0.86)	(0.00)
Tracking error	–0.0028	0.0913	–0.0822***	0.1733**
	(–0.13)	(1.39)	(–3.33)	(0.01)
Adjusted R–squared	0.063			0.066
Number of observations	32,050			32,050

Table F.4: Fund performance and Active share for funds with different benchmark types: Benchmark–adjusted returns

This table reports the results from estimating our tests in Table 4.8, where we explain differences in how *Active share* affects the performance of quantitative and non–quantitative funds with different benchmark types, except that we use benchmark–adjusted returns as our performance measure. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. See Appendix E for variable definitions.

	All funds	Quantitative	Non–quantitative	Quantitative minus Non–quantitative (p–value)
	(1)	(2)	(3)	(4)
Active share x All–cap	0.0167***	0.0025	0.0175***	–0.0150
	(4.73)	(0.24)	(4.72)	(0.18)
Active share x Large–cap	0.0238***	0.0021	0.025***	–0.0225**
	(7.30)	(0.21)	(7.20)	(0.03)
Active share x Mid–cap	0.0063**	–0.0125	0.0074**	–0.0199**
	(2.31)	(–1.39)	(2.49)	(0.02)
Active share x Small–cap	0.0139***	–0.0039	0.0149***	–0.0194**
	(4.86)	(–0.43)	(4.92)	(0.03)
Tracking error	–0.0177	0.0409	–0.0189	0.0589
	(–0.82)	(0.64)	(–0.85)	(0.38)
Adjusted R–squared	0.068			0.071
Number of observations	32,050			32,050

Table F.5: Fund performance and Active share: Gross four–factor alpha

This table reports the results from estimating our tests in Table 4.6, where we explain differences in the impact of *Active share* on the performance of quantitative and non–quantitative funds, except that we use gross four–factor alpha as our performance measure. Gross four–factor alpha is computed by adding back total expense ratio to net four–factor alpha. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. See Appendix E for variable definitions.

	All funds	Quantitative	Non–quantitative	Quantitative minus Non–quantitative (p–value)
	(1)	(2)	(3)	(4)
Active share	0.0249***	–0.0178*	0.0279***	–0.0457***
	(6.15)	(–1.69)	(6.48)	(0.00)
Tracking error	–0.2279***	–0.2526***	–0.2255***	–0.0270
	(–9.16)	(–3.40)	(–8.79)	(0.73)
Adjusted R–squared	0.069			0.072
Number of observations	32,050			32,050

Table F.6: Fund performance and Active share for funds with different levels of Active share: Gross four–factor alpha

This table reports the results from estimating our tests in Table 4.7, where we explain differences in the predictive power of *Active share* for quantitative and non–quantitative funds with different levels of *Active share*, except that we use gross four–factor alpha as our performance measure. Gross four–factor alpha is computed by adding back total expense ratio to net four–factor alpha. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. See Appendix E for variable definitions.

	All funds	Quantitative	Non–quantitative	Quantitative minus Non–quantitative (p–value)
	(1)	(2)	(3)	(4)
Active share (Q1)	0.0110	0.0127	0.0110	0.0017
	(1.23)	(0.64)	(1.11)	(0.96)
Active share (Q2)	–0.0003	–0.0017	–0.0005	0.0005
	(–0.14)	(–0.26)	(–0.21)	(0.97)
Active share (Q3)	0.0041	–0.0086	0.0048	–0.0117
	(1.28)	(–1.06)	(1.40)	(0.46)
Active share (Q4)	0.0053	–0.0077	0.0062	–0.0122
	(1.43)	(–0.83)	(1.55)	(0.41)
Active share (Q5)	0.0090**	–0.0178*	0.0109**	–0.0287*
	(2.22)	(–1.73)	(2.50)	(0.06)
Tracking error	–0.2394***	–0.1719**	–0.2393***	0.0680
	(–9.42)	(–2.39)	(–9.14)	(0.38)
Adjusted R–squared	0.070			0.073
Number of observations	32,050			32,050

Table F.7: Fund performance and Active share for funds with different benchmark types: Gross four–factor alpha

This table reports the results from estimating our tests in Table 4.8, where we explain differences in how *Active share* affects the performance of quantitative and non–quantitative funds with different benchmark types, except that we use gross four–factor alpha as our performance measure. Gross four–factor alpha is computed by adding back total expense ratio to net four–factor alpha. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. See Appendix E for variable definitions.

	All funds	Quantitative	Non–quantitative	Quantitative minus Non–quantitative (p–value)
	(1)	(2)	(3)	(4)
Active share x All–cap	0.0133	–0.0011	0.0143	–0.0153
	(1.27)	(–0.04)	(1.29)	(0.64)
Active share x Large–cap	0.0212***	–0.0076	0.0231***	–0.0301**
	(4.58)	(–0.55)	(4.75)	(–0.01)
Active share x Mid–cap	0.0485***	–0.0361***	0.0548***	–0.0909***
	(5.07)	(–2.63)	(5.50)	(0.00)
Active share x Small–cap	0.0344***	–0.0211*	0.0459***	–0.0670***
	(4.07)	(–1.67)	(4.40)	(0.00)
Tracking error	–0.2313***	–0.2403***	–0.2302***	–0.0101
	(–9.30)	(–3.21)	(–8.97)	(0.90)
Adjusted R–squared	0.077			0.079
Number of observations	32,050			32,050

Table F.8: Fund performance and Active share: Controlling for fund turnover

This table reports the results from estimating our tests in Table 4.6, where we explain differences in the impact of *Active share* on the performance of quantitative and non–quantitative funds, except that we add to our control variables fund turnover. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. See Appendix E for variable definitions.

	All funds	Quantitative	Non–quantitative	Quantitative minus Non–quantitative (p–value)
	(1)	(2)	(3)	(4)
Active share	0.0326***	–0.0053	0.0342***	–0.0395***
	(7.22)	(–0.41)	(7.19)	(0.00)
Tracking error	–0.2652***	–0.2592***	–0.2633***	0.0040
	(–11.00)	(–3.48)	(–10.58)	(0.96)
Turnover	–0.0231***	–0.0112	–0.0244***	0.0132
	(–8.44)	(–1.40)	(–8.37)	(0.12)
Adjusted R–squared	0.100			0.103
Number of observations	26,797			26,797

Table F.9: Fund performance and Active share for funds with different levels of Active share: Controlling for fund turnover

This table reports the results from estimating our tests in Table 4.7, where we explain differences in the predictive power of *Active share* for quantitative and non–quantitative funds with different levels of *Active share*, except that we control for fund turnover. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. See Appendix E for variable definitions.

	All funds	Quantitative	Non–quantitative	Quantitative minus Non–quantitative (p–value)
	(1)	(2)	(3)	(4)
Active share (Q1)	0.0085	0.0039	0.0094	–0.0055
	(0.83)	(0.41)	(0.86)	(0.29)
Active share (Q2)	0.0015	–0.0072	0.0011	–0.0138
	(0.54)	(–0.90)	(0.39)	(0.21)
Active share (Q3)	0.0086**	–0.0120	0.0088**	–0.0263**
	(2.40)	(–1.18)	(2.30)	(0.02)
Active share (Q4)	0.0094**	–0.0201*	0.0101**	–0.0357***
	(2.25)	(–1.73)	(2.27)	(0.00)
Active share (Q5)	0.0135***	–0.0288	0.0140***	–0.0483***
	(2.95)	(–2.64)	(2.88)	(0.00)
Tracking error	–0.2756***	–0.1933***	–0.2738***	0.0800
	(–11.20)	(–2.70)	(–10.80)	(0.29)
Turnover	–0.0220***	–0.0160**	–0.0231***	0.0070
	(–8.02)	(–2.00)	(–7.89)	(0.40)
Adjusted R–squared	0.100			0.103
Number of observations	26,797			26,797

Table F.10: Fund performance and Active share for funds with different benchmark types: Controlling for fund turnover

This table reports the results from estimating our tests in Table 4.8, where we explain differences in how *Active share* affects the performance of quantitative and non–quantitative funds with different benchmark types, except that we add to our control variables fund turnover. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively. See Appendix E for variable definitions.

	All funds	Quantitative	Non–quantitative	Quantitative minus Non–quantitative (p–value)
	(1)	(2)	(3)	(4)
Active share x All–cap	0.0251**	0.0301	0.0243*	0.0058
	(2.13)	(0.86)	(1.96)	(0.87)
Active share x Large–cap	0.0292***	0.0179	0.0296***	–0.0115***
	(5.59)	(1.04)	(5.38)	(0.01)
Active share x Mid–cap	0.0501***	–0.0679***	0.0564***	–0.1193***
	(4.34)	(–1.76)	(4.75)	(0.00)
Active share x Small–cap	0.0425***	–0.0059*	0.0533***	–0.0592***
	(4.37)	(–0.35)	(4.39)	(0.00)
Tracking error	–0.2670***	–0.2558***	–0.2664***	0.0110
	(–11.07)	(–3.39)	(–10.70)	(0.89)
Turnover	–0.0228***	–0.0112	–0.0238***	0.0120
	(–8.29)	(–1.39)	(–8.15)	(0.14)
Adjusted R–squared	0.100			0.103
Number of observations	26,797			26,797