LSF Research Working Paper Series

N°. 13-08

Date: July 2013

Title: The Lure of the Brand: Evidence from the European Mutual Fund Industry

Author(s)*: Jan Jaap Hazenberg, Fabian Irek, Willem van der Scheer, Mariela Stefanova

Abstract: We investigate the effect of the fund provider's brand on mutual fund flows by using a unique data set that represents a direct assessment of the brand image of European fund providers. A superior brand image increases the sensitivity of flows to past performance, while an inferior brand decreases it. Funds with a superior brand are not protected against outflows when there is underperformance. A superior brand, coupled with high past performance, generates persistent inflows and performance persistence so investors will benefit when a superior brand fund with high past performance is chosen.

JEL Classification : G11, G23

***Corresponding Author's Address:** Tel: +352 46 66 44 5780; Fax : +352 46 66 44 6835
E-mail address: fabian.irek@uni.lu

The opinions and results mentioned in this paper do not reflect the position of the Institution.

The LSF Research Working Paper Series is available
online:
http://www.en.uni.lu/recherche/fdef/luxembourg_school_of_finance_research_in_finance/working_papers

For editorial correspondence, please contact:
martine.zenner@uni.lu

University of Luxembourg
Faculty of Law, Economics and
Finance
Luxembourg School of Finance
4 Rue Albert Borschette
L-1246 Luxembourg

The Lure of the Brand: Evidence from the European Mutual Fund Industry*

Jan Jaap Hazenberg
Fabian Irek
Willem van der Scheer
Mariela Stefanova

Second Version, July 2013

Keywords: Mutual funds, fund flows, fund performance, marketing, brand image.

JEL Classifications: G11, G23

*We are grateful to Fund Buyer Focus for making their brand data available. Jan Jaap Hazenberg and Willem van der Scheer are from ING Investment Management. Mariela Stefanova is from Triodos MeesPierson, but conducted this research while at ING Investment Management. Fabian Irek is from Luxembourg School of Finance, University of Luxembourg, and Said Business School, University of Oxford. Corresponding Author: fabian.irek@uni.lu, 4 Rue Albert Borschette, L - 1246 Luxembourg, Tel: +352-4666445780. Fabian Irek is supported by the National Research Fund, Luxembourg.

Abstract

We investigate the effect of the fund provider's brand on mutual fund flows by using a unique data set that represents a direct assessment of the brand image of European fund providers. A superior brand image increases the sensitivity of flows to past performance, while an inferior brand decreases it. Funds with a superior brand are not protected against outflows when there is underperformance. A superior brand, coupled with high past performance, generates persistent inflows and performance persistence so investors will benefit when a superior brand fund with high past performance is chosen.

1. Introduction

For fund management companies,¹ net flows into their funds as a result of investors purchasing and selling mutual fund units, translate directly into incremental assets under management and revenues. Based on empirical evidence, it is well-documented that investors tend to chase past performance when selecting funds². This finding is consistent with the notion that investors deduct information about contemporaneous management ability from past performance.

There is extensive marketing literature that suggests that the brand of a product or service can affect its sales. Keller (1993, p. 8) defines consumer-based brand equity as “the differential effect of brand knowledge on consumer response to the marketing of the brand”, whereby brand knowledge has two components: brand awareness, defined along the dimensions of brand recall and brand recognition, and brand image. Shankar, Azar and Fuller (2008, pp. 570-571) present a conceptual framework, applied to a case study in the insurance industry, linking brand equity to advertising and shareholder value, whereby brand equity is “the incremental NPV of earnings from a product or service attributable to brand image”.

In the event that these insights from the marketing literature apply in the fund management industry, one would expect investors to direct their flows not only based on objective measures, such as past performance, but also in response to marketing efforts and considering brand image of funds.

There is ample anecdotal evidence that fund advertising can be effective and that the brand image of fund providers has an influence on fund flows. Fidelity, for example, is said to have spent EUR 107.5 million on its pan-European marketing and advertising effort in the five-year period up to 2000 in order to break into the European mutual fund market³.

¹In this study, we use the following terms interchangeably: “fund management company”, “fund provider” and “provider”.

²See for example, Ippolito (1992), Gruber (1996), Chevalier and Ellison (1997), Sirri and Tufano (1998) for the U.S., Keswani and Stolin (2008) for the U.K., and Ferreira et al. (2012) for an international comparison.

³See Wall Street Journal Europe, February 8, 2001.

From its market entry in continental Europe in 1990, Fidelity grew to become the number 11 fund management company in Europe in terms of total net assets at the end of 2001⁴. There are also examples of how a drop in brand image can result in fund outflows. For example, when Putnam's reputation became tarnished in 2003 because of its involvement in the late trading and market timing scandal in the U.S., investors in that market withdrew USD 54 billion of assets from Putnam funds in the fourth quarter of 2003 alone⁵.

Existing empirical academic studies investigating fund flows provide more information by analyzing choice factors other than past performance. Gruber (1996) suggests that, in addition to past performance, marketing effort and general reputation also play a role in fund flows. With previous period flows as a proxy for these marketing-related elements of the fund industry, both Gruber (1996) and Frye (2001) find that these flows have significant explanatory power for subsequent flows. According to Ippolito (1992), transaction costs are a reason not to disinvest from funds that are underperforming. With the search costs concept, Sirri and Tufano (1998) make the connection between fund costs and marketing efforts. By charging higher fees and spending the proceeds on marketing, fund providers can reduce search costs and stimulate flows. Jain and Wu (2000), Wei et al. (2011) and Peng et al. (2011) find that fund investors are sensitive to advertising. Frye (2001) finds evidence that the business and distribution model used by the fund management company is relevant to fund flows. Bank-managed fund flows are less dependent on past performance than non-bank fund flows, which suggests that bank clients are sensitive to the bank's marketing efforts and reputation.

This paper is related to these earlier studies investigating the relationship between fund flows and marketing and distribution aspects of the fund management business. Our main contribution is that we do not use indirect proxies for brand image, such as fund family size, fee level, media attention and advertising, but a more direct, survey-based assessment

⁴Source: Lipper FMI FundFile.

⁵See J.W. Markham, 2006, A financial history of modern U.S. corporate scandals: from Enron to reform, M.E. Sharpe, Inc., New York, p. 434.

of this variable. The research adds to the existing marketing literature by establishing a direct relationship between the brand image of a product (in this case, a mutual fund) and subsequent sales (in this case, the net new money invested by consumers). To the best of our knowledge, we are the first to use a unique dataset consisting of the brand image assessment by professional fund selectors and distributors in Europe.

This study has rendered several findings. We find that brand has a substantial effect on fund flows. Funds with a good brand receive more inflows, while funds with an inferior brand do not have more outflows than those with a mediocre brand. Furthermore, brand has a strong influence on the convex flow-performance relationship. A superior brand increases the magnitude of the convexity, while a poor brand decreases it. In particular, for high-performing funds, brand has a positive impact on flows. However, when funds underperform, it is not the case that superior brand funds have better protection from outflows than funds with mediocre and inferior brands.

Both performance and brand sensitivity of flows differ for funds managed by independent fund management companies and fund management companies that are owned by banks or insurers. Brand seems to be much more important for independent firms and independent firm fund flows have a higher sensitivity to past performance than those of dependent firm funds.

While all brand proxies have a positive impact on flows, none of them changes the flow sensitivity to past performance like brand does. Our findings therefore suggest that brand cannot be proxied as easily as other papers suggest.

Our results indicate that superior brand funds yield a higher return. At the same time, a superior brand and high past performance generate persistent flows, which is not true for funds with an inferior brand or low past performance. There is strong evidence of performance persistence in our sample for funds with superior brand and high past performance. Finally, the expenses of superior brand and inferior brand funds are practically the same. Thus, we conclude that although a superior brand lures investors into funds, it also seems

to be for the benefit of investors.

The remainder of this paper is organized as follows: In section 2, a summary is presented of the main findings in the existing academic literature, with a particular focus on the studies devoted to the marketing and distribution aspects of the mutual fund industry. In section 3, the sample and data selection processes are described, followed by an explanation of the main hypotheses and estimation techniques in Section 4. In Section 5, we examine the relationship between mutual fund flows and brand image and present the major outcomes of our analysis. Section 6 summarizes the results.

2. Existing literature

2.1. Past performance

The existing literature leaves little doubt that there is a positive relationship between mutual fund performance and subsequent investor cash flows. Several studies of U.S. domestic equity funds analyzing fund growth rates (cash flows relative to fund size, also called relative flows) draw attention to the non-linear nature of the relationship where investors tend to reward winning funds more than they punish losing funds (Ippolito 1992, Gruber 1996, Chevalier and Ellison 1997, Sirri and Tufano 1998, Barber, Odean and Zheng 2005, Huang, Wei and Yan 2007). This finding seems to be irrespective of the performance period and performance measure used. This non-linearity is also found in fund domiciles other than the U.S. Keswani and Stolin (2008) find the same pattern for domestic equity funds in the U.K., both for individual and institutional investors. Ferreira et al. (2012) investigate the flow-performance relationship in 28 domestic fund markets and find that it is statistically significantly convex in ten markets, including the U.S. and the U.K. However, the authors excluded funds domiciled in Luxembourg, while our study focuses specifically on this group of funds.

The following research explains that the convexity of the flow-performance relationship

is related to marketing (Gruber 1996, Sirri and Tufano 1998, Huang et al. 2007, Peng et al. 2011), costs (Ippolito 1992, Sirri and Tufano 1998, Huang et al. 2007), other market imperfections (Gruber 1996), investors' behavioral biases (Goetzmann and Peles 1997, Peng, et al. 2011) and anticipated changes to the fund management (Lynch and Musto 2003). The remainder of this section briefly summarizes the empirical findings and explanations related to marketing aspects of the fund management industry, which are directly relevant to this study.

2.2 Indirect proxies for marketing and brand

According to Gruber (1996), only the sophisticated clientele makes fund investments and disinvestments based on past performance. The unsophisticated clientele directs its money based on other influences, such as advertising and broker advice. For the group of disadvantaged investors, it is unattractive or impossible to disinvest from inferior funds, either due to capital gains tax (tax disadvantaged investors) or because they face a restricted choice in their pension scheme (institutionally disadvantaged investors). The author makes proxies of marketing effort and general reputation using previous period flows, which have strong explanatory power for future flows of equity funds. Frye (2001) confirms this result for bond funds.

Ippolito (1992) attributes the difference in response between underperformance and outperformance to the transaction costs associated with buying and selling funds, since the flows of load funds are less performance-sensitive than those of no-load funds. Sirri and Tufano (1998) suggest that this asymmetric relationship is caused by the marketing spotlight focusing on past winners, whereas poor performers receive limited marketing attention. The authors argue that the choice of which funds investors purchase might not only depend on past performance, but could also be a function of search costs. They argue that when collecting and processing information is costly, consumers buy funds that are easier or less costly to find. The authors find that fund buyers are sensitive to fees; funds that have lower

fees, and funds that reduce their fees, grow faster. However, fee increases are not associated with outflows. This finding could be the result of the counterbalancing effect of lower search costs, in the case where the higher fees are spent on marketing or incentives for distributors.

Three proxies for search costs are used in their study, specifically, fund complex size, marketing and distribution expenditures and media coverage. They find that funds belonging to larger complexes and receiving more media attention, indeed, grow more rapidly than other funds. However, good performance funds belonging to large complexes or with high media coverage do not receive more inflows. That is the case for good performance funds with higher fees, which are assumed to be spent on marketing and distribution, in part and, therefore, used as a proxy for marketing expenditures. This finding is consistent with the results found by Barber et al. (2005), where there is a positive relationship between flows and 12b-1 fees, the part of the ongoing expenses that are intended for marketing and distribution expenditures. They find a significant negative relationship between front-end loads and flows, along with an insignificant relationship between total operating expenses and flows. The authors argue that investors have learned more quickly to avoid front-end loads, which are much more visible on transaction confirmations than ongoing fees.

Huang et al. (2007) argue that funds without superior past performance can attract flows from new investors by lowering the participation costs, which consist of both transaction costs and the costs of collecting and analyzing fund information before a first investment is made. Marketing can lower these participation costs. Using total fees and their distribution expenses share, measured as the sum of 12b-1 fees and front-end loads, as a proxy for marketing expenses, the authors find that for funds with high fees, a moderate level of performance is sufficient to attract inflows. Funds where these marketing expenditure proxies are lower require superior performance before inflows are attracted. Based on these studies, we conclude that apparently, costs are a two-edged sword. On the one hand, higher costs reduce future returns and therefore, could have a negative impact on fund flows. However, on the other hand, when additional costs are spent on marketing and distribution, they could

result in higher fund flows.

Other proxies used by Huang et al. (2007) for lower participation costs are brand recognition, measured as the fund family size, and whether or not a fund is part of a fund family that has produced star funds. For funds that have superior performance, it does not matter whether or not they are part of a star family; however, their flow-performance sensitivity is lower when they are part of a large family. Funds with moderate performance attract higher flows as a benefit of being part of either a large or a star family. Such star fund spillover effects on the remaining funds within the same fund family are also found by Nanda, Wang and Zheng (2004) and Del Guercio and Tkac (2008). These results are consistent with the hypothesis that funds in a star family or large family have better brand recognition and face a lower inflow barrier due to participation costs.

2.3 Direct proxies for marketing and brand

Jain and Wu (2000) study fund advertising in relationship to performance and flows, using a sample of U.S. domestic equity funds and advertisements that promote past performance. They find that in the one-year period prior to the advertisement, the performance of funds that advertised is significantly better than the benchmarks, but inferior in the year after the advertisement. In the sample of funds that advertise, there is no evidence of performance persistence, but rather a reversal of performance. Compared to a control group of funds that are similar in terms of past performance, past flows and fund size, flows into funds that advertise are larger than flows into funds that do not advertise. That investors seem to be sensitive to advertising is a result confirmed by Yankow, Smythe, Lesseig and Jones (2011), although in their study, it is subject to the distribution channel and fund asset class analyzed. Advertising seems most effective for the load share class of domestic equity funds, which is sold through brokers, irrespective of whether the advertisements promote past performance or not. Advertising domestic equity funds is also related to higher flows for the no-load share classes, which are distributed directly to consumers, but only when

the advertisements promote past performance. The results are inconsistent for funds in the international and special equity categories, as well as for fixed income funds.

Wei et al. (2011) and Peng et al. (2011) investigate samples of funds domiciled in Taiwan. The former study investigates the advertising spillover effect, which is the effect of advertising for one product on the enhancement of sales of other products from the same firm through improved brand awareness. There is evidence of a positive spillover effect for high-performing funds, but not for mediocre and poorly performing funds. The advertised funds themselves are also found to have higher flows. Using actual redemption data, rather than estimated net flows, the latter study investigates investors' post-purchase behavior, in particular, whether advertising affects the asymmetric flow-performance relationship. The authors find a significantly negative relationship between advertising and redemptions, consistent with the hypothesis that advertising can moderate outflows. Analyzing advertising in conjunction with past performance, they find that investors are more reluctant to redeem both high and low performing funds that are part of families with high advertising expenditures, as opposed to those that are part of families with low advertising expenditures.

2.4 Business and distribution model

Frye (2001) compares bank-managed and non-bank-managed bond funds in the U.S. Reasons for investing in bank-managed funds, other than for performance, could be related to lower search costs. Investors investing in bank-managed funds are likely to have a relationship with the same bank for other financial services and might appreciate the convenience of one-stop shopping. The study finds that non-bank funds have higher returns, but there is no evidence that bank funds underperform non-bank funds on a risk-adjusted basis. Bank funds are managed more conservatively, leading to a lower standard deviation of returns and a lower risk relative to the index. The average expense ratio of bank-managed funds is lower than that of non-bank managed funds, despite bank funds being smaller and therefore, less able to benefit from economies of scale. The lower costs could be a result of the revenues that

banks make on other services offered to the same clients. The study shows that percentage flows into bank-managed funds are less dependent on past performance than flows into non-bank-managed funds, which suggests that bank clients invest based on the bank’s marketing efforts and its reputation.

3. Sample and data

3.1. Luxembourg fund domicile

We investigate a sample of open-end equity funds domiciled in Luxembourg. While most studies analyze the U.S. fund market, there is only a small group of papers that uses non-U.S. data⁶. In terms of total net assets, Luxembourg is the second largest fund domicile in the world. In the 1980-2012 period, it grew from a domicile of 76 funds with assets of EUR 2.9 billion to 13,420 funds with assets of EUR 2.4 trillion⁷.

Such a growth rate would not have been possible without the European Union (E.U.) UCITS Directive⁸, which was adopted in 1985. Before this directive, fund management and fund distribution were primarily domestic activities. The UCITS Directive marks the start of the development of cross-border funds. Its goals were to harmonize E.U. national laws for investment funds, including rules to enhance investor protection, and to create a single market for investment funds in the E.U. Under this directive, funds domiciled in one E.U. country and operating within the UCITS rules can obtain a “European Passport”, which facilitates registration and distribution outside of the fund’s domicile country (Hazenbergh 2012).

The role of banks in the European fund industry is different from that in the U.S., where

⁶Otten and Bams (2002) are the first to give an overview of the European mutual fund industry. More recent papers include Walter and Weber (2006) who analyze the German fund market, and Ferreira et al. 2012 who analyze 28 different markets. None of these papers analyzes Luxembourg domiciled mutual funds. Hazenbergh (2012) investigates costs and performance of Luxembourg funds in relationship to governance aspects.

⁷Source: ALFI/CSSF.

⁸UCITS stands for Undertakings for Collective Investment in Transferable Securities.

banks were latecomers to the fund management industry. The Glass-Steagall Act of 1933 allowed banks to manage fund assets, but limited them to distribution of funds that they did not manage. These regulations were relaxed starting in 1992, allowing the growth of banks as managers and distributors of funds (Frye 2001, p. 422).

In most continental European countries, the fund market is traditionally dominated by the fund management arms of domestic banks. Before the year 2000, the majority of European banks had what is referred to as a closed-architecture, meaning that they only actively offered funds managed by their in-house fund management company. Opportunities for cross-border fund management companies, often firms from the U.S. or U.K. without an affiliated distribution network, were limited to private banks, wealth managers, institutional investors and (networks of) independent financial advisors. From the early years of this millennium however, an important trend has been the development of less restricted distribution models, with online brokers and fund supermarkets embracing a fully open-architecture distribution strategy, in principle, offering any fund available. Many banks have opted for a guided-architecture, in which they offer funds of a limited, selected group of fund management companies (Hazenbergh 2012).

3.2. Fund sample

We use Morningstar Direct to construct a sample of Luxembourg-domiciled equity funds that can be distributed on a pan-European basis, based on their UCITS status. Morningstar Direct includes information about funds that are no longer in existence and can be considered free of survivorship bias. The data for returns and other performance-related variables is available on a monthly basis. The database also includes other fund-specific data, including the expense ratio, regulatory status (UCITS or non-UCITS) and portfolio composition. Morningstar allocates funds to investment categories based on their reported prospectus objective and their actual portfolio composition.

We start the sample selection by identifying the 25 largest Morningstar Categories (here-

inafter also category) in terms of total assets under management of all Luxembourg-domiciled equity funds at three points in time, specifically the beginning, the middle, and the end of the chosen research period (January 2005 to December 2011). The combination of these three top-25 lists results in 30 individual Morningstar Categories. Except for non-UCTIS funds, fund-of-funds, guaranteed funds and funds that available only to institutional investors, all Luxembourg-domiciled funds that are in these categories during the research period are included in the sample. In order to avoid survivorship bias, funds that became inactive after the start of the research period are included in the sample.

The sample consists of 2,871 funds and covers approximately 60 percent of all assets under management in Luxembourg equity funds with UCITS status at each of the three points in time (see Appendix 1).

3.3 Brand image

In this study, we confront a relative measure for brand image that is specific for the mutual fund industry with fund flows, reflecting the purchasing behavior of investors. Keller (1993, pp. 3-4) defines brand image as “perceptions about a brand as reflected by the brand associations held in consumer memory”. He decomposes brand image along various dimensions, including product-related and non-product-related attributes, and indicates that product-related attributes vary by product or service. In their study of brand equity in the U.S. insurance industry, Shankar et al. (2008) model brand image based on eight brand attributes that are of relevance for the insurance industry and make estimates using survey data.

To be able to compare the brand image of funds in our sample, we use the brand score for fund management companies in Europe, developed and measured by Fund Buyer Focus (hereinafter FBF)⁹. This brand score is an overall score that is calculated as a sum

⁹Fund Buyer Focus is a service of MackayWilliams PLC (previously known as Fund Market Focus, then part of Metrinomics), a London-based mutual fund market analysis and research company. We are grateful to them for making this proprietary brand data available for the purpose of this study. FBF uses the terms

of ten equally-weighted scores for individual brand attributes which are relevant within the mutual fund industry. These ten attributes are client-oriented thinking, appealing investment strategy, stability of investment management team, keeping best informed, quick adaptation to market evolution, experts in what they do, key international player, innovative power, local knowledge and solidity (see Appendix 2 for definitions).

In order to evaluate fund providers based on the ten brand attributes, FBF has conducted annual surveys among professional fund buyers from eleven countries since October 2004. Professional fund buyers are people who are involved professionally in the fund selection process for their clients, representing one or more fund distribution channels, specifically, retail banking, private client advisory portfolio management, private client discretionary portfolio management, independent financial advisors, insurance, fund supermarket/online bank and fund-of-fund management. These professionals determine which funds are available to clients on the platform of the distributor they represent and which funds are actually recommended. In the case of discretionary portfolio management and fund-of-fund management, these professionals have the discretion to initiate fund subscriptions and redemptions for their clients, within the mandate given. Given the importance of these distribution channels in Europe¹⁰, we expect these professionals to have a significant influence on which funds investors buy and sell and, therefore, on the fund flows of the European fund management industry.

In 2004, the survey covered 826 fund buyers, increasing to 908 fund buyers by 2011. In the survey, professional fund buyers are asked to assign one gold, one silver and one bronze medal to the three fund management companies that they value most on each of the brand attributes. The Brand Attribute Score of provider x for attribute i ($BAS_{x,i}$) is calculated as follows:

brand image and brand performance synonymously.

¹⁰According to 2011 Cerulli Associates estimates of the percentage of mutual fund assets by distribution channel, together, these channels represent 80.9% of the European mutual fund market. Direct distribution and institutional investors represent the remaining 19.1%.

$$BAS_{x,i} = \frac{m_i}{\sum_{i=1}^n m_i} MQ_{x,i} \quad (1)$$

where:

- m_i = Number of medals, gold, silver and bronze, that provider x received for Brand attribute i
- n = Total number of providers
- $MQ_{x,i}$ = Weighted Average Medal Quality that provider x received with regard to the individual brand attribute i, whereby gold medals have a weight of 1, silver medals have a weight of 2/3 and bronze medals have a weight of 1/3.

The overall Brand Image Score of provider x (BIS_x) is calculated as the sum of the scores for the ten individual attributes:

$$BIS_x = \sum_{i=1}^{10} BAS_{x,i} \quad (2)$$

We use two brand image measures. The first one is simply the Brand Image Score, of which we take the natural LOG because superior brands tend to have much higher scores, while many mediocre to inferior scoring brands have similar scores. Taking the natural LOG partially offsets this issue. Our second measure is Brand Image Rank, the rank of the Brand Image Score, for which we calculate fractional ranks based on the Brand Image Score within each Morningstar category and month. The Brand Image Rank measure is a continuously distributed variable from zero to one and is, therefore, robust to extreme values.

It should be noted that the brand image measures are variables at the fund provider level. We manually link the providers in the FBF sample to the funds in our sample using the Morningstar Direct branding name data point. When funds change brand as a result of merger activity or other corporate restructuring, we assign the different brands for different sub-periods in the research period. After funds are linked to FBF brands, we assign the two brand measures of that brand to all funds in the sample that are linked to that brand, whereby the annual brand measures are assigned to each month in the calendar year. For some funds or some fund-month combinations, no brand measures could be assigned because

the relevant fund provider was not evaluated by FBF in that year or at all. Of the 2,871 funds in our sample, 2,254 could be matched to FBF brands in at least one year. Our sample has 221 different FBF brands. In the following analysis, we use the term fund family for all funds with the same FBF brand. This means that there are no different brands within the same fund family.

3.4 Cash flow and Total Net Assets (TNA)

This study investigates the relationship of the provider’s brand image with purchasing behavior by customers, measured as the net monthly cash flow per fund. We obtain TNA and cash flow data from Lipper FMI FundFile, which is also free of survivorship bias. For these variables, this database has a better coverage than Morningstar Direct. Consistent with previous academic research (e.g., Gruber 1996), the net monthly cash flow is defined as the growth of the fund i TNA from the previous month beyond reinvested dividends or capital gains:

$$Flow_{i,t}\% = \frac{TNA_{i,t} - TNA_{i,t-1} * (1 + R_{i,t})}{\sqrt{1 + R_{i,t}} * TNA_{i,t-1}} * 100 \quad (3)$$

Where TNA_{it} is the Total Net Assets of fund i at the end of month t, $TNA_{i,t-1}$ is the Total Net Assets of fund i at the end of month t-1, and R_{it} is the raw return of the fund i over time. By using the square root of $(1+R_{it})$ in the denominator, Lipper assumes that flows come in continuously. By not using the square root, one assumes that flows come in at the end of the month, which seems rather unrealistic (see footnote 8 in Sirri and Tufano 1998). For robustness, we compute an alternative measure of flows without the square root component. The correlation between both flow measures is of 0.92, and using the alternative flow measure leads to the same results.

To correct for the size of the fund, we calculate relative flows, $Flow_{i,t}\%$. This measure is preferred over the absolute amount because large funds tend to have larger flows, regardless

of performance or brand. The net flow for every fund is expressed as a percentage of the fund i TNA at the end of month t-1.

As an alternative measure of fund flows we calculate the market share changes as in Spiegel and Zhang (2013). They state that the conventional, relative flow measure is prone to misspecification error. On the other hand, their market share measure is more robust and will, if sufficient control variables are included in the regressions, detect a true convex flow-performance relationship with a high probability in case it exists in the data. Thus, this measure is used for robustness.

The market share changes are defined as

$$\Delta m_{i,t} = \frac{TNA_{i,t}}{TNA_t^{all}} - \frac{TNA_{i,t-1}}{TNA_{t-1}^{all}} \quad (4)$$

where $TNA_{i,t}$ and $TNA_{i,t-1}$ are as above, TNA_{t-1}^{all} is the sum of all funds' TNA in month t-1, and TNA_t^{all} is the sum of all funds' TNA in month t that were alive in month t-1.

Small TNA figures are often associated with young funds that exhibit high abnormal flows in comparison to their relatively small size. As a result, the percentage flow of these funds could cause a distortion in the flow distribution. In order to prevent outliers from driving our results, monthly TNA_{t-1} observations that are less than EUR 5 million are excluded from the calculations. We also winsorize all flows and market share changes by the top and bottom 0.5 percent.

3.5 Business and distribution model

Many of the fund providers in the sample are part of larger financial groups, banks and/or insurance companies, with their own fund distribution network in Europe. Fund providers without an affiliated distribution network need to rely on direct and third-party distribution. How investors select funds from these two types of fund management companies and how they respond to past performance and brand could differ. We capture the two

different business models with the business model dummy variable that equals one if a fund is managed by an independent fund management company, or zero if it is managed by a bank or insurer-owned fund management company. Lipper FMI FundFile links each fund, via its fund management company, to a Master Group, the group to which the fund management company belongs. We use the Master Group Business Type¹¹ data point from Lipper FMI to determine each fund’s business model.

3.6 Excess returns, alphas and risk

The performance of each fund is calculated based on the oldest share class that is available for retail clients. When multiple retail share classes have the same inception date, the one with the highest TNA for the last month of available data is selected. As a measure of fund performance, we calculate the category-adjusted return, which is the fund return in a certain period, relative to the average return of funds in the same category. This can be seen as the return in excess of the return of an equally-weighted portfolio of all funds in the same category, rebalanced monthly. We first calculate the rolling one-year geometric average return of each fund i by using the last twelve monthly returns taken from Morningstar Direct. As a second step, the one-year category return over the previous twelve months is calculated. The difference between these two variables shows how much return a fund generates in excess of the respective average category return. We calculate excess return only if, in the 12-month period, the Morningstar category of the fund remained the same, so that the average return of funds in that category can be considered an appropriate comparison. As a measure of risk, the rolling standard deviation of monthly excess return is calculated over the same 12-month period. Since, in practice, investors compare the results achieved to that of available alternatives, this measure for the relative performance of a fund is intuitive and practical.

Most studies use raw or benchmark-adjusted returns because mutual fund investors

¹¹Generally, there is just one brand or fund family per master group. However, there are some exceptions where a master group operates under different brands. For example, the Master Group ABN AMRO operated under the brand ABN AMRO as well as Alfred Berg.

chase past (excess) returns, not alphas. Nevertheless, we compute alphas for robustness. In a first step, we estimate the market model separately for each fund i at month t :

$$R_{i,t} - R_{ft} = c_i + \beta_i * (MKTR_t - R_{ft}) + \epsilon_{i,t} \quad (5)$$

using the previous 36 monthly observations. We use return data starting three years earlier than our brand data such that there are no missing observations. For the market return $MKTR_t$ we use the respective Morningstar category benchmark return, and the riskfree rate R_{ft} is the return of the 3 Month Euribor. Similar as in Carhart (1997), we then use the estimated market betas $\hat{\beta}_{i,t}$ to compute time-varying alphas as

$$\alpha_{i,t} = R_{i,t} - R_{ft} - \hat{\beta}_{i,t} * (MKTR_t - R_{ft}) \quad (6)$$

The correlation between category excess returns and the time varying alphas is 0.77 and thus high¹².

3.7 Other variables

As a measure for the fund's ongoing expenses, we calculate the monthly net expense ratio as the annualized difference between the monthly gross and net return reported in Morningstar Direct, using the same retail share class as is used for performance calculations. In Europe, subscription and redemption charges – which can be compared to front-end and back-end loads in the U.S. – are generally included in a fund's prospectus as a relatively high maximum (e.g., 5 percent). Up to that level, each distributor can set the actual charge. These actual charges accrue to the distributor and differ significantly across channels (e.g. direct channel versus advisory channel), distributors and markets. Therefore, it is not possible to determine what investors actually pay in terms of subscription and redemption charges and, for that reason, we exclude the effect of transaction fees in this analysis.

¹²We find qualitatively similar results when using alphas instead of category excess returns but omit results to save space except for the persistence test where we use alphas.

To control for the age, we determine how long a fund has been in existence as of the end of the month. Fund age is calculated as the difference in years between the fund’s inception date, taken from Lipper FMI, and the date of the last day of the month.

Funds that operate in certain categories could attract more flows than others due to the current economic environment and market sentiment for the specific category. To capture this effect, we create an additional category flow measure that is constructed as the ratio of the sum of all cash flows and the sum of all TNA of all funds that are part of a particular category at month t , excluding the cash flows and TNA of the particular fund under analysis.

In the same manner, larger fund providers could attract more cash flows than smaller ones, due to the fact that fund managers could rely on present and historical success of multiple funds and/or fund ranges within the fund family. In order to capture the size of the fund provider, we obtain, from Lipper FMI, for each month the Master Group TNA, which is the sum of the TNAs of all open-end funds domiciled in Europe belonging to that Master Group. Panel A in Table 1 shows summary statistics of the main variables of interest. The average of relative flow is not statistically significant while the average of market share changes¹³ is negative and significant. The average (unadjusted) monthly return is of 32 bps and the average alpha of -8 bps. Both are significant. There is considerable variation in fund size. The smallest fund has only 5 million Euros of TNA (our lower bound) while the largest fund has 24 billion Euros of TNA.

[Table 1]

¹³We have slightly less observations for market share changes because they are computed differently than relative flows. The first denominator uses only information of funds that were alive in the previous month. See section 3.4 for more details.

4. Hypotheses and methodology

4.1. *Hypotheses*

Based on the existing literature in finance and marketing discussed above, we expect superior brand image to contribute positively to fund flows. In particular, we expect that among funds with good performance, those with a stronger brand image benefit with additional inflows, as the positive brand image gives investors an additional reason to direct their flows to those particular funds. This hypothesis would be in line with the results of studies using indirect (Sirri and Tufano 1998, Huang et al. 2007) or direct proxies (Wei et al. 2011) for marketing and brand, which find that these variables affect the flow-performance relationship of high-performing funds. Peng et al. (2011) find in the Taiwanese market that advertising can help moderate outflows in the event of poor performance. In line with that finding, we expect, in the case of poor performance, that investors are more inclined to give the benefit of the doubt to funds with stronger brands, rather than to funds with weaker brands, resulting in more modest outflows. Concretely, we will test the following two hypotheses with regard to the relationship between mutual fund brand image, past performance and subsequent cash flows:

H1: Investors tend to direct their money to funds with superior past performance and thereby favor funds with superior brands.

H2: In case of underperformance, investors tend to disinvest less forcefully from superior brands.

Empirical evidence from the U.S. points to different responses to past performance in different distribution channels (Frye 2001, Yankow et al. 2011). Based on this finding, together with the characteristic of the European fund market that banks are the main fund distribution channel and, at the same time, owners of fund management businesses (Hazen-berg 2012), we also expect flow differences between funds of fund management companies that are a part of banks or insurers and independent fund management companies. The for-

mer can sell funds on the basis of a broader client relationship and therefore, we expect their fund flows to be less sensitive to performance and brand. Therefore, the third hypothesis that we will test is:

H3: Fund flows of independent fund management companies are more sensitive to brand and past performance than fund flows of fund management companies that are a part of banks or insurers.

4.2 Methodology

To investigate the relationship between mutual fund brand image and flows, we use two approaches: the first is single and double sorts and the second is a panel regression analysis.

In order to perform sorts, we create five fund portfolios each month by sorting them according to one or two criteria. Funds with the largest values of the variable by which we sort are assigned to quintile 5 and funds with the smallest values are assigned to quintile 1. We first calculate averages for each quintile and month, and then take the time series averages of the quintiles and of the difference between quintiles 5 and 1, denoted by q5-1.

We use a piecewise linear regression and build three variables, LOW, MID, and HIGH, for each fund in each month, similar to what was done in Sirri and Tufano (1998). For this purpose, we first calculate fractional ranks based on the previous twelve-month excess returns for each month and category. FRANK is a continuous variable ranging from zero to one. The funds that belong to the lowest relative performance quintile in their category are then placed into the LOW performance group, the funds in the three middle quintiles are placed into the MID group, and the funds in the highest performing quintile are placed into the HIGH group:

$$LOW = \min(FRANK, 0.2) \quad (7)$$

$$MID = \min(0.6, FRANK - LOW) \quad (8)$$

$$HIGH = FRANK - LOW - MID \quad (9)$$

The following results are based on the multivariate regression:

$$\begin{aligned} Flow_{i,t} = & a_i + b_{1,i} * LOW_{i,t} + b_{2,i} * MID_{i,t} + b_{3,i} * HIGH_{i,t} \\ & + c_{1,i} * LOW_{i,t} * Interactionterms + c_{2,i} * MID_{i,t} * Interactionterms \\ & + c_{3,i} * HIGH_{i,t} * Interactionterms + CONTROLS_{i,t} + \epsilon_{i,t} \end{aligned} \quad (10)$$

where $Flow_{i,t}$ are either the relative flows of equation (3) or the market share changes of equation (4). The following control variables are used: the age of each fund, computed monthly as the natural LOG of (1+age), the expense ratio, the rolling standard deviation of monthly excess returns, the fund category flow, the size of each fund, defined as in Chevalier (1997), which is the natural LOG of the ratio of the previous month TNA and the geometric TNA over all funds per year and category, and the previous month relative flow or market share changes. All control variables are lagged one month except for expenses, which are lagged by one year, and fund category flow, which is not lagged. We estimate equation (10) as a pooled OLS regression with year and category fixed effects and t-statistics clustered at the fund level. If the fund's Morningstar category changed in the past 12 months or in the month of analysis, then we exclude the observations. Of the sample of 2,254 funds that could be matched with Brand Image Scores, there are 1,712 funds of 185 different brands for which we also have the data on all control variables in at least one month. Our data set for the regression analyses includes 80,702 fund-month observations.

5. Results

5.1 Single and double sorts

As a first test of hypothesis H1, we check for cross-sectional patterns when relative fund flows are sorted by Brand Image Score, as shown in the middle part of Panel A in Table 2. We denote the lowest Brand Image Score quintile as the inferior brand, the three mid-range quintiles as mediocre brand and the highest quintile as superior brand. The panel shows that superior brand funds get larger inflows than the inferior brand funds. The difference is 63 basis points per month or approximately 7.5 percent per year. This is of large economical significance. Note the non-monotonic brand-fund flow relationship, which we analyze in more detail below. For example, quintile 4 has outflows, but the average is statistically not significant. Panel B shows that inferior brand funds of quintile 1 have negative and significant market share changes while the ones of superior brand funds of quintile 5 are negative but nonsignificant.

It is well known that aggregate mutual fund flows are autocorrelated (Warther 1995). Individual fund flows also show some autocorrelation. We calculate the first (lag 1) autocorrelation of each fund and calculate cross-sectional averages within each brand quintile. The results are presented at the top in Panel A. Superior brand relative flows have an autocorrelation of 0.15, which is more than three times as large as that of funds with inferior brand. The difference is also statistically significant. In Panel B, the average autocorrelation coefficient of market share changes of superior brand funds is even more than four times as large than the one of inferior brand funds. A potential limitation of this result is its univariate nature. It could be the case that other fund variables explain the higher autocorrelation. For example, the higher autocorrelation could be due to the different investment objectives or liquidity of holdings for superior brand funds. We check this possibility with our regressions below.

The top of Panel C in Table 2 shows that superior brand funds have a monthly category

excess return that is 7 basis points higher than that of inferior brand funds. This difference is significant. Below, the difference between average alphas is marginally not significant but shows a similar pattern as the excess returns. The bottom of Panel C shows averages of yearly expense ratios. The difference between inferior and superior brand funds is statistically significant but seems economically small, as it is only four basis points per year.

It is well known that investors chase past returns¹⁴. The bottom parts of Panel A and B show average relative flow and average market share changes when sorted by past 12 month category excess returns. The relationship between relative flows or market share changes and past performance seems to be monotonic but not linear. The funds with low past performance of quintile 1 have lower average outflows or lower negative market share changes than one would expect given the size of the average inflows or positive market share changes of funds with high past performance of quintile 5. This indicates a possible convex flow-past performance relationship.

Since brand image might be another proxy for past performance, it is important to perform a double sort. In Panel A in Table 3, we first sort funds by their Brand Image Score (see the horizontal part of the table) and then split the brand quintile into five groups by the previous twelve-month excess performance of each fund (see the vertical part of the table). The last row, denoted q5-1, shows that funds with high past performance receive more inflows than low performing funds. However, the level of inflows also depends on brand.

Comparing the economic impact of performance on flows and that of brand on flows, it seems that the impact of performance is stronger and more consistent. Analyzing Table 3 vertically, the results show that in each of the brand quintiles, relative flows and market share changes increase monotonically from the lowest to the highest performance quintile. This result is not the case horizontally; within each performance quintile, average flows do not improve with each step up in brand quintiles. In most cases, the size of the flow or market share changes difference between performance quintiles is also larger than that

¹⁴See the extensive literature given in footnote 2.

between brand quintiles. The bottom row of Panel A shows that in each of the brand quintiles, the difference between the lowest and the highest performance quintile is more than 3 percentage points and highly significant. The last column at the right of the Panel shows that, within each of the performance quintiles, the relative flow difference between the lowest and the highest brand quintile is smaller. Poorly performing funds with inferior brands have an average outflow (-1.49 percent per month) that is essentially the same as that of funds with the strongest brands, but with similar poor performance (-1.54 percent). Well-performing funds with a superior brand, however, get more relative inflows than well-performing funds with an inferior brand. Contrary to the poor performers, the difference of 2.51 percent is highly significant. In the second best performance quintiles, the relative flow difference between inferior and superior brand is smaller, but still statistically significant. Panel B shows that similar results are obtained for market share changes. In addition to the results in Panel A, the negative difference between inferior and superior brand funds with lower past performance is significant and of -0.07 and -0.11. Hence, there is evidence that brand is not just another proxy for past performance.

The results indicate that the mutual funds that exhibit high past performance, in combination with strong brand image, tend to attract more flows. This finding offers a new perspective to the widely-accepted notion that investors are chasing past performance as a proxy of future performance. While sorts offer a convenient method for robust analysis, we do not control for factors other than past performance and brand. We therefore deepen our analysis in the subsequent section, using the panel regression methodology described above.

[Tables 2 + 3]

5.2 Brand and performance

We start by analyzing fund flows, market share changes, brand and investment performance, allowing for an asymmetric flow-performance relationship.

Model 1 in Table 4 shows that Brand Image Score has a positive and significant coefficient. The adjusted R2 is low, which stems from the yearly frequency of brand and its measurement at the fund family level. Relative flow, on the other hand, is measured at the individual fund level and on a monthly frequency. In Model 2, we control for past performance and other fund characteristics. Note that the coefficient of Brand Image Score stays significant. In line with the findings by Sirri and Tufano (1998) for the U.S., and Feirreira et al. (2012) for several markets globally, including the U.S., the flow-performance relationship is convex. The flows of high-performing funds are more performance-sensitive than flows of low-performing funds. Mid-performing funds are the least performance-sensitive. In Panel B, we test if the relative performance variables are statistically different from each other. The three differences - between HIGH and MID, between MID and LOW and between HIGH and LOW - are significant. In Model 3, we use Brand Image Rank instead of Brand Image Score and obtain the same result.

From the perspective of a fund family, it might be worthwhile to obtain a superior brand if it can help to maximize assets under management. We split the Brand Image Score into quintiles as in our earlier sorts. In Model 4, we insert a superior brand dummy that equals one if the Brand Image Score lies within the best quintile and zero otherwise. The interaction term between the dummy and lagged flow is highly significant. Thus, the result of the autocorrelation pattern found above still holds¹⁵. Models 5 and 6 use market share changes instead of flow. The results are very similar to the ones in Models 2 and 3. Thus, even when using market share changes, there is evidence for a convex flow-past performance relationship.

In all regressions, the control variable for the fund category flow is positive and highly significant, which means that the category-wide flow is an important determinant of flows at

¹⁵ An alternative explanation is that fund flows are autocorrelated due to performance, rather than brand. When inserting interaction terms between the three relative past performance variables and the superior brand dummy, only the interaction with HIGH is significant. The coefficient of the interaction term with lagged flow stays significant and of similar size. The same result is obtained when using lagged market share changes but is omitted to save space.

the individual fund level. Investors tend to direct flows to market segments and industries that are more attractive than others due to their current return (Warther 1995). The coefficient for expenses is insignificant, which is in line with most existing studies controlling for ongoing expenses that have either insignificant or inconsistent results (Frye 2001, Barber et al. 2005, Wei et al. 2011, Yankow et al. 2011, Ferreira 2012), but deviates from Nanda et al. (2004), where a negative relationship was found.

The other control variables have the sign and level of significance expected from most previous research. As in Chevalier and Ellison (1997), Sirri and Tufano (1998), Jain and Wu (2000), Nanda et al. (2004), Barber et al. (2005), Huang et al. (2007), Yankow et al. (2011), Wei et al. (2011) and Ferreira et al. (2012), we find that larger funds receive statistically significantly lower flows. Older funds also receive lower flows, in line with results by Chevalier and Ellison (1997), Barber et al. (2005), Huang et al. (2007) and Ferreira (2012) using U.S. data, but contrary to Wei et al. (2011) using a dataset from the Taiwanese fund market. For the remainder of this study, we perform all regressions with controls, but omit their coefficients to save space.

[Table 4]

In table 5, we add the three interaction terms between the performance variables and brand. In all our Models, only the Brand*LOW interaction is not significant. In Models 1 and 4, we use the Brand Image Score in the interaction terms with relative flow and market share changes as dependent variables, while in Models 2 and 5, we use the Brand Image Rank. In all four regressions, the interaction terms of funds with relative high past performance are much larger than the ones of funds with mid performance. Panel B shows that the differences are only significant for market share changes, but for percentage flows the coefficients are of similar size. This is an indication that, in particular for high-performing funds, brand has a positive impact on flows.

The analysis so far does not allow us to see if brand itself has a nonlinear relationship with flows. We define a second dummy variables. The inferior brand dummy equals one if the Brand Image Score lies within the worst quintile and zero otherwise.

In Model 3, we add interaction terms between the two brand dummies and the relative performance variables, LOW and HIGH. The interaction variables were subsequently entered into the regression to detect any multi-collinearity issues. We find strong evidence that brand changes the sensitivity of fund flows to past performance. Model 3 shows that if the fund brand is superior, the relative flow sensitivity to low past performance doubles and the sensitivity to high past performance increases by one third¹⁶. An inferior brand, on the other hand, decreases the sensitivity for both LOW and HIGH performing funds. The former effect is insignificant, but the size of the coefficients points into this direction. Model 6 provides additional support that superior and inferior brand have different effects on the flow sensitivity to past performance, as the coefficients of interaction terms show a similar pattern when using market share changes. Thus, we find that the fund flow sensitivity on past performance is strongly influenced by brand. A superior brand increases the sensitivity while an inferior brand decreases it. As a result, the convexity of funds with a superior brand also increases. This finding supports our first hypothesis H1. When investors choose a superior brand fund, they tend to chase high past performance more fervently than when choosing a mediocre or inferior brand. On the other hand, a superior brand does not stop investors from withdrawing their money in the case of past underperformance, but also leads to higher sensitivity. This finding is in contrast to hypothesis H2. If a superior brand fund underperforms, it will have higher outflows than a fund with a mediocre or inferior brand. For example, if a fund with superior brand has a decrease in past performance from the HIGH to the LOW performance group, which in terms of yearly category excess returns equals a change of roughly -2 percent, then this decrease leads to a percentage outflow similar in size

¹⁶From 5.36 to $5.36+6.74=12.10$ for funds with LOW performance and from 12.83 to $12.83 +5.40=18.23$ for funds with HIGH performance.

to its previous inflows¹⁷.

Note that this result is consistent with our earlier double sort of market share changes in Panel B in Table 3 but not apparent from the double sort in Panel A. In the regressions, however, we control for other fund characteristics that the sort¹⁸ does not.

Forced to reject hypothesis H2, we ask the question, what drives the unexpected result that superior brands get punished more for underperformance than weaker brands? We believe the answer might have to do with the structure of the European fund industry. The strong brands, as assessed by professional fund selectors, are the ones competing on the Pan-European fund market, where fund providers operate cross-border and where their funds are evaluated constantly by professional fund selectors. The results indicate that this market segment is highly competitive; underperformance results in outflows, whatever the quality of the brand. The weaker brands tend to be the ones that operate more domestically. It seems that this market segment is less competitive, so that underperformance is not punished as heavily, possibly because these funds do not face the continuous scrutiny of funds selectors in the whole of Europe. A second explanation could be that the fund providers with superior performance also tend to be the ones with more funds. Therefore, in case of underperformance, it might be easier to switch to another fund within the same fund family.

[Table 5]

¹⁷The average monthly excess return over the previous twelve months for each quintile is computed from a single sort of the variable on itself. The q1-5 difference is -0.16. Multiplying this number by 12 yields approximately -2 percent.

¹⁸In addition, our regression weights each monthly fund observation equally, while the sorting procedure weights each monthly observation equally. Since our panel data set is not perfectly balanced, the number of observations per month differs, and as a consequence, the sorting procedure does not weight each monthly fund observation equally. In unreported results, we regress the funds of the 25 different Brand Image Score/past performance groups on a constant, which is equivalent to taking means, and cluster standard errors at the fund level. Unlike the double sort in Panel A, the flow difference between funds with poor performance and inferior brand and funds with poor performance and superior brand is significant, which is in line with our regression results.

5.3 Brand and business model

We proceed by relating the business model to performance and brand and investigate its impact on fund flows. Our hypothesis is that fund management companies that are a part of banks or insurers are able to sell their funds through the mother company's distribution channels based on a wider client relationship, so that flows are less dependent on brand and especially past performance.

We define a business model dummy variable that equals one for funds of independent firms and zero if the fund is managed by a bank or insurer-owned fund provider. Models 1 and 3 in Table 6 show that the dummy variable is positive and significant when using relative flows or market share changes as dependent variables. Model 1 indicates that funds of independent fund providers have a 0.20 percent higher inflow per month than funds of dependent firms, after controlling for other fund or category characteristics. We insert interaction terms between Brand Image Score and the business model dummy as well as interactions variables between the business model dummy and the three relative performance variables in Model 2. The interaction term Business Model Dummy*Brand Image Score is highly significant, whereas comparing the coefficient for brand (for funds of dependent firms) with that of brand in Model 2 in Table 4 shows that it shrinks in size and loses its significance. Thus, we find evidence for our hypothesis H3. Brand seems to be more important for independent firms. Model 4 shows that when using market share changes as dependent variable, the interaction term becomes insignificant, so the evidence for our third hypothesis seems not that clear cut. On the other hand, the coefficient of Brand Image Score is insignificant, too, whereas it was significant in Model 5 in Table 4. Thus, the interaction term, although not significant, seems to soak up the significance of Brand Image Score when using that variable alone.

The interaction terms between the business model dummy and the past performance variables show some significance, but the pattern of interaction terms in Models 2 and 4 in Table 6 seem not to be exactly the same. Panel B shows that the difference in interaction terms in the relative flow and market share changes regressions makes the negative MID-LOW

difference insignificant for independent funds when using relative flows (from -2.91 to -3.82) while the positive MID-LOW difference becomes significant in the market share changes regression (from 0.01 to 0.41). On the other hand, the HIGH-LOW difference increases for independent funds in both the relative flow and the market share changes regression (from 6.26 to 9.39 and from 0.59 to 0.92). Thus, flows of funds of independent firms are more sensitive to performance if they belong to the high-performance quintile. Note that this result is in line with Frye (2001), who finds that U.S. bond funds that are managed by bank-owned firms are less sensitive to past performance.

[Table 6]

5.4 Brand and fund family variables

As mentioned above, previous research has used indirect proxies for marketing and brand (Sirri and Tufano 1998, Nanda et al. 2004 and Huang et al. 2007). In this section, we challenge these variables with our survey-based brand data. We use five proxies previously used for brand: the number of funds in a fund family, the number of fund categories in a fund family, the group size, which is the natural logarithm of the previous month TNA of all open-end funds of the Master Group in Europe, also capturing funds outside of our sample, the number of star funds in a fund family, and a star fund family dummy that equals one if the fund family has one or more star funds. We define a fund as a star fund if it is the best-performing fund in its category in the past 12-month period. Since we are interested in spillover effects of star funds on other funds that are in the same fund family, we exclude star funds when testing the number of star funds in a fund family and the star fund family dummy because we want to ensure that the star funds themselves are not driving our results.

Panel B in Table 1 shows that the Brand Image Score and Brand Image Rank have correlations with the five brand proxies which are quite high in some cases. This means

that these proxies seem to represent a considerable, but not too large, amount of our brand variable. A high correlation could lead to multi-collinearity issues. Therefore, in Table 7, we first use an indirect approach and compare the impact of the brand proxies on the three relative performance variables with our results in Table 5. Panel A used relative flows as dependent variable. While all of the brand proxies except group size are significant (see Models 1, 3, 5, 7, and 9), none of the interaction terms is significant (see Models 2, 4, 6, 8, and 10). This is in strong contrast to the results in Table 5 where both brand variables, the Brand Image Score and the Brand Image Rank, and the interaction terms with MID and HIGH performance are highly significant.

Panel B uses market share changes as dependent variable. While some of the interaction terms are significant (see Models 2, 4, 8, and 10), only the number of categories is significant in the regressions without interaction terms (see Models 1, 3, 5, 7, and 9). This is very different to the results in Panel A and to the results in Table 5.

In summary, all brand proxies tested here have a positive impact on relative flows, but none of them changes the flow sensitivity to past performance like our brand variables. When using market share changes, the results of the brand proxies are not consistent either.

[Table 7]

We proceed by a close contest between the five brand proxies and Brand Image Score by using them in the same regressions¹⁹. Panel A in Table 8 uses relative flows, and Panel B uses market share changes as dependent variable. The table shows that the Brand Image Score variable is more often significant than the brand proxies. Model 2 in Panel A is the only case when a proxy is significant and Brand Image Score is not. Our findings therefore suggest that brand cannot be proxied as easily as other papers suggest.

[Table 8]

¹⁹Using Brand Image Rank leads to the same results.

5.5 *Brand and performance persistence*

The final question that we address is whether or not it is good for investors to follow past performance and favor strong brands. Berk and Green (2004) show that return chasing makes past performance a bad predictor of future fund performance. As money flows to skilled fund managers, who have decreasing returns to scale, it eventually decreases their performance and destroys persistence in fund returns.

Tests of fund persistence sort funds by their performance into portfolios at some time t and then track performance over the subsequent periods. Carhart (1997), for example, sorts funds at the beginning of each year by their previous year return and then analyzes fund performance over the next five years. Bollen and Busse (2005) find only evidence for persistence on shorter horizons. Results of our persistence test are presented in Table 9. As before, a fund has a superior (inferior) brand if it lies within the highest (lowest) quintile of a sort by Brand Image Score. Individual fund alphas are estimated by equation (6). At the beginning of each year, we sort funds based on their average alpha from January to December of the previous year. We then compute average monthly alphas for the 25 portfolios over the subsequent 12 months, and repeat the sorting procedure again at the beginning of the next year. Strikingly, only funds with high past performance and superior brand show significant performance persistence. Within the quintile of funds with highest past year alphas, funds with superior brand outperform funds with inferior brand in the subsequent year by 17 bps per month or 2 percent per year. Thus, it seems that the superior brand attribute leads to persistence in performance. If fund investors use the signal of past performance to make their contemporaneous trades, they benefit when investing in funds with superior brand.

[Table 9]

6. Conclusions

Net mutual fund inflows that are the result of investors' wealth allocations are immediately added to or subtracted from the fund provider assets under management and, as a result, have a direct impact on the revenues that fund management companies earn in the form of management fees. Therefore, understanding how investors select funds, and when they decide to disinvest, is of particular relevance to fund providers. Based on the extensive marketing literature on the concept of brand, which suggests that consumers not only base their purchase decisions on an evaluation of objective product attributes, but also on non-product attribute components (e.g., Keller 1993 and Shankar et al. 2008), we hypothesize that fund flows might be driven not only by objective fund characteristics, such as past performance and fees, but also by the brand image of the fund provider.

We confirm past performance as the primary driver of fund flows, but we also find evidence that brand image plays an important role. Brand image changes the sensitivity of fund flows to past performance. While past performance remains a stronger determinant of fund flows than brand, the interaction between both variables seems to be important.

We find that a superior brand increases the sensitivity to past performance, while an inferior brand decreases it. This finding could be the result of lower new investor search costs for superior brand funds. However, the result is also consistent with the idea that investors do not rely on past performance alone when assessing fund quality and making investment decisions. Knowing that past outperformance gives, at best, a weak indication of future outperformance (see e.g., Carhart 1997), it might be that investors see past outperformance as a necessary, but not a sufficient condition in order to invest. A superior brand could add to their confidence that they are selecting a winning fund that is able to repeat its outperformance streak in the future. It should be noted that our results do not support the hypothesis that a superior brand image protects against outflows. On the contrary, in the case of underperformance, the flows of funds with a superior brand image are more sensitive to past performance than the flows of funds with a mediocre or inferior brand image.

Our results indicate that fund flows of independent firms are influenced more by brand, and that independent firm fund flows are more sensitive to high past performance than dependent firm fund flows. This is consistent with fund providers, which are a part of banks or insurers, also having the ability to distribute their funds through their affiliated distribution channels to a broader client relationship network of investors who, after they have selected a financial institution for a broader set of financial products, are assessing funds' brand image and past performance less critically.

Prior research has used different variables as brand proxies. We find that these proxies, although correlated with brand image, generally lose significance when used in the same regression. Furthermore, most of the brand proxies fail to change at all the relationship between fund flow and past performance or with a magnitude that is comparable to the strong effect of the brand image.

We find that a superior brand generates persistent flows. This is not the case for funds with an inferior brand. Our results imply that investment outperformance, together with a superior brand, is a powerful combination to attract fund inflows. For fund providers, this result is a justification for paying attention to and spending resources on not only the investment performance that they achieve, but also the positioning of their brand image among investors. However, the results also show that a superior brand image alone is not sufficient to attract inflows when it is coupled with mid-range or poor performance. This finding implies that a fund management company business strategy that relies on branding and marketing alone, either to win new assets under management or to protect existing assets, is unlikely to succeed without coupling this to the goal of achieving investment outperformance.

While our results suggest that a superior brand image attracts investors into funds, it is not to their disadvantage. Our results indicate that funds with a superior brand yield a higher average return. More importantly, the outcome of this study shows that only funds with superior brand and high past performance are likely to outperform in the subsequent year. Given the fact that investors appear to use both past performance and brand image

as selection criteria in their investment decision process, we can conclude that investors will only be lured into funds that combine a superior brand with outperformance. Since it is this group of funds that shows persistence in performance, the result is a mutual benefit for the fund providers in question and for the fund investors.

References

- Barber, B.M., Odean, T., Zheng, L., 2005, Out of sight, out of mind: The effects of expenses on mutual fund flows, *Journal of Business* 78, 2095-2119.
- Berk, J.B., Green, R.C., 2004, Mutual fund flows and performance in rational markets, *Journal of Political Economy* 112, 1269-1295.
- Bollen, N. P. B., Busse, J.A., 2005, Short-Term Persistence in Mutual Fund Performance, *Review of Financial Studies* 18, 569-597.
- Carhart, M., 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57-82.
- Chevalier, J., Ellison, G., 1997, Risk taking by mutual funds as a response to incentives, *Journal of Political Economy* 105, 1167-1200.
- Del Guercio, D., Tkac, P.A., 2008, Star power: The effect of Morningstar ratings on mutual fund flow, *Journal of Financial and Quantitative Analysis* 43, 907-936.
- Frye, M.B., 2001. The performance of bank-managed mutual funds, *Journal of Financial Research* 24, 419-442.
- Ferreira, M.A., Keswani, A., Miguel, A.F., Ramos, S.B., 2012, The flow-performance relationship around the world, *Journal of Banking and Finance* 36, 1759-1780.
- Goetzmann, W., Peles, N., 1997, Cognitive dissonance and mutual fund investors, *Journal of Financial Research* 20, 145-158.
- Gruber, M.J., 1996, Another puzzle: The growth in actively managed mutual funds, *Journal of Finance* 51, 783-810.
- Hazenbergh, J.J., 2012, Investment fund governance; An empirical investigation of Luxembourg UCITS, PhD dissertation, University of Luxembourg.
- Huang, J., Wei, K.D., Yan, H., 2007, Participation costs and the sensitivity of fund flows to past performance, *Journal of Finance* 62, 1273-1311.
- Ippolito, R.A., 1992, Consumer reaction to measures of poor quality: Evidence from the mutual fund industry, *Journal of Law and Economics* 35, 45-70.

- Jain, P.C., Wu, J.S., 2000, Truth in mutual fund advertising: Evidence on future performance and fund flows, *Journal of Finance* 55, 937-958.
- Keller, K.L., 1993, Conceptualizing, measuring and managing customer-based brand equity, *Journal of Marketing* 57, 1-22.
- Keswani, A., Stolin, D., 2008, Which money is smart? Mutual fund buys and sells of individual and institutional investors, *Journal of Finance* 63, 85-118.
- Lynch, A., Musto, D., 2003, How Investors Interpret Past Fund Returns, *Journal of Finance* 58, 2033-2058.
- Nanda, V., Wang, Z.J., Zheng, L., 2004, Family values and the star phenomenon: Strategies of mutual fund complexes, *Review of Financial Studies* 17, 667-698.
- Otten, R., Bams, D., 2002, European Mutual Fund Performance, *European Financial Management*, 75–101.
- Peng, C., Chen, M., Wei, A., 2011, Does advertising moderate mutual fund investor post-purchase decisions?, National Sun Yat-sen University Working paper.
- Shankar, V., Azar, P., Fuller, M., 2008, BRAN*EQT: A multicategory brand equity model and its application at Allstate, *Marketing Science*, 27, 4, 567-584.
- Sirri, E., Tufano, P., 1988, Costly search and mutual fund flows, *Journal of Finance* 53, 1589-1622.
- Spiegel, M., Zhang H., 2013, Mutual fund risk and market share-adjusted fund flows, *Journal of Financial Economics*, 108, 2, 506–528.
- Walter, A., Weber, F. M. , 2006, Herding in the German Mutual Fund Industry, *European Financial Management*, 12, 375–406.
- Warther, V., 1995. Aggregate mutual fund flows and security returns, *Journal of Financial Economics* 39, 2-3, 209-235.
- Wei, A., Chen, M., Peng, C., 2011, The advertising spillover effect: Implications for mutual fund families, National Sun Yat-sen University Working paper.
- Yankow, J.J., Smythe, T.I., Lesseig, V.P., Jones, M.A., 2011, The impact of advertising

on fund flows in alternative distribution channels, *International Journal of Financial Research* 2, 2-22.

Table 1: Summary Statistics and Correlations

Panel A shows summary statistics. We calculate the sample average, the standard deviation, the minimum, the maximum and the total number of observations. Relative flow, return, alpha, and expense are in percentage. Market share changes have been multiplied by 10,000. TNA is in millions. Age is in years. Panel B shows Pearson correlation coefficients between Brand Image Score, Brand Image Rank and five brand proxies: The number of funds within a fund family, the number of categories offered by the family, the Group size which is the natural LOG of the one month lagged TNA of all open-end funds of the Master Group in Europe, the number of star funds within a fund family, and a dummy variable which equals one if the fund family has one or more star funds. All correlations are significant at the 1 percent level.

Panel A: Summary statistics							
Variable	Average	Std Dev	Min	Max	Nobs		
Relative Flow	0.06	11.81	-100.00	108.54	86,758		
Market Share Changes	-0.01	0.79	-3.93	4.16	84,982		
TNA (in millions of Euro)	330.27	814.06	5.00	24,474.12	86,759		
Return	0.32	5.52	-38.51	36.91	85,475		
Alpha	-0.08	1.90	-25.11	16.41	71,847		
Age (in years)	8.60	5.75	0.00	45.78	86,759		
Brand Image Score	13.38	20.73	0.01	102.01	86,759		
Expense	1.93	0.54	0.09	14.43	82,153		
Panel B: Correlations							
	Brand Image Score	Brand Image Rank	Number of funds	Number of categories	Group size	Number of star funds	Star fund family dummy
Brand Image Score	1.00						
Brand Image Rank	0.75	1.00					
Number of funds	0.64	0.70	1.00				
Number of categories	0.63	0.75	0.92	1.00			
Group size	0.49	0.59	0.64	0.64	1.00		
Number of star funds	0.38	0.37	0.42	0.38	0.28	1.00	
Star fund family dummy	0.16	0.29	0.30	0.38	0.21	0.14	1.00

Table 2: Single Sorts: Cross-Sectional Flow Characteristics

This table shows autocorrelations and single sorts of relative flow in Panel A, of market share changes in Panel B, and of other variables in Panel C. Horizontally, quintile 1 has the inferior brand funds and quintile 5 has the superior brand funds. The column denoted by quintile 5-1 shows differences between quintile 5 and 1. We compute first (lag 1) autocorrelations of each fund and calculate cross-sectional averages within each brand quintile. In Panel C, we measure past 12 month performance as the return of each fund in excess of its category return. Time-varying market model alphas are estimated similar as in Carhart (1997). We calculate monthly time series averages of cross-sectional averages within each brand quintile or intersection of quintiles. Every parameter estimate has its t-statistic below in parenthesis which has been adjusted for heteroskedasticity and autocorrelation according to the method of Newey and West (1987) using four lags. *** denotes significance at the 1 percent, ** at the 5 percent and * at the 10 percent level. In each last row, we show the number of observations for each quintile.

Panel A: Autocorrelations and Single Sorts of Relative Flow					
q1	q2	q3	q4	q5	q5-1
Average ACF(1)					
0.046***	0.056***	0.049***	0.061***	0.151***	0.105***
(4.85)	(5.74)	(5.05)	(5.85)	(11.78)	(6.71)
583	541	594	575	380	
Single Sort by Brand Image Score					
0.048	-0.102	-0.091	-0.299	0.676*	0.628***
(0.17)	(-0.45)	(-0.33)	(-1.14)	(1.86)	(4.06)
16,475	17,108	16,627	16,891	17,933	
Single Sort by past 12 month Excess Return					
-1.771***	-0.794***	-0.290	0.435	2.670***	4.441***
(-6.27)	(-3.42)	(-1.07)	(1.38)	(5.97)	(13.08)
15,992	16,966	16,983	16,966	17,938	
Panel B: Autocorrelations and Single Sorts of Market Share Changes					
Average ACF(1)					
0.040***	0.074***	0.048***	0.092***	0.179***	0.139***
(3.98)	7.10	(4.64)	(8.40)	(14.37)	(8.72)
581	537	593	575	379	
Single Sort by Brand Image Score					
-0.011*	-0.012*	-0.014	-0.006	-0.012	-0.001
(-1.91)	(-1.80)	(-1.51)	(-0.67)	(-0.85)	(-0.03)
15,887	17,421	17,050	17,194	19,207	
Single Sort by past 12 month Excess Return					
-0.108***	-0.073***	-0.056***	0.007	0.155***	0.263***
(-9.66)	(-7.47)	(-10.42)	(1.07)	(9.40)	(9.79)
15,992	16,966	16,983	16,966	17,938	
Panel C: Autocorrelations and Single Sorts of other variables					
Single Sort of Excess Return by Brand Image Score					
-0.010	-0.014	0.005	0.002	0.063**	0.073**
(-0.71)	(-0.83)	(0.29)	(0.12)	(2.59)	(2.31)
15,887	17,421	17,050	17,194	19,207	
Single Sort of Market Alphas by Brand Image Score					
-0.078	-0.110*	-0.070	-0.082	-0.031	0.047
(-1.31)	(-1.92)	(-1.39)	(-1.64)	(-0.51)	(1.63)
15,887	17,421	17,050	17,194	19,207	
Single Sort of Expense by Brand Image Score					
1.975***	1.914***	1.891***	1.943***	1.933***	-0.042***
(148.37)	(189.04)	(165.38)	(259.68)	(251.06)	(-4.55)
15,887	17,421	17,050	17,194	19,207	

Table 3: Double Sorts: Cross-Sectional Flow Characteristics

This table shows results of double sorts by Brand Image Score (horizontally) and past 12 month performance (vertically) of relative flow in Panel A and of market share changes in Panel B. On the horizontal part of the table, quintile 1 has the inferior brand funds and quintile 5 has the superior brand funds. On the vertical part, quintile 1 has the funds with lowest past 12 month performance and quintile 5 has the funds with highest past 12 month performance. The column denoted by quintile 5-1 shows differences between quintile 5 and 1. We measure past 12 month performance as the return of each fund in excess of its category return. We calculate monthly time series averages of cross-sectional averages within each brand quintile or intersection of quintiles. Every parameter estimate has its t-statistic below in parenthesis which has been adjusted for heteroskedasticity and autocorrelation according to the method of Newey and West (1987) using four lags. *** denotes significance at the 1 percent, ** at the 5 percent and * at the 10 percent level.

Panel A: Relative Flow by Brand Image Score (hor.) and past 12 month Excess Return (vert.)						
	q1	q2	q3	q4	q5	q5-1
q1	-1.492*** (-3.91)	-1.556*** (-4.51)	-1.557*** (-4.49)	-1.792*** (-5.94)	-1.536*** (-4.21)	-0.044 (-0.14)
q2	-0.676** (-2.18)	-0.981*** (-3.95)	-0.706* (-1.97)	-1.281*** (-3.76)	-0.532* (-1.73)	0.144 (0.53)
q3	-0.128 (-0.40)	-0.013 (-0.05)	-0.362 (-1.30)	-0.961*** (-3.07)	0.087 (0.23)	0.215 (0.82)
q4	0.490 (1.22)	-0.054 (-0.17)	0.165 (0.58)	0.048 (0.11)	1.370*** (3.36)	0.880** (2.53)
q5	2.007*** (4.91)	2.550*** (4.68)	1.939*** (4.46)	2.540*** (5.61)	4.513*** (5.68)	2.506*** (4.32)
q5-1	3.499*** (10.72)	4.106*** (7.12)	3.496*** (8.89)	4.333*** (10.98)	6.049*** (8.78)	
Panel B: Market Share Changes by Brand Image Score (hor.) and past 12 month Excess Return (vert.)						
	q1	q2	q3	q4	q5	q5-1
q1	-0.063*** (-7.31)	-0.071*** (-4.42)	-0.058*** (-3.05)	-0.110*** (-6.95)	-0.136*** (-5.31)	-0.073*** (-2.80)
q2	-0.067*** (-4.35)	-0.056*** (-3.63)	-0.052*** (-3.14)	-0.089*** (-4.75)	-0.173*** (-7.48)	-0.106*** (-3.71)
q3	-0.032*** (-2.75)	-0.048*** (-4.26)	-0.036** (-2.11)	-0.090*** (-4.60)	-0.091*** (-2.82)	-0.059 (-1.59)
q4	0.003 (0.32)	-0.000 (-0.02)	-0.008 (-0.58)	0.011 (0.52)	0.090*** (3.03)	0.086*** (2.64)
q5	0.076*** (5.07)	0.101*** (5.22)	0.100*** (3.57)	0.142*** (3.84)	0.332*** (6.23)	0.256*** (4.88)
q5-1	0.139*** (8.00)	0.171*** (5.37)	0.158*** (4.52)	0.252*** (5.96)	0.468*** (7.65)	

Table 4: The Effect of Brand on Flow

This table shows piecewise regressions in panel A and t-test of differences in panel B. The left part of Panel A uses relative flow and the right part uses market share changes. We use two brand variables, the natural LOG of Brand Image Score and Brand Image Rank. We calculate fractional ranks based on the previous twelve month excess returns for each month and category. FRANK is a continuous variable ranging from zero to one. The three relative performance variables are defined as: LOW=min(FRANK,0.2); MID=min(0.6, FRANK - LOW); HIGH=FRANK - LOW - MID. We include as (one month lagged) control variables the natural LOG age of funds, monthly expenses, the excess return standard deviation over the prior twelve months, fund size, the flow into the respective category, and lagged flow or market share changes. All variables are as defined in the data section. Every parameter estimate has its t-statistic below in parenthesis. We control for year and category fixed effects and cluster the standard errors at the fund level. *** denotes significance at the 1 percent, ** at the 5 percent and * at the 10 percent level.

Panel A: Piecewise Regressions						
Dependent Variable:	Relative Flow				Market Share Changes	
Variable	MODEL1	MODEL2	MODEL3	MODEL4	MODEL5	MODEL6
Intercept	1.699*** (5.38)	-0.492 (-1.17)	-0.528 (0.89)	-0.416 (-1.01)	-0.064 (-1.63)	-0.066* (-1.69)
Brand Image Score	0.153*** (3.21)	0.135*** (3.26)			0.008** (2.47)	
Brand Image Rank			0.567*** (3.14)			0.034*** (2.63)
LOW		5.748*** (4.88)	5.744*** (4.87)	5.987*** (5.09)	0.019 (0.27)	0.019 (0.27)
MID		2.656*** (11.25)	2.663*** (11.28)	2.602*** (11.01)	0.139*** (7.78)	0.140*** (7.80)
HIGH		13.324*** (11.25)	13.344*** (11.25)	12.960*** (11.04)	0.722*** (7.60)	0.724*** (7.60)
Age		-0.623*** (-7.47)	-0.621*** (-7.46)	-0.620*** (-7.41)	-0.011* (-1.93)	-0.011* (-1.92)
Expense		-0.022 (-0.27)	-0.020 (-0.24)	-0.028 (-0.34)	0.005 (0.77)	0.005 (0.79)
Return Std Dev		0.002 (0.16)	0.002 (0.18)	0.002 (0.21)	0.001 (0.99)	0.001 (1.01)
Size		-0.204*** (-4.81)	-0.202*** (-4.77)	-0.204*** (-5.01)	-0.028*** (-5.19)	-0.027*** (-5.13)
Flowcategory		49.472*** (16.99)	49.499*** (17.02)	49.226*** (16.84)	2.763*** (10.81)	2.765*** (10.82)
lagged dependent variable		0.153*** (15.65)	0.153*** (15.65)	0.131*** (12.50)	0.301*** (22.04)	0.301*** (22.04)
Superior Brand Dummy				0.508*** (4.39)		
Superior Brand Dummy *lagged relative flow				0.091*** (3.83)		
ADJRSQ	0.01	0.07	0.07	0.07	0.13	0.13
Nobs	86,758	80,661	80,661	80,661	79,165	79,165
Nfunds	1,916	1,712	1712	1712	1,712	1,712
Panel B: T-test of Differences						
HIGH-MID		10.669*** (8.21)	10.681*** (8.22)		0.583*** (5.67)	0.584*** (5.68)
MID-LOW		-3.093** (-2.38)	-3.081** (-2.37)		0.120 (1.5)	0.121 (1.51)
HIGH-LOW		7.576*** (4.84)	7.600*** (4.85)		0.703*** (5.81)	0.704*** (5.80)

Table 5: The Effect of Brand on the Flow-Performance Relationship

This table shows piecewise regressions on flow in panel A and t-test of differences in panel B. The left part of Panel A uses relative flow and the right part uses market share changes. We use two brand variables, the natural LOG of Brand Image Score and Brand Image Rank. The Superior (Inferior) Brand Dummy equals one if the Brand Image Score lies within the best (worst) quintile and zero otherwise. We calculate fractional ranks based on the previous twelve month excess returns for each month and category. FRANK is a continuous variable ranging from zero to one. The three relative performance variables are defined as: LOW=min(FRANK,0.2); MID=min(0.6, FRANK - LOW); HIGH=FRANK - LOW - MID. We include as (one month lagged) control variables the natural LOG age of funds, monthly expenses, the excess return standard deviation over the prior twelve months, fund size, the flow into the respective category, and lagged flow or market share changes. All variables are as defined in the data section. Every parameter estimate has its t-statistic below in parenthesis. We control for year and category fixed effects and cluster the standard errors at the fund level. *** denotes significance at the 1 percent, ** at the 5 percent and * at the 10 percent level.

Panel A: Piecewise Regressions						
Dependent Variable:	Relative Flow			Market Share Changes		
Variable	MODEL1	MODEL2	MODEL3	MODEL4	MODEL5	MODEL6
Brand Image Score	-0.251 (-1.60)			-0.011 (-1.04)		
Brand Image Rank		-0.925 (-1.35)			-0.029 (-0.63)	
LOW	4.806** (2.44)	4.935** (2.13)	5.357*** (3.77)	0.137 (1.40)	0.211* (1.76)	0.061 (0.73)
MID	1.595*** (3.84)	1.285*** (2.59)	2.641*** (11.19)	0.023 (0.83)	-0.010 (-0.33)	0.143*** (7.99)
HIGH	10.539*** (5.63)	9.590*** (4.19)	12.827*** (7.63)	0.305*** (2.55)	0.172 (1.25)	0.484*** (4.09)
Brand*LOW	0.870 (0.95)	2.659 (0.66)		-0.042 (-0.63)	-0.295 (-1.03)	
Brand*MID	0.565*** (3.08)	2.560*** (3.10)		0.063*** (3.63)	0.282*** (4.10)	
Brand*HIGH	1.515* (1.89)	7.300* (1.91)		0.226*** (3.07)	1.064*** (3.43)	
Inferior Brand Dummy			0.555 (1.15)			0.030 (1.38)
Superior Brand Dummy			-0.827 (-1.58)			-0.032 (-0.65)
Superior Brand Dummy*LOW			6.741** (2.45)			0.109 (0.43)
Superior Brand Dummy*HIGH			5.399** (1.97)			1.100*** (4.32)
Inferior Brand Dummy*LOW			-2.406 (-0.94)			-0.216* (-1.84)
Inferior Brand Dummy*HIGH			-5.020* (-1.93)			-0.271* (-1.65)
ADJRSQ	0.07	0.07	0.07	0.13	0.13	0.13
Nobs	80,661	80,661	80,661	79,165	79,165	79,165
Nfunds	1,712	1,712	1,712	1,712	1,712	1,712
Panel B: T-test of Differences						
Brand*(HIGH-MID)	0.950 (1.06)	4.74 (1.12)		0.162** (1.98)	0.782** (2.30)	
Brand*(MID-LOW)	-0.304 (-0.30)	-0.099 (-0.02)		0.105 (1.36)	0.577* (1.78)	
Brand*(HIGH-LOW)	0.645 (0.57)	4.64 (0.89)		0.267*** (2.83)	1.35*** (3.32)	

**Table 6: The Effects of
the Business Model and Brand on Flow and the Flow-Performance Relationship**

This table shows piecewise regressions on flow in panel A and t-test of differences in panel B. The left part of Panel A uses relative flow and the right part uses market share changes. The business model dummy equals one for independent funds and zero if the fund is owned by insurers or banks. We calculate fractional ranks based on the previous twelve month excess returns for each month and category. FRANK is a continuous variable ranging from zero to one. The three relative performance variables are defined as: LOW=min(FRANK,0.2); MID=min(0.6, FRANK - LOW); HIGH=FRANK - LOW - MID. We include as (one month lagged) control variables the natural LOG age of funds, monthly expenses, the excess return standard deviation over the prior twelve months, fund size, the flow into the respective category, and lagged flow or market share changes. All variables are as defined in the data section. Every parameter estimate has its t-statistic below in parenthesis. We control for year and category fixed effects and cluster the standard errors at the fund level. *** denotes significance at the 1 percent, ** at the 5 percent and * at the 10 percent level.

Panel A: Piecewise Regressions				
Dependent Variable:	Relative Flow		Market Share Changes	
Variable	MODEL1	MODEL2	MODEL3	MODEL4
LOW	5.928*** (5.05)	5.317*** (4.05)	0.035 (0.49)	0.085 (1.03)
MID	2.636*** (11.16)	2.408*** (8.76)	0.135*** (7.65)	0.095*** (4.90)
HIGH	13.216*** (11.18)	11.579*** (8.12)	0.713*** (7.52)	0.676*** (5.77)
Business Model Dummy	0.203* (1.76)	-1.014** (-2.00)	0.03** (2.52)	0.009 (0.35)
Brand Image Score		0.041 (0.79)		0.005 (1.29)
Business Model Dummy*Brand Image Score		0.218*** (2.98)		0.006 (0.73)
Business Model Dummy*LOW		1.818 (0.63)		-0.247 (-1.64)
Business Model Dummy*MID		0.908* (1.72)		0.156*** (3.44)
Business Model Dummy*HIGH		4.949* (1.93)		0.085 (0.43)
ADJRSQ	0.07	0.07	0.13	0.13
Nobs	80,661	80,661	79,165	79,165
Nfunds	1,712	1,712	1,712	1,712
Panel B: T-test of Differences				
HIGH-MID		9.171*** (5.89)		0.581*** (4.63)
MID-LOW		-2.908** (-2.00)		0.01 (0.11)
HIGH-LOW		6.263*** (3.42)		0.591*** (4.13)
Business Model Dummy*(HIGH-MID)		13.212*** (5.71)		0.509*** (2.89)
Business Model Dummy*(MID-LOW)		-3.818 (-1.36)		0.413*** (2.71)
Business Model Dummy*(HIGH-LOW)		9.394*** (3.01)		0.922*** (4.43)

Table 7:

The Effect of Indirect Brand Proxies on the Flow-Performance Relationship

This table shows piecewise regressions on relative flow in panel A and on market share changes in panel B. We present five brand proxies: The number of funds within a fund family, the number of categories offered by the family, the Group size which is the natural LOG of the one month lagged TNA of all open-end funds of the Master Group in Europe, the number of star funds within a fund family, and a dummy variable which equals one if the fund family has one or more star funds. We calculate fractional ranks based on the previous twelve month excess returns for each month and category. FRANK is a continuous variable ranging from zero to one. The three relative performance variables are defined as: LOW=min(FRANK,0.2); MID=min(0.6, FRANK - LOW); HIGH=FRANK - LOW - MID. We include as (one month lagged) control variables the natural LOG age of funds, monthly expenses, the excess return standard deviation over the prior twelve months, fund size, the flow into the respective category, and lagged flow or market share changes. All variables are as defined in the data section. Every parameter estimate has its t-statistic below in parenthesis. We control for year and category fixed effects and cluster the standard errors at the fund level. *** denotes significance at the 1 percent, ** at the 5 percent and * at the 10 percent level.

Panel A: Piecewise Regressions on Relative Flow						
Proxy used:	Number of funds		Number of categories		Group size	
Variable	MODEL1	MODEL2	MODEL3	MODEL4	MODEL5	MODEL6
Proxy	0.012*** (3.16)	-0.004 (-0.3)	0.038*** (4.67)	-0.002 (-0.05)	0.0113 (1.48)	-0.019 (0.17)
LOW	5.727*** (4.88)	4.76** (2.29)	5.576*** (4.75)	4.50* (1.77)	5.822*** (4.96)	4.925*** (2.72)
MID	2.678*** (11.33)	2.272*** (5.07)	2.674*** (11.32)	1.986*** (3.52)	2.682*** (11.32)	2.595*** (6.72)
HIGH	13.35*** (11.25)	13.237*** (6.52)	13.486*** (11.37)	10.977*** (4.48)	13.296*** (11.21)	12.156*** (6.92)
LOW*Proxy		0.055 (0.69)		0.109 (0.65)		0.131 (0.73)
MID*Proxy		0.017 (1.05)		0.048 (1.34)		0.010 (0.28)
HIGH*Proxy		0.008 (0.11)		0.196 (1.23)		0.163 (0.85)
ADJRSQ	0.07	0.07	0.07	0.07	0.07	0.07
Nobs	80,661	80,661	80,661	80,661	80,661	80,661
Nfunds	1,712	1,712	1,712	1,712	1,712	1,712

Proxy used:	Number of star funds		Star fund family dummy	
Variable	MODEL7	MODEL8	MODEL9	MODEL10
Proxy	0.214*** (3.41)	-0.135 (-0.41)	0.882*** (4.13)	1.059 (1.52)
LOW	5.758*** (4.91)	5.378*** (4.30)	5.602*** (4.78)	7.924* (1.92)
MID	2.670*** (11.25)	2.590*** (10.02)	2.683*** (11.30)	2.086** (2.20)
HIGH	12.984*** (10.08)	12.796*** (8.89)	13.017*** (10.10)	7.392 (1.58)
LOW*Proxy		1.476 (0.77)		-2.492 (-0.58)
MID*Proxy		0.207 (0.66)		0.639 (0.65)
HIGH*Proxy		0.356 (0.24)		5.852 (1.20)
ADJRSQ	0.07	0.07	0.07	0.07
Nobs	79,215	79,215	79,215	79,215
Nfunds	1,709	1,709	1,709	1,709

Panel B: Piecewise Regressions on Market Share Changes						
Proxy used:	Number of funds		Number of categories		Group size	
Variable	MODEL1	MODEL2	MODEL3	MODEL4	MODEL5	MODEL6
Proxy	0.00 (1.04)	-0.001 (-0.69)	0.002*** (3.01)	-0.001 (-0.86)	-0.001 (-1.11)	-0.001 (-0.45)
LOW	0.024 (0.34)	0.095 (0.96)	0.014 (0.19)	0.098 (0.87)	0.031 (0.43)	0.051 (0.62)
MID	0.14*** (7.81)	0.072** (2.47)	0.14*** (7.82)	0.025 (0.72)	0.139*** (7.78)	0.130 (5.44)
HIGH	0.72*** (7.57)	0.476*** (3.34)	0.729*** (7.63)	0.25 (1.47)	0.715*** (7.55)	0.601 (4.56)
LOW*Proxy		-0.002 (-0.43)		-0.003 (-0.32)		-0.002 (-0.18)
MID*Proxy		0.003** (2.20)		0.008*** (2.93)		0.001 (0.46)
HIGH*Proxy		0.012* (1.90)		0.037*** (2.67)		0.016 (1.16)
ADJRSQ	0.13	0.13	0.13	0.13	0.13	0.13
Nobs	79,165	79,165	79,165	79,165	79,165	79,165
Nfunds	1,711	1,711	1,711	1,711	1,711	1,711

Proxy used:	Number of star funds		Star fund family dummy	
Variable	MODEL7	MODEL8	MODEL9	MODEL10
Proxy	0.001 (0.19)	-0.001 (-1.46)	0.012 (1.08)	-0.005 (-0.24)
LOW	0.037 (0.52)	0.049*** (0.68)	0.034 (0.48)	0.087 (0.94)
MID	0.137*** (7.68)	0.137*** (7.10)	0.137*** (7.66)	0.080** (1.96)
HIGH	0.797*** (7.50)	0.671*** (5.84)	0.797*** (7.50)	0.147 (0.77)
LOW*Proxy		-0.034 (-0.19)		-0.050 (-0.41)
MID*Proxy		0.004 (0.14)		0.060 (1.34)
HIGH*Proxy		0.282* (1.79)		0.677*** (3.12)
ADJRSQ	0.12	0.12	0.12	0.12
Nobs	77,763	77,763	77,763	77,763
Nfunds	1,708	1,708	1,708	1,708

Table 8: The Close Contest between Indirect Brand Proxies and Brand

This table shows piecewise regressions on relative flow in panel A and on market share changes in panel B. We present five brand proxies (from left to right): The number of funds within a fund family, the number of categories offered by the family, the Group size which is the natural LOG of the one month lagged TNA of all open-end funds of the Master Group in Europe, the number of star funds within a fund family, and a dummy variable which equals one if the fund family has one or more star funds. Brand is the natural LOG of the Brand Image Score. We calculate fractional ranks based on the previous twelve month excess returns for each month and category. FRANK is a continuous variable ranging from zero to one. The three relative performance variables are defined as: LOW=min(FRANK,0.2); MID=min(0.6, FRANK - LOW); HIGH=FRANK - LOW - MID. We include LOW, MID and HIGH in the regression. We include as (one month lagged) control variables the natural LOG age of funds, monthly expenses, the excess return standard deviation over the prior twelve months, fund size, the flow into the respective category, and lagged flow or market share changes. All variables are as defined in the data section. Every parameter estimate has its t-statistic below in parenthesis. We control for year and category fixed effects and cluster the standard errors at the fund level. *** denotes significance at the 1 percent, ** at the 5 percent and * at the 10 percent level.

Panel A: Piecewise Regressions on Relative Flow					
Proxy used:	Number of funds	Number of categories	Group size	Number of star funds	Star fund family dummy
Variable	MODEL1	MODEL2	MODEL3	MODEL4	MODEL5
Proxy	0.006 (1.40)	0.042*** (3.77)	-0.007 (-0.8)	0.151** (2.3)	0.764*** (3.51)
Brand	0.083 (1.61)	-0.023 (-0.41)	0.155*** (3.23)	0.095** (2.16)	0.093** (2.22)
ADJRSQ	0.07	0.07	0.07	0.07	0.07
Nobs	80,661	80,661	80,661	79,215	79,215
Nfunds	1,712	1,712	1,712	1,709	1,709
Panel B: Piecewise Regressions on Market Share Changes					
Proxy used:	Number of funds	Number of categories	Group size	Number of star funds	Star fund family dummy
Variable	MODEL1	MODEL2	MODEL3	MODEL4	MODEL5
Proxy	-0.000 (-1.37)	0.001 (1.59)	-0.003*** (-2.94)	-0.005 (-0.83)	0.003 (0.24)
Brand	0.012*** (2.73)	0.004 (0.94)	0.015*** (3.37)	0.008** (2.40)	0.007** (2.13)
ADJRSQ	0.13	0.13	0.13	0.12	0.12
Nobs	79,165	79,165	79,165	77,763	77,763
Nfunds	1,711	1,711	1,711	1,708	1,708

Table 9: Performance Persistence

This table shows monthly average alphas of a persistence test. We sort funds by Brand Image Score (horizontally) and their average alpha from January to December of the previous year (vertically) as calculated in equation (6). On the horizontal part of the table, quintile 1 has the inferior brand funds and quintile 5 has the superior brand funds. On the vertical part, quintile 1 has the funds with lowest previous year average alpha, and quintile 5 has the funds with the highest previous year average alpha. The column denoted by quintile 5-1 shows differences between quintile 5 and 1. We calculate monthly time series averages of cross-sectional averages within each brand quintile or intersection of quintiles. Every parameter estimate has its t-statistic below in parenthesis which has been adjusted for heteroskedasticity and autocorrelation according to the method of Newey and West (1987) using four lags. *** denotes significance at the 1 percent, ** at the 5 percent and * at the 10 percent level.

Monthly Alphas by Brand Image Score (hor.) and previous year average Alphas (vert.)						
	q1	q2	q3	q4	q5	q5-1
q1	-0.130 (-1.14)	-0.087 (-1.49)	-0.065 (-0.64)	-0.127 (-1.15)	-0.011 (-0.12)	0.119 (1.45)
q2	-0.123* (-1.82)	-0.144*** (-3.04)	-0.156*** (-3.59)	-0.122*** (-2.66)	-0.052 (-0.97)	0.070 (1.46)
q3	-0.099 (-1.59)	-0.156*** (-3.28)	-0.037 (-0.60)	-0.171*** (-3.67)	-0.058 (-0.97)	0.041 (1.29)
q4	-0.054 (-0.68)	-0.105** (-2.05)	-0.088 (-1.27)	-0.087* (-1.69)	-0.058 (-0.88)	-0.004 (-0.06)
q5	-0.114 (-0.86)	-0.072 (-0.76)	-0.021 (-0.22)	-0.079 (-0.76)	0.056 (0.48)	0.169** (2.27)
q5-1	0.017 (0.11)	0.015 (0.17)	0.044 (0.49)	0.048 (0.36)	0.067 (0.57)	

Appendix 1: Morningstar Categories in the Sample and TNA (in billions of Euros)

Morningstar Category	TNA	TNA	TNA
	Dec 2004	Jun 2008	Dec 2011
Asia ex Japan Equity	7.8	18.7	30
Asia-Pacific ex-Japan Equity	4.2	8.1	9.6
Asia-Pacific inc. Japan Equity	3.3	3.1	2.4
China Equity	2.7	9.2	10
Emerging Europe Equity	6.6	14.8	6.5
Europe Flex-Cap Equity	4.5	5.3	3.1
Europe Large-Cap Blend Equity	41.2	33	33.6
Europe Large-Cap Growth Equity	2.4	3.2	3.5
Europe Large-Cap Value Equity	12.3	21	13.3
Europe Small-Cap Equity	5	3.1	1.9
Eurozone Large-Cap Equity	20.8	18.9	12
Global Emerging Markets Equity	12.5	34.2	44.3
Global Flex-Cap Equity	2.2	2.2	2.5
Global Large-Cap Blend Equity	12.7	20.3	22.1
Global Large-Cap Growth Equity	4.4	4.8	3.9
Global Large-Cap Value Equity	10.2	13.9	14
Greater China Equity	1.9	3.9	5.3
India Equity	3	11.4	11.2
Japan Large-Cap Equity	17.9	15.6	9.5
Latin America Equity	2	15.3	13.7
Property - Indirect Global	0.2	1.6	2.1
Sector Equity Consumer Goods & Services	1.1	2.3	6.6
Sector Equity Ecology	0.1	4.1	2.3
Sector Equity Financial Services	1.8	1.6	0.8
Sector Equity Healthcare	2.7	2.4	2.9
Sector Equity Natural Resources	1.6	14.3	14.6
Sector Equity Technology	4.1	2.6	2.4
Switzerland Large-Cap Equity	1.5	1.6	1.3
US Large-Cap Blend Equity	27.4	14.4	19.1
US Large-Cap Growth Equity	4.5	7.4	15.5
Total TNA sample (1)	222.7	312.4	320.1
Total TNA Luxembourg UCITS: All (2)	929.3	1480.9	1655.5
Total TNA Luxembourg UCITS: Equity funds (3)	349.2	548.5	575.2
(1) / (2)	24.00%	21.10%	19.30%
(1) / (3)	63.80%	57.00%	55.70%
Source:			
(1) Lipper FMI			
(2) ALFI/CSSF			
(3) ALFI/CSSF			

Appendix 2: Ten FBF brand attributes that together form brand image

Brand attribute	Definition
Client-oriented thinking	Client-orientation captures whether a fund provider is client-centric or not (i.e., an attitude variable). Some groups are perceived to be more client-oriented in their approach than product-driven.
Appealing investment strategy	Brand attribute that focuses on the existence of any differentiating features of the investment strategy being offered but also incorporates the supplier's underlying corporate strategy.
Stability of investment management team	Investors are buying into an investment process and fund distributors want to be sure that the process is stable and will not deliver any unexpected surprises. The stability of the investment team is an important aspect of a stable process.
Keeping best informed	Information provision ensures a smooth day-to-day business relationship. It relates not only to appropriate provision but also to the accuracy and timeliness of information. Information provision is an important element for fund selection.
Quick adaptation to market evolution	Brand attribute that stands for the ability of an asset management company to take advantage of opportunities that arise from quick market shifts (i.e., whether the company can adjust quickly and/or launch new products and/or services).
Experts in what they do	Expertise is assumed if funds have a good track record and fund buyers are satisfied that the asset management company has a robust investment strategy. Reputation as expert is also included.
Key international player	Brand attribute that captures whether the asset manager is perceived to have more freedom in order to create products. It also stands for economies of scale and is strongly associated with high levels of professional strength.
Innovative power	Innovative power is viewed from two angles, specifically, product innovation and communication, relationship and contractual improvements.
Local knowledge	An understanding of the local issues that define and constrain investment behavior is an important attribute for all fund providers. This brand attribute measures the level of this understanding.
Solidity	Brand attribute that assesses the group's chances of surviving market cracks and tremors.