Fund Promotion and Individual Investors' Fund Flows*

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Abstract

Using data from an online broker we empirically evaluate individual investors' buying and selling decisions induced by the broker's promotion strategy. Every month the broker selects a fund of the month (FOM), generates attention by promoting it on the company's website and offers it at a substantially reduced front load fee. The broker's promotion strategy aims at generating a combined buying motive for the FOM triggered by attention and cost effects (a price promotion strategy). Using detailed individual portfolio holdings we are able to identify relevant drivers for in- and net-fund flows and to empirically separate the attention from the cost effects. Looking at the joint effect we find that investors strongly react to the promotion strategy. Relating attention activated flows to behavioral and cost activated flows to rational buying decisions it turns out that flows are driven by both, strong cost and attention effects. This leads us to conclude that investors decisions are governed by rational behavior jointly with behavioral biases, an argument that has not received a lot of attention in the literature.

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1 Introduction

Purchasing and selling decisions of mutual fund investors are the focus of a large body of theoretical and empirical research in asset management. One of the central results in this literature has for a long period of time been classified as an investment anomaly. Empirical studies found that fund flows are not driven by expected return and risk characteristics but by past performance instead (investors chase past returns), despite the fact that performance is not persistent and investment strategies of active asset managers do not systematically outperform the market. Berk and Green (2004) are the first to provide a rational explanation for this behavior. They show that if investors supply funds competitively to asset managers with differential abilities that are subject to decreasing returns to scale, investments will not earn excess returns in equilibrium but they must rationally be driven by past performance. While past performance is an important driver of fund flows, empirical research documents that aggregate flows are governed by a variety of additional fund characteristics including fees, taxes, a fund's family, and its attention generated by media or other advertising/promotion activities.

The empirical literature on fund flows almost exclusively concentrates on studying aggregate flows and hence explores the impact of average investor behavior on aggregate purchasing and selling decisions. This is mainly rooted in available data. While there exist large data sets on aggregate fund flows, portfolio buying and selling decisions at the individual investors' level are rarely available except for data originating from online brokers or local exchanges. Shu, Chiu, Chen, and Yeh (2004) are the first to use individual investor funds trading data from Taiwan. They study buying and selling decisions of investors separately and group investors according to their invested volumes and wealth levels. They find that investors buying large mutual funds are small-amount investors while those buying small funds invest large amounts. Small-amount investors buying large funds chase past performance but are more reluctant to invest in actively managed funds. Large-amount investors buying small funds seem to be unemotional buyers not chasing past performance but they are more likely to hold performance improving funds.

Barber, Odean, and Zheng (2005) also evaluate individual investors' fund flow decisions. Using a data set from an US online broker they explore how salient, attention grabbing information influences the purchase decisions. They find that investors are more sensitive to salient, in-your-face-fees (like front loads and commissions), than operating expenses. Moreover, investors buy funds that attract their information through exceptional performance, advertising and marketing. Ivkovic and Weisbenner (2009) use a similar data set at the disaggregate individual investors' level and identify three channels that determine fund flows. First, investors are reluctant to sell funds that have appreciated in value in the past. Second, they are willing to sell loosing funds. Third, investors are very sensitive to the fee structure of the fund, both in terms of operating and front load fees and they are sensitive to past performance in distinct ways. While inflows are driven by relative performance outflows are related to absolute performance. Outflows and hence new money seek the best performers in the field.

Karlsson, Massa, and Simonov (2007) analyze the impact of menu representation on the mutual fund choices of Swedish individual investors selecting funds for their retirement accounts. They document that individual investors' choices of mutual funds are a function of the way in which those assets are represented in the available menu. In particular, individuals prefer mutual funds that belong to fund categories which are over represented in the menu. They also show that exogenous changes of the fund menu strongly influences investors' fund choices. If representation of a fund category in the menu increases, investors raise their demand for funds belonging to this category.

The empirical literature on individual investment choices suggests that advertisements about funds, attention, and media coverage seem to be important characteristics that determine fund flows. While fund characteristics such as the fund family, fee structures, and past performance are consistent with rational investment decisions, attention grabbing events and media coverage can help to uncover potential behavioral biases. **?** show that media coverage affects how investors allocate money across funds. Their main finding, however, documents that past returns of funds attracts additional flows only if the funds were recently featured in the media. Kaniel, Starks, and Vasudevan (2007) also investigate the role of media coverage on investment decisions of mutual fund investors. They find that media coverage strongly affects fund flows consistent with attention and learning effects of individual investors. Phillips, Pukthuanthong, and Rau (2013) examine how uninformative advertising and the form of (performance) disclosure affects investors' fund flows. They find that investors are unable to differentiate between information about new and stale returns.

This paper studies individual investors' fund flows using data from an online broker that implemented a promotion policy to grab attention for funds traded through this platform. The promotion policy of the broker was running over several years and executed on a monthly basis. The fund promotion strategy consisted of two distinct actions. Every month the broker selected a fund of the month (FOM), generated attention for this fund by advertising it extensively on the company's website, and offered it at a substantially reduced front load fee to existing and new clients. The fee reduction corresponded to a 90% discount of the front load fee. This combined strategy (attention for the fund and front load fee reduction) allows us to quantitatively assess the effects of the promotion strategy composed of a fee reduction and attention grabbing activities, by empirically evaluating corresponding funds' in- and outflows. Using individual investors' transaction data we address the following empirical issues. To which extent is the promotion of the FOM through advertising activities and cost reductions an attention grabbing event in the terminology of Barber and Odean (2008)? What are the consequences of this event for the buying and selling decisions of individual investors and are funds of the month characterized by different buying decisions of investors compared to regular funds? Is it possible to determine a specific investor type who is particularly responsive to the fund of the month promotion and are investors with specific characteristics more prone to trading the fund of the month?

The promotion strategy of the online broker can be classified as a combined strategy that seeks to grab attention through advertising (attention effect) and to promote sales by reductions in front load fees (cost effect). Following the existing literature we relate fund flows caused mainly by an attention effect to a behavioral motive and flows originating form the cost effect to an outcome of rational fund investing (see Bailey, Kumar, and Ng (2011) for a detailed discussion about behavioral biases in fund investing). In addition to the effects caused by the promotion strategy we are interested in fund flow dynamics related to cost sensitivity, past performance and additional fund characteristics. In particular, we look at past performance of funds, operating and front load fees and fund family characteristics that are important drivers of flows even at the individual investors' level.

To our knowledge, this paper is the first one to empirically evaluate the importance of attention and promotion on individual investor fund flows,jointly. Our empirical analysis is based on mutual fund trades and flows initiated by individual investors. This is the main distinguishing feature of our paper to existing research that analyzes the effects of advertising and promotion at an aggregate fund level. Our paper is related to two strands of the literature, research which explores the influence of advertising on aggregate mutual fund flows, and empirical research that analyzes individual investors trading decisions of mutual funds.

The role of advertising on aggregate mutual fund inflows is studied by Jain and Wu (2000) who analyze the post-advertisement performance and fund flows to 294 mutual funds which are advertised in Barron's or Money magazine. They show that advertised funds generate more inflows than non-advertised funds with similar characteristics. They find that the promoted funds outperform benchmarks in the one year period before the advertisement, but are not able to show superior performance in the post-promotion period. Reuter and Zitzewitz (2006) find that fund recommendations in personal finance magazines do significantly increase flows into the advertised funds, but do not predict future performance. However, fund recommendations are correlated with past advertising expenditures by the fund, allowing for the conclusion that personal finance magazines bias their recommendations to favor advertisers. Gallaher, Kaniel, and Starks (2008) investigate the role of fund families and related family advertising on inflows into the family. They find that advertising, the choice of the distribution channel, and expense ratios have a significant effect on investors fund flows. Cronqvist (2006) makes use of content analysis and examines the role of informative advertising on investors' fund and portfolio choices. He finds most of fund advertising is uninformative but nevertheless does influence the fund flows. Higher advertising does not necessarily signal ex-ante exceptional manager skills because it is not associated with higher fund performance. Sosyura (2007) examines the effect of marketing on mutual fund portfolio choice. He argues that funds strategically select stocks with high media coverage as top positions which are widely reported. As small investors suffer from familiarity bias, this strategy increases fund inflows but has a negative effect on performance.

This paper is related to research which analyzes the impact of attention grabbing events on the stock investment behavior of individual investors. Barber and Odean (2008) test the hypothesis that individual investors are net buyers of attention grabbing stocks, i.e., stocks that are in the news or do have, for example, extreme one-day returns. They find that stocks which catch an investor's attention experience high abnormal trading volume that goes beyond the influence of traditional fund characteristics. Attention-driven buying is explained by the difficulty of an individual investor to overlook the huge universe of possible alternatives and therefore to choose funds rationally rationally only. They note that individuals face a tremendous search problem when buying stocks. Motivated by a paper of Sirri and Tufano (1998) who state that current media attention received by a fund decreases investors' search costs considerably, we are convinced that individual investors are confronted with a similar search problem when investing in mutual funds. Barber and Odean (2008) choose the inclusion of a stock in the news as an attention grabbing event which might alleviate the search problem. The attention grabbing event in our study is the selection of a fund as fund of the month and the opportunity to buy this fund at a substantial transaction cost discount.

The main results of the paper can be summarized as follows. The fact that a mutual fund becomes a fund of the month has a strong impact on fund flows. Using buy and sell imbalances we are able to show that flows into a fund of the month strongly shoot up by a factor between 4 and 5 during the promotion phase. This behavior is independent of investors' characteristics such as gender, age, education, and trading behvior. Investors with higher education, more experience and an eye on past performance are those who prefer to invest in the fund of the month. Decomposing the total promotion effect into attention and cost effects it turns out that investors are responsive to both effects. We interpret this result that the buying motive of individual investors is a complex combination of rational and behavioral motives. We use several empirical measures to decompose the promotion effect into attention and cost effects. Using fund flow regressions we find that individual investors' buying and selling decisions are mainly driven by past performance, low fees and the fund of the month characteristics. To better accommodate the two stage process of FOM choice and investors' fund flows we apply the Heckman correction for sample selection and repeat our analysis using a two stage regression model. The results found for the model with sample selection support our main findings.

The remainder of this paper is organized as follows. Section 2 introduces the data. Section 3 presents the methods and results of the empirical analysis. Section 4 concludes.

2 Data

The data used in this paper are provided by an Austrian online broker over the period September 2001 to July 2007. The data consist of several components, related to individual trades, investor characteristics, data on fund promotion, and fund characteristics and performance data.

Individual investors' accounts. We obtain all trades of $22,776$ investors in stocks, options, and mutual funds over the entire observation period on a daily basis. The investors are able to trade financial products in those asset classes worldwide, i.e. they are not restricted to local investment products. For our purposes, we extract purchases and sales of mutual funds from the original trade file. We end up with $111,860$ distinct trades to be analyzed. For each trade, we obtain the following information: the trade date, a unique identifier of the traded security, the quantity traded, the trade price (before transaction costs), a buy-sell indicator, the currency of the trade, and the relevant exchange rate in case the security has been traded in another currency than Euro. Most of our analysis is based on a subsample of 55,887 discretionary trades. For this subsample, we exclude transactions that are transfers (at zero price), transactions that are offset the same day at the same price (most likely cancelations) and fund savings plans. The latter are identified as non-integer trade amounts in fund shares, as savings plans typically involve a fixed, e.g. monthly, euro amount that is invested in a varying number of shares traded month by month. Purging the transactions data in this way reduces the number of transactions by 50%. However, the transaction volume in Euro is reduced by 26% only, due to exclusion of predominantly small trades and zero cost transactions.

Socio-demographic characteristics. We have a dataset available that contains socio-demographic characteristics of individual investors, like age, gender, nationality and education. The academic degrees awarded by Austrian universities and in neighbor countries differ according to the program and the major chosen at university. We can infer from the degrees whether an investor has graduated from an engineering program (*Diplom-Ingenieur*), a business or economics program (*Diplom-Kaufmann, MBA*), or a doctoral program (*Dr.*), or has obtained the equivalent of a master's degree (*Magister*). Due to a unique account identifier, we are able to match the demographic data and the trading histories unambiguously. In addition, we construct two dummy variables related to individuals indicating whether an investor ever has traded options and stocks respectively. Table 1 presents summary statistics for the investor base. About a third of the investors trades in mutual funds, i.e. 7,628 investors. Only 1,261 of these investors are female. 2,708 are known to have an academic degree. Table 2 presents more details about the subset of mutual fund investors. 83% of these investors are male, more than half also trade options and more than 80% trade equities. The average age of the investors is 39 years. They make on average 15 transactions of approximately €3,500 per year.

Table 1: Investor Base

	All Traders	Equity Traders	Mutual Fund Traders
All Investors	22,776	16,708	7,628
Female	3,528	2,511	1,261
Male	19,248	14,197	6,367
No Degree	15,901	11,609	4,920
Degree	6,875	5,099	2,708
Female and No Degree	2,708	1,948	946
Female and Degree	820	563	315
Male and No Degree	13,193	9,661	3,974
Male and Degree	6,055	4,536	2,393

Table 2: Portfolio and investor characteristics

Characteristic	All Traders	Degree	No Degree
Proportion Option Trader	52.69%	52.51%	52.78%
Proportion Equity Trader	83.63%	83.49%	82.15%
Proportion Male	83.47%	88.37%	80.77%
Average Age	39.20	39.32	39.13
Average Number Trades	14.66	16.53	13.64
Median Number Trades	5	5	4
Average Trade Size	€3,588	€4,489	€3,257

Fund promotion. The third subset of data provides information on a promotion strategy which the online broker has been running from November 2005 to July 2009, referred to as the *fund of the month* promotion. Each month, the company advertises a specific fund which may be bought by its clients at a substantial price discount. During the promotion period, the front load fee of the *fund of the month* is reduced by 90 percent. In addition, the fund is prominently featured on the website of the brokerage company and account holders are informed through e-mails. While the promotion of the fund of the month was initiated in November 2005 and ended in July 2009, our data set only runs through July 2007. Therefore we work with 21 fund of the month events and corresponding mutual funds that were selected as the *fund of the month*. Table 3 demonstrates that the set of funds selected for the promotion strategy leans towards equity funds and funds originating from Luxembourg. There seems, however, to be no bias towards a specific asset management firm as the 21 funds are managed by 14 different asset managers.

Additional data sources. For funds held in any brokerage account during at least one point in time, we obtain fund characteristics including fund ratings and information on fees from Morningstar. Furthermore, we download data on net asset values and performance from Thomson Reuters Datastream.

Table 3: Descriptive statistics of the FOM

Fund Types	Equity	Fixed Income	Commodities	Other
No of Funds	15	1	1	4
Domicile	Austria	Luxembourg	Ireland	Germany
No of Funds	3	15	2	1
Total				
No of Funds		21		
No of AM Companies		14		

3 Individual Investors' Fund Flows

The central theme that we explore in this paper is how a broker's promotion strategy affects individual investors' fund flows. The answer to this empirical problem seems to be obvious, as the substantial reduction in front load fees (the cost effect of the promotion strategy) has to attract money from investors. As the promotion strategy, however, is composed of a cost and an attention effect our interest is not only centered around quantifying the total effect but identifying and measuring both sub-effects. To achieve this we use a three step approach. In a first step we measure the flow effects triggered by fund promotion in total. We make use of buy and sell imbalances to report a simple descriptive measure of additional flows if a fund becomes the *fund of the month*. The measure of buy and sell imbalances has been introduced by Barber and Odean (2008) to study attention effects of stock investments. This measure can easily be applied and has a very intuitive economic interpretation. If an event causes a substantial increase in fund inflows and no outflows the buy and sell imbalance has to converge to one. Since it is the ratio of flows triggered by the event to total flows it reflects the percentage change of flows caused by the event. In case an event triggers only outflows the measure converges to -1. The distinguishing feature of our analysis relative to Barber and Odean (2008) is the fact that we do not need to find a proxy for the attention event but are able to identify it with an observable event.

Quantifying buy and sell imbalances for funds that are FOM and comparing them to those that never have been FOM identifies the total effect associated with fund promotion. To isolate the attention from the cost effect we make use of the following identification strategy. If a fund receives a lot of attention through advertising, it is to be expected that the corresponding attention effect on inflows carries over to the subsequent months for which the fund has been the FOM. This is not true for the cost effect. Immediately after the one month period is over, the front load fees of the preceding FOM are back to their original levels. As a consequence flows triggered by the cost effect should be back to normal levels immediately after the month is over. Hence, looking at fund flows after a fund has been the FOM helps us to identify which of the two effects is stronger. Although this logic provides insights into cost and attention effects separately it does not fully discriminate between the two. Fund flow regressions can be used to explore these issues further. We specify a simple regression model that includes an interaction term of FOM and front load fees that can be used to quantify the size of the cost and the attention effect.

In a second step we conduct an econometric analysis in which we quantify the relationship between fund characteristics and fund flows. Guided by the theoretical foundations introduced by Berk and Green (2004), we use past performance and cost characteristics as drivers of fund flows. Additionally, we introduce a dummy for the FOM, use fund size, its Morningstar ranking, and its age as explanatory variables to explain fund flows. These estimates help us to empirically evaluate if individual fund flows are driven by similar forces than aggregate flows are. As mentioned in the preceding paragraph we can use these estimates also to quantitatively decompose the attention and the cost effects. If investors are very cost sensitive we expect that both front load and operating fees need to be significant flow drivers.

We can use fund flow regressions to get more detailed insights into which of the two effects (attention and front load fee reductions) dominates. For that purpose we estimate flow equations in which on top of standard fund characteristics we include a dummy variable for the *fund of the month*, the official front load fees and an interaction term that simultaneously accounts for the FOM and the cost reduction. If the dummy for FOM and the official front load fees in this regression are statistically significant we conclude that the promotion together, i.e. the *fund of the month* event, is the main fund flow driver. If the interaction term between FOM and front load fee reductions is statistically significant we are able to quantify how large the cost effect conditional on a FOM is. We use these estimates to disentangle the cost and the attention effects.

In a third step we analyze characteristics of investors who buy the *fund of the month*. Employing a standard probit model we use the level of education, the age, the experience, the importance of past performance, and investments in other asset classes (stocks and options) as investor characteristics. Finally we report estimates about the additional returns investors generated for holding the *fund of the month*.

3.1 Fund of the Month: Total Effects

To study the buy and sell imbalances of individual investors triggered by the broker's promotion strategy, we make use of the concepts introduced by Barber and Odean (2008) who study the effect of attention grabbing news on the stock buying behavior of investors. We intend to determine the extent to which individual investors are net buyers of the fund of the month. Each month, we partition buy and sell transactions into those belonging to the fund of the month, and those related to all other funds. We then calculate buy and sell imbalances based on the value of funds traded (value imbalance), the number of fund shares traded (number imbalance), and the number of related transactions (transaction imbalance).

The value imbalance VI_{pt} for partition p and month t is defined as follows:

$$VI_{pt} = \frac{\sum_{i=1}^{n_{pt}} VB_{it} - \sum_{i=1}^{n_{pt}} VS_{it}}{\sum_{i=1}^{n_{pt}} VB_{it} + \sum_{i=1}^{n_{pt}} VS_{it}},$$

where p is either the partition containing the fund of the month or the one containing all other funds, n_{pt} is the number of funds in partition p during month t, VB_{it} is the value of all fund purchases and and VS_{it} the value of sales of fund i during month t respectively.

The number imbalance NI_{pt} for partition p and month t is calculated as follows:

$$NI_{pt} = \frac{\sum_{i=1}^{n_{pt}} NB_{it} - \sum_{i=1}^{n_{pt}} NS_{it}}{\sum_{i=1}^{n_{pt}} NB_{it} + \sum_{i=1}^{n_{pt}} NS_{it}},$$

where NB_{it} and NS_{it} are the number of shares of fund i purchased and sold during month t, respectively. The transaction imbalance TI_{pt} for partition p and month t is calculated as follows:

$$TI_{pt} = \frac{\sum_{i=1}^{n_{pt}} TB_{it} - \sum_{i=1}^{n_{pt}} TS_{it}}{\sum_{i=1}^{n_{pt}} TB_{it} + \sum_{i=1}^{n_{pt}} TS_{it}},$$

where TB_{it} and TS_{it} are the number of buy transactions and sell transactions of fund i during month t, respectively.

Table 4 shows value imbalances for the fund of the month as well as all other funds traded, presented for different investor groups distinguished with respect to their socio-demographic attributes. The results are displayed for all investors, male investors, female investors, individuals with university degree and those without degree. We observe an immense responsiveness of individual investors to the *fund of the month* promotion strategy: Investors are almost exclusively net buyers of funds which are promoted as the *fund of the month* while they are weak net buyers for those which are not. The average value imbalance for all investors is 90.11% for the *funds of the month*, and 30.54% for all other funds. Value imbalances for all investors calculated for the *funds of the month* one month prior to becoming the FOM are 20.82%. Among the different investor groups considered, investors with no university degree are the strongest net buyers of the fund of the month (VI: 93.08%), followed by female investors (VI: 91.17%), investors who also trade options (VI: 90.65%), and male investors (VI: 89.83%). For all no FOM funds, the value imbalance is 32.43% for all female investors, 33.69% for investors with degree, 30.09% for male investors, 25.24% for investors who also trade options, and 29.25% for investors who in addition trade stocks.

Table 4: Value imbalances for different investor types

	FOM	FOM.L1	no FOM	previous
All investors	90.11	20.82	30.54	−37.27
Male	89.83	21.04	30.09	−40.66
Female	91.17	14.32	32.43	−15.26
Degree	88.62	20.05	33.69	−39.20
No Degree	93.08	28.63	28.32	−35.66
Option Trader	90.65	−4.58	25.24	−42.55
Equity Trader	89.63	18.97	29.25	−38.30

Table 5 reports number imbalances for funds that have been selected to be a *fund of the month*, and those which have not. We find that buy and sell imbalances are at a similar levels when number imbalances are used. They are at 90.10% for the *fund of the month* and all investors, and 27.97% for all other funds. Investors without degree are most responsive to the fund of the month promotion with a number imbalance equal to 93.06%, followed by female investors (NI: 91.12%), option trades (NI: 90.61%), male investors (NI: 89.83%) and investors who also trade stocks (NI: 89.62%). For all other funds, the number imbalance is on average 27.95% for all investors, 32.32% for investors with degree, 28.30% for male investors, 27.16% for investors who also trade equities, and 25% for investors without degree.

Table 6 shows transaction imbalances which are calculated by aggregating the number of purchases and sales. We observe similar magnitudes as for value and number imbalances. All investors are strong net buyers of the *fund of the month* with a transaction imbalance of 95.03%. Investors with degree respond most sensitive to the fund of the month promotion (TI: 95.40%), followed by male investors (TI: 95.14%), investors who also trade stocks (TI: 94.82%), and investors with no university degree (TI: 92.56%).

To sum up we find that all investor types react very strongly to the

Table 5: Number imbalances for different investor types

	FOM	FOM.lag1	no FOM	previous
All investors	90.10	20.96	27.95	−32.56
Male	89.83	21.16	28.30	−37.12
Female	91.12	14.65	24.67	−8.91
Degree	88.60	20.15	32.32	−38.15
No Degree	93.06	28.71	25	−30.69
Option Trader	90.61	−4.43	20.10	−41.82
Equity Trader	89.62	19.10	27.16	−32.22

Table 6: Transactions imbalances for different investor types

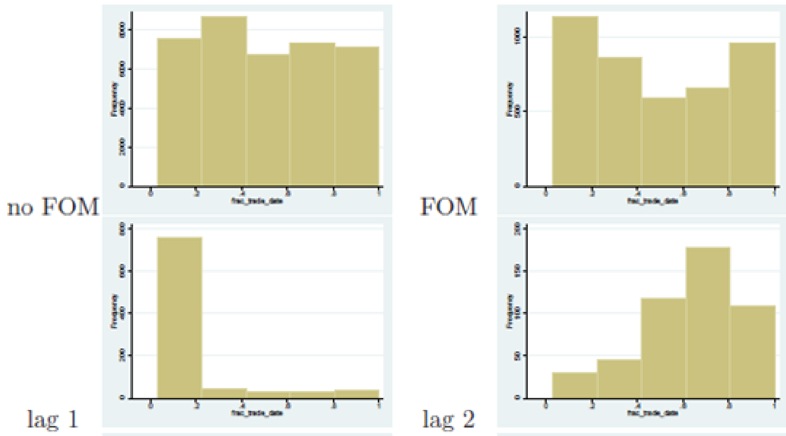
	FOM	FOM.L1	no FOM	previous
All investors	95.03	29.70	42.26	−10.94
Male	95.14	28.03	42.64	−11.70
Female	93.03	26.74	40.24	−7.28
Degree	95.40	26.39	43.07	−6.99
No Degree	94.67	29.23	41.82	−13.78
Option Trader	93.50	8.10	36.13	−22.36
Equity Trader	94.82	31.14	40.51	−12.90

broker's promotion strategy. Buy and sell imbalances more than double from average levels prior to the FOM period while no FOM stay at their original levels.

3.2 Fund of the Month: Cost and Attention Effects

The descriptive statistics from the preceding section already demonstrated the importance of the broker's promotion strategy for fund flows. In this subsection we are interested in how the timing of trades vary across different funds. For that reason we divide a month in five subperiods of equal length and report the trading activities in each sub-period. We look at four different fund types. The *funds of the month*, funds that have been FOM in the preceding month, and two month ago and all other funds. Figure 1 reveals very interesting insights. While all funds that are not FOM exhibit equal trading activities across the five subintervals the FOM is characterized by U-shaped timing. This implies that investors strongly demand the fund of the month at the beginning of the promotion period, while effects slow down during the middle of the month but pick up again at the end of the month. Hence the promotion effect is strongest at the beginning and at the end of the month when a fund is FOM and declines substantially during the second and third quarter of the month. Relating this to attention effects it is fair to say that attention is strongest when a fund becomes the FOM, declines thereafter and picks up again when the fund is about to loose its FOM status again.

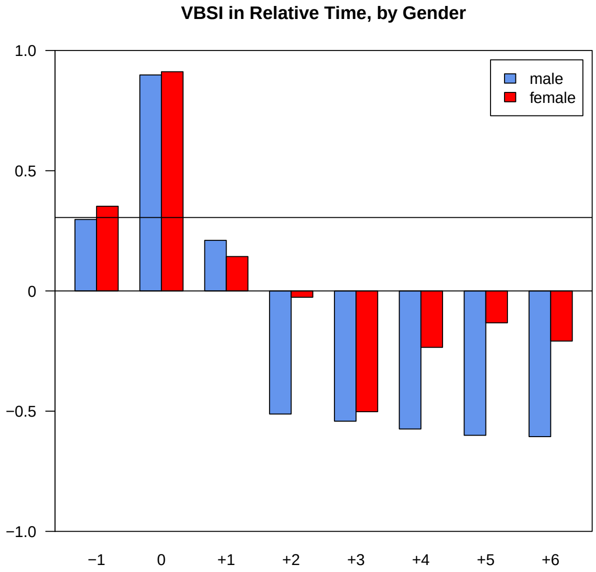
Figure 1: Timing of purchases



Next, we isolate the attention from the cost effect. If a fund receives a lot of attention through a campaign, it seems to be natural that we observe a strong attention effect resulting in higher inflows. Attention, however, implies that the fund moves onto the radar screen of investor and stays there for some time. This implies that strong attention effects should not only be present during the period when a fund is FOM but should possibly carry over to subsequent months for which the fund has ceased to be FOM. This cannot be true for the cost effect. Immediately after the one month period is over, the front load fees of the recent FOM are back to their original levels. As a consequence flows triggered by the cost effect should be back to normal immediately after the month is over. Hence, looking at fund flows prior and after a fund has been the FOM can reveal valuable information when it comes to identify cost and attention effects.

Figures 2, 3, and 4 record value imbalances for different investor types for the *funds of the month* across eight different months, one month prior to the

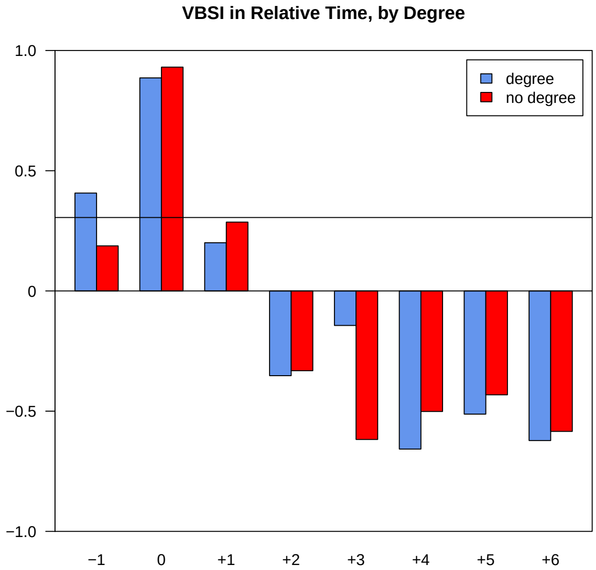
Figure 2: Subsequent value imbalances, by gender



FOM period, the FOM period and six lagged periods after a fund has been a *fund of the month*. While all value imbalances shoot up substantially when the FOM period starts, they are all back to levels below the initial one in the period immediately following the FOM, irrespective of the type of investor (male, female, investors with and without university degree, investors who additionally trade stocks or options). This result is also confirmed by Figure 1. As a consequence the total promotion effect disappears immediately after the FOM period and turns negative in the subsequent periods. The negative value imbalances imply that investors start to sell the *funds of the month*. Using the argument from above we conclude that if there is an attention effect it does not go beyond the event period. This is a strong sign for the cost effect to be dominant. We need to stress the point, however, that the dynamic value imbalances alone cannot be used to discriminate between the attention and cost effects.

This insight is strongly supported by Figure 5. The figure exhibits aggregate holdings of the FOM under the assumption that they are normalized to one during the FOM period. We see that holdings prior to the FOM period are very low, then they shoot up to their normalized levels and decline immediately after that period. This behavior strongly supports the hypothesis that the total promotion effect is dominated by the cost effect and attention

Figure 3: Subsequent value imbalances, by degree



plays a minor role.

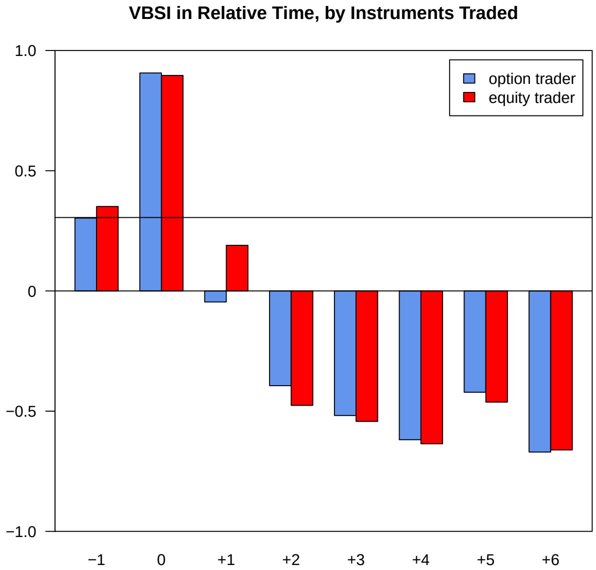
To quantitatively support the results based on descriptive measures we run a simple fund flow equation to find out about the importance of the attention and the cost effects. For that purpose we specify the following fund flow equation.

$$Flow_t = \alpha + \beta FOM_t + \gamma FLF_t + \delta FLF_t \times FOM_t + \pi Per_t + \omega Char_t + \epsilon_t \quad (1)$$

$Flow_t$ measures inflows and onetflows for a given period, FOM_t is a dummy variable for the fund of the month, FLF_t is the official front load fee of the fund, $FLF_t \times FOM_t$ captures the reduced front load fees in case a fund is FOM, Per_t is the past performance of a fund, and $Char_t$ is a set of additional fund characteristics such as size, age, minimum initial investment, rating, etc.

The results of this regression can be found in Table 7. We find that the FOM variable has a statistically significant effect on inflows and netflows. Fund flows increase in case a fund becomes a fund of the month. Fund flows decrease if the net expense ratio of the fund increases. Fund flows are, however, not sensitive to management fees. The results is opposite to what Barber and Odean (2008) find. Flows strongly react to front load fees and the interaction of front load fees and being an FOM. This confirms the result that the driving force behind the flow effects of the promotion strategy is the cost effect. Investors do, however, also react to past performance.

Figure 4: Subsequent value imbalances, by instruments traded

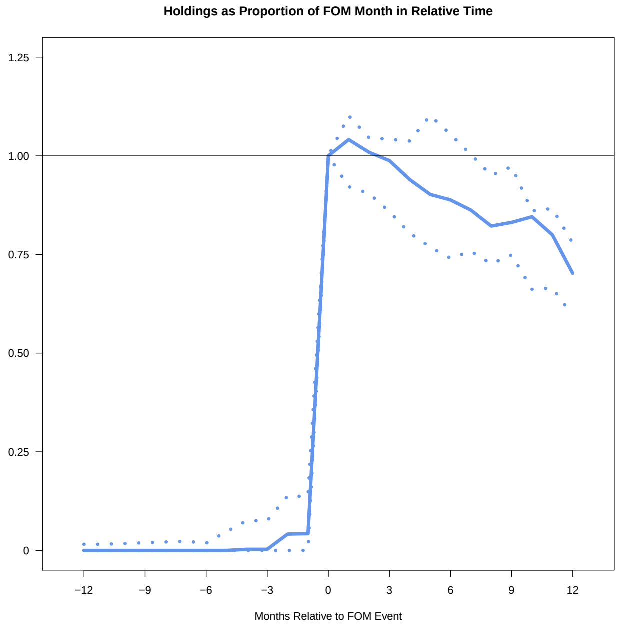


3.3 Fund Flows: Structural Analysis

In the preceding subsections we have analyzed fund flows by applying buy and sell imbalances as simple descriptive statistics and by using a standard fund flow regression. Next, we want to explore fund flows in more detail by extending the regression analysis. Hence, we conduct econometric tests and quantify the impact different explanatory variables have on fund flows. As already argued in the introduction to his chapter past performance and the fee structure are theoretically well grounded as explaining fund flows. Additionally we use the fund of the month characteristic, the size of the fund, its age, and its minimum investment as exogenous variables to explain fund flows. As pointed out above Table 7 presents results for two alternative specifications, one with inflows and the other one with net-flows as endogenous variables. Consistent with many existing empirical studies we find that long term past performance significantly drives fund flows as does the fund of the month, net expense ratio, and the interaction of the reduced front load fee with the FOM dummy. Management fees, fund size, fund age and minimum initial investments are not statistically significant.

The important results in Table 7 are the strong significance of the FOM dummy, the interaction of the official front load fee with the FOM dummy

Figure 5: Aggregate holdings relative to FOM event month



and the official front load fee. The economic implication of the statistical significance of the interaction with the official front load fee and the FOM is that the cost effect of the promotion strategy is important and dominates the total FOM effect in terms of its total size. As a consequence, we conclude that the total promotion effect is strongly driven by the cost effect. While the attention effect does plays a significant role its size is substantially smaller than that of the cost effect. These findings are consistent with our analysis based on the value imbalances presented above.

Finally Tables 8 and 9 check robustness of our results by estimating a version that applies a Heckman correction for the sample selection by identifyng the variables that are responsible for the choices of the individual *funds of the month*. The estimation of the selection equation is carried out with two alternative approaches. In the first approach, Table 8, the selection process is estimated as a single linear regression with top performance as the relevant explanatory variable. In the second approach we estimate a two stage model in which the selection equation is estimated in the first stage and a fund flow equation in the second stage. The results of both regressions support our findings.

3.4 What Characterizes a Fund of the Month Investor?

In the preceding analysis we have focused on what determines fund flows. In this subsection, we present a logit regression analysis in a panel setting to analyze the decision who trades the *fund of the month*. Each month over the observation period, we check whether a particular investor is or is not responding to the fund of the month promotion. If the investor trades the fund of the month, the variable *FOM Trader* takes value 1, and value 0 otherwise. We get a time series of this binary variable for each investor and use it as dependent variable. The independent variables consist of investor-specific characteristics as well as information regarding the fund of the month: *Lagged FOM Performance* describes the return of a specific fund of the month over the previous month (before promotion started). *Absolute Fee Reduction* refers to the difference between the standard front-load fee and the reduced front-load fee during the promotion period for a specific fund of the month. *Equity Trader* and *Option Trader* are binary variables indicating whether the investor trades stocks or options in addition to mutual funds, respectively. *Male* is a gender dummy variable. *Age* refers to the age of a particular investor for each observation month. *Degree, Econ, Tech, Long_Educ* and *Mag* refer to the education of the investor. The first variable indicates in general whether a trader has a university degree. The other variables give information about specific degrees and backgrounds of the investor. We add two variables that measure the trading activity of the investor. *Average Turnover* is investor-specific and displays the average total turnover rate for a particular investor. *Monthly Turnover* is both investor-specific and month-specific and is given by the total turnover rate for a particular investor over a particular observation month.

Table 10 shows the coefficients resulting from these panel logit regressions. A favorable recent performance of the fund as well as the size of the front-load fee reduction have a positive impact on the decision to buy the fund of the month. In model (1), the odds of buying the fund of the month increase by a factor of $e^{(5.4083 \cdot 0.01)} = 1.06$ if the 1-month lagged return of the fund is raised by 1 percent, and by a factor of $e^{(35.2226 \cdot 0.01)} = 1.42$ if the fee reduction goes up by 1 percent. Diversification across asset classes increases the likelihood of being a FOM trader. The odds of buying the fund of the month go up by a factor of $e^{0.8577} = 2.36$ if the trader invests in stocks besides mutual funds, and by a factor of 1.44 if she trades options in addition to mutual funds. For every year the investor is older, the odds of investing in the fund of the month increase by a factor of 1.03. Investors with a degree are more likely to react to the fund of the month promotion: the odds of being a

FOM trader go up by a factor of 1.35. If the degree variable is split up into different backgrounds in model (2) in Table 10, we observe that each specific degree has a positive impact on the decision to trade the fund of the month, with the "Econ"investors being most responsive to the promotion strategy. Similarly, investors who are on average more active over their trading life are more likely to react to the promotion strategy. If the average turnover rate goes up by 1 percent, the odds of being a fund of the month trader increase by a factor of 1.02. However, the investor turnover rate during a specific promotion month does not influence the decision to buy the fund of the month.

3.5 Do Investors Benefit From Trading the FOM?

In the last subsection, we present a basic performance analysis for different trader groups. To calculate the performance of an individual investors mutual fund portfolio, we adapt the approach by Barber and Odean (2000), who calculate the performance of the stock portfolio of private investors. We make use of detailed transaction data and information on fees. As data on management fees are not available, we include the front-end load fees only when calculating net returns. We report gross and net of fees performance with and without risk adjustment. We report the performance measures for various investor groups that are formed according to the general fund of the month trading behavior of the sample investors as well as according to the number of fund of the month purchases. In detail, we present gross returns before transaction costs, net returns including actual front-load fees and net returns which are computed with non-reduced front-load fees only and neglect the fund of the month promotion. We also include the differential between these return measures. We call the difference between the net returns considering and neglecting the fund of the month promotion *FOM Differential* and use it to determine the actual performance impact of the promotion for the individual investor. We also calculate various alphas by regressing the monthly excess mutual fund portfolio return on the monthly excess return of the Austrian Traded Index (*Alpha ATX*), on the monthly excess return of the MSCI World Index (*Alpha MSCI*), and on the monthly excess return of a global market factor and a global HML factor as proposed by Fama and French (1998). We have decided to apply different market indexes because the choice of the correct benchmark is not clear in our setting. Although the investors are clients of an Austrian online broker, they are not necessarily Austrians themselves and are not limited to trading Austrian-domiciled mutual funds only.

Figure 6: Investor performance.

Trader Type	Gross (1)	Net with FOM Promotion (2)	Gross minus Net (1)-(2)	Net without FOM Promotion (3)	FOM Differential (2)-(3)	No. Investors
All Traders	0.0147***	0.0123***	0.0025***			7217
(a)	(72.22)	(57.52)	(34.47)			
FOM Traders	0.0176***	0.0147***	0.0029***	0.0147***	0.0001***	1874
(b)	(58.04)	(45.51)	(23.81)	(45.29)	(9.75)	
Never FOM Traders	0.0137***	0.0114***	0.0023***			5343
(c)	(54.29)	(43.23)	(26.75)			
Difference	0.0039***	0.0033***				
(b) - (c)	(9.86)	(7.98)				
First Time FOM Buyers	0.0176***	0.0152***	0.0024***	0.0152***	0.0000***	1630
(d)	(55.3)	(45.43)	(21.64)	(45.35)	(6.96)	
Rebuy FOM Traders	0.0172***	0.0104***	0.0068***	0.0100***	0.0003***	244
(e)	(38.00)	(17.94)	(15.57)	(17.42)	(9.66)	

Table 6 presents the return measures for all sample investors who trade mutual funds (*All Traders*), investors who include the fund of the month at least once in their portfolio (*FOM Traders*), individuals who never buy the fund of the month (*Never FOM Traders*), investors who buy a fund of the month with no existing holdings of the fund *First Time FOM Traders* and investors who have holdings of a fund when it becomes the fund of the month and rebuy more shares during the promotion period (*Rebuy FOM Traders*). We find that the average mutual fund investor achieves a monthly gross portfolio return of 1.47%, and a net return of 1.23%. Traders who invest in at least one fund of the month over the observation period represent 26% of the sample investors. They perform better than investors who never respond to the fund of the month promotion (gross: 1.76% vs. 1.37%; net: 1.47% vs. 1.14% respectively). Looking at the *FOM Differential*, we observe that the performance impact of the transaction cost reduction is relatively small with 1 basis point per month.

Table 7 presents gross and net mutual fund portfolio returns for FOM traders according to the number of funds of the month that are included in their portfolio. We observe that the majority of investors (56.14%) buys the fund of the month just once over the observation period. 18.99% of the FOM traders buy two funds of the month, 8.80% invest in three, 5.44% in four, and 10.62% in more than four funds of the month. We find that investors who buy one fund of the month achieve a monthly gross mutual fund portfolio return of 1.72% (see column (1)). The gross return pattern according to the number of funds of the month bought is hump-shaped. The gross return for investors with two, three, four or more than four fund of the month purchases is 1.75%, 1.96%, 1.80%, and 1.81% respectively. Similarly, the net

Figure 7: Investor performance by number of FOMs traded

No. FOM Purchases	Gross (1)	Net with FOM promotion (2)	Gross minus Net (1) - (2)	Net without FOM promotion (3)	FOM Differential (2) - (3)	No. Investors
1	0.0172***	0.0143***	0.0029***	0.0143***	0.0000***	1052
	(37.24)	(29.17)	(16.74)	(29.05)	(-5.47)	
2	0.0175***	0.0149***	0.0026***	0.0148***	0.0001	356
	(26.84)	(21.73)	(9.98)	(21.64)	(0.02)	
3	0.0196***	0.0161***	0.0034***	0.0161***	0.0001***	165
	(26.65)	(19.85)	(8.56)	(19.73)	(3.57)	
4	0.0180***	0.0155***	0.0025***	0.0154***	0.0001***	102
	(22.73)	(17.83)	(6.02)	(17.63)	(3.56)	
More than 4	0.0181***	0.0150***	0.0032***	0.0149***	0.0001***	199
	(33.86)	(24.20)	(9.97)	(23.99)	(6.24)	

return calculated with actual frontload fees (column (2)) for one, two, three, four, or more than four fund of the month purchases is 1.43%, 1.49%, 1.61%, 1.55%, and 1.50% respectively. The difference between gross and net returns in column (3) is always positive and statistically significant. However, the performance impact of the FOM promotion measured by the FOM differential is minimal across all observations and yields on average 1 basis point per month.

4 Conclusions

This paper empirically analyzes the impact of a promotion strategy on the mutual fund investments of individual investors. We use data from an online broker that include the mutual fund trades of private investors on a daily basis as well as information on a monthly promotion strategy which advertises a specific fund at a front load fee discount.

Our main results are as follows. First, we show that the individual trades in our sample display an immense responsiveness to the fund of the month promotion. The average investor is more likely to be a net buyer of funds which are promoted than of all other funds traded in the sample. Second, we show that individuals are more likely to trade the fund of the month if it has achieved a good recent track record and if the size of the fee reduction increases. Investors who trade options and stocks in addition to mutual funds and hold a university degree are more likely to buy the fund of the month promotion. Third, we find that investors who trade the fund of the month achieve a higher net performance than investors who never respond to the fund of the month promotion. However, the reduced front-load fee of the fund of the month has small long-term performance consequences for the average investor.

Table 7: Flow regressions

This table reports the results from pooled regression models explaining fund flows. The dependent variable *inflows* is the monthly Euro inflow into a given fund, *netflows* is the difference of Euro inflows and Euro outflows. *FOM* is a dummy variable that takes the value one if a fund is fund of the month and zero otherwise, and enters the regression with current, lagged and leading values. *Number Holdings* is the number of positions a fund holds. Further explanatory variables are *net expense ratio*, the annualized *managmeent fee*, the *official front load no FOM* (for fund other than the FOM). *Interaction Actual FL FOM* is the reduced front load for funds of the month. Further lagged values of the funds *1 month performance*, *12 month performance*, and a dummy that takes the value of one if the 12 month performance of the fund was in the top decile among all funds in the dataset in the previous month. *Total client holdings* is the aggregated value of fund shares held by all clients of the brokerage. *Fund age* is measured in years. *Min initial investment* is the minimum investment amount required for first time purchases. t-statistics are given in parenthesis.

	Dependent variable:	
	inflows	netflows
FOM (1 month lead)	0.976	0.688
	(0.98)	(0.68)
FOM	566.792***	556.532***
	(40.49)	(39.09)
FOM (1 month lagged)	6.152***	$-$2.285**
	(6.15)	(-2.24)
Previous FOM	0.443	$-$5.717***
	(1.56)	(-19.85)
Number holdings	$-$0.0002**	$-$0.00003
	(-2.18)	(-0.33)
Net expense ratio	$-$0.162***	$-$0.102***
	(-6.68)	(-4.15)
Management fee	0.051	$-$0.099**
	(1.22)	(-2.34)
Official front load noFOM	$-$5.783**	4.541*
	(-2.51)	(1.93)
Interaction Official FL FOM	$-$183.270***	$-$180.184***
	(-32.47)	(-31.38)
1 month performance (lagged)	1.277***	3.366***
	(3.03)	(7.86)
12 months performance (lagged)	2.062***	0.946***
	(17.88)	(8.06)
Top performance decile (lagged)	0.947***	0.583***
	(15.23)	(9.22)
Total client holdings (lagged)	0.00005***	$-$0.00002***
	(13.85)	(-5.92)
Fund size	$-$0.000	0.000
	(-0.09)	(0.29)
Fund age	$-$0.001	0.0003
	(-0.46)	(0.17)
Min initial investment	$-$0.000	$-$0.000
	(-0.61)	(-0.70)
Constant	0.397***	0.175***
	(6.44)	(2.80)
Observations	42,372	42,372
R^2	0.277	0.252
Adjusted R^2	0.277	0.251
F Statistic (df = 16; 42355)	1,015.584***	889.615***
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 8: Probit explaining FOM selection

This table displays a probit model explaining fund of the month selection. The dependent variable *FOM* has value one if the fund is selected as fund of the month in a given calendar month, and value 0 otherwise. The independent variables are as follows: *official front load*, *management fee*, lagged values of the funds *1 month performance*, *12 month performance*, and a dummy that takes the value of one if the 12 month performance of the fund was in the top decile among all funds in the dataset in the previous month, and *fund age* measured in years. z-statistics are given in parenthesis.

	Dependent variable:
	FOM
Official front load	13.013^{*}
	(1.74)
Management fee	0.394^{**}
	(2.45)
1 month performance (lagged)	-2.480^{*}
	(-1.71)
12 months performance (lagged)	-0.092
	(-0.20)
Top performance decile (lagged)	0.453^{**}
	(2.14)
Fund age	-0.005
	(-0.38)
Constant	-4.349^{***}
	(-12.07)
Observations	50,539
	(50,523 negative and 16 positive)
Log Likelihood	-134.656
χ^2	20.537^{***} (df = 6)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 9: Flow regressions – sample selection model

This table reports the results from a sample selection models explaining fund inflows. The selection equation explains nonzero fund/month combinations, where the dependent variable is a dummy that takes the value one when the inflow is positive and zero otherwise. Explanatory variables are the *Morningstar rating*, the *official front load*, lagged values of the funds *1 month performance* and *12 month performance*. The outcome equation explains determinants of nonzero flows. Dependent variable is the monthly inflow into a fund. Explantory variables are dummy variable indicating that a fund is current fund of the month *FOM*, in the preceding month *FOM (1 month lagged)*, or in a previous month *previous FOM*. *Total client holdings* is the aggregated value of fund shares held by all clients of the brokerage, and *top performance decile (lagged)* is a dummy that takes the value of one if the 12 month performance of the fund was in the top decile among all funds in the dataset in the previous month. t-statistics are given in parenthesis.

	Selection equation
Morningstar rating	0.120***
	(14.34)
Official front load	−13.558***
	(-10.12)
1 month performance (lagged)	0.835***
	(3.77)
12 month performance (lagged)	1.450***
	(29.75)
Constant	−1.344***
	(-30.55)
	Outcome equation
FOM	127.877***
	(46.87)
FOM (1 month lagged)	5.676*
	(1.83)
Previous FOM	3.544**
	(2.26)
Total clients holdings (lagged)	0.0001***
	(4.71)
Top performance decile (lagged)	2.257***
	(7.62)
Constant	7.144***
	(12.55)
Observations	29,736
Log Likelihood	−29,518.720
ρ	−0.429*** (0.039)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 10: Table Panel Logit Regressions

This table displays the coefficients resulting from a panel logit analysis. The dependent variable *FOM Trader* has value one if the investor trades the fund of the month during the promotion month, and value 0 otherwise. The independent variables are as follows: *Lagged FOM Performance* is the return of the fund of the month over the previous month. *Absolute Fee Reduction* describes the difference between the regular front load fee of the management company and the reduced promotional fee. *Equity Trader* and *Option Trader* are dummy variables that indicate whether the investor trades stocks or options besides mutual funds respectively. *Male* is a gender dummy. *Age* displays the age of the investor during a specific observatio month. *Degree*, *Econ*, *Tech*, *Long Education* and *Mag* are education dummies. *Average Turnover* is the average total turnover rate of the investor over the observation period. *Monthly Turnover* is the total turnover rate of the investor during a particular observation month. z-statistics are given in parenthesis.

	Dependent variable: FOM Trader			
	(1)	(2)	(3)	(4)
Lagged FOM Performance	5.408***	5.411***	4.753***	4.757***
	(8.67)	(8.67)	(7.74)	(7.75)
Absolute Fee Reduction	35.223***	35.206***	35.402***	35.398***
	(10.19)	(10.18)	(10.18)	(10.18)
Equity Trader	0.858***	0.862***	0.887***	0.892***
	(7.59)	(7.64)	(7.78)	(7.83)
Options Trader	0.366***	0.361***	0.283***	0.278***
	(5.12)	(5.06)	(3.94)	(3.87)
Age	0.028***	0.026***	0.028***	0.027***
	(9.87)	(9.17)	(10.04)	(9.28)
Male	0.046	0.049	0.045	0.027
	(0.49)	(0.51)	(0.48)	(0.47)
Degree	0.299***		0.236***	
	(4.41)		(3.47)	
Econ		0.741**		0.735**
		(2.30)		(2.27)
Tech		0.224**		0.168*
		(2.41)		(1.80)
Long Education		0.479***		0.425***
		(3.95)		(3.50)
Mag		0.250***		0.172*
		(2.60)		(1.77)
Average Turnover	1.979***	1.976***		
	(17.39)	(17.37)		
Monthly Turnover			-0.517	-0.524
			(-1.46)	(-1.48)
Constant	-7.187***	-7.130***	-6.501***	-6.436***
	(-29.46)	(-29.02)	(-26.58)	(-26.13)
No. Observations	30734	30734	30734	30734
No. Groups	6414	6414	6414	6414
Note:				*p<0.1; **p<0.05; ***p<0.01

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