The role of brokers and financial advisors behind investments into load funds*

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December 2006

Abstract

This paper finds that load funds with higher loads tend to receive higher flows, suggesting that brokers and financial advisors exercise a substantial degree of influence on the investments into load funds. As a result, fund families have been steadily increasing fund loads since the mid 1990s. Investments into load funds exhibit similar behaviors as those into no-load funds in chasing past performance and investing in fund families with more options. However, load fund investors are more likely to be directed by brokers and financial advisors into smaller funds, which might experience better performance, while no-load fund investors flock into larger funds with more visibility.

JEL classification: G23; G11

Keywords: Mutual funds; Loads; Brokers and financial advisors; Fund flows

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*I would like to thank Julie Agnew, John Boschen, Denise Jones, Erik Lie, George Oldfield, Chris Taber, Wanda Wallace, Russ Wermers, and seminar participants at College of William & Mary, Virginia Tech, China Europe International Business School (CEIBS), and the 2005 China International Conference in Finance for very helpful comments. Any errors are my responsibility.

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1. Introduction

Mutual funds have become an increasingly important investment vehicle for individual investors. By the end of 2001, more than half of the 105.5 million U.S. households had invested in mutual funds.[1] In general, an individual mutual fund investor may either invest in no-load funds, which largely rely on direct sales to investors, or load funds, which are primarily sold through brokers and financial advisors. Consequently, a natural question to investigate is what role brokers and financial advisors play in the investments into load funds, which now account for 75% of total retail mutual funds. Do brokers and financial advisors simply follow the instructions of individual investors or, instead, do brokers and advisors exercise a substantial degree of influence on the investment decisions? If the latter, how do brokers and financial advisors influence the investments into load funds? Very limited research has been conducted to study these issues, and this paper intends to fill this void in the current literature.[2]

To investigate the role of brokers and financial advisors, this paper first studies the effects of fund loads on the net flows into load funds. As noted in Nanda, Narayanan, and Warther (2000) and Sirri and Tufano (1998), as a component of the expenses encountered by mutual fund investors, fund loads are used primarily to compensate brokers and financial advisors. Consequently, if load fund investors rely on the assistance of brokers and financial advisors primarily for convenience, by and large treating them as order takers, we would expect that fund loads have a negative effect on flows, because, all else being equal, rational investors should stay away from funds with

[1] See *2002 Mutual Fund Fact Book* by Investment Company Institute.
[2] A concurrent working paper by Bergstresser, Chalmers, and Tufano (2005) also tries to analyze the potential benefits of brokers and financial advisors in the mutual fund industry by comparing various characteristics of funds sold through the broker and direct distribution channels.

higher expenses, and, in particular, higher loads, since they are salient in-your-face fees, as argued by Barber, Odean, and Zheng (2005). However, if brokers and financial advisors exercise a sizeable degree of influence over the investment decisions instead, flows might be positively associated with fund loads, because higher loads, as suggested by Sirri and Tufano (1998), should motivate brokers and financial advisors to sell more aggressively.

Barber, Odean, and Zheng (2005) and Sirri and Tufano (1998) have studied the effects that fund loads and changes in loads have on flows, respectively.[3] However, how this paper studies the effects of fund loads differs from the literature in the following ways. First, in the current literature, the effects of fund loads are investigated using a data set of both load funds and no-load funds. Two offsetting effects might be combined in such a setting and cannot be distinguished from one another. Nanda, Narayanan, and Warther (2000) suggest that different investor clienteles might exist for load and no-load funds, with load funds catering to unsophisticated investors. Therefore, sophisticated investors might simply stay away from any load fund, because they should understand that load funds underperform no-load funds after adjusting for loads (see, e.g., Elton et al., 1993; Gruber, 1996; Carhart, 1997; Morey, 2003), generating a negative effect for fund loads. However, for the clientele who do invest in load funds, the stronger incentives due to the higher compensation to brokers and financial advisors from higher loads might actually lead to higher flows, indicating a positive relationship between fund loads and flows. In other words, using a data set of both load funds and no-load funds, the effects

[3] Barber, Odean, and Zheng (2005) do not study the effect that changes in loads have on flows. Although the change in loads appears as an explanatory variable in Table 6 of Barber, Odean, and Zheng (2005), it is not used to study its effect on flows, because the dependent variable in Table 6 is the change in expense ratios.

of fund loads on flows might be non-linear: no-load funds and high-load funds might both receive higher flows than low-load funds. Consequently, in this paper, to isolate the effect of loads on flows into load funds, I first only include observations from load funds in the estimation.[4] In estimations using both load funds and no-load funds, I include both load fund dummies and load levels to control for the non-linearity. Second, partially due to data limitations, most papers in the literature only include front-end load funds in their study and treat fund loads simply just as front-end loads. In this paper, I further disaggregate load funds according to load types into front-end load funds, back-end load funds, and level-load funds and study the effects of front-end and back-end loads separately. Such a practice sheds more light on the decision-making process of investments into different types of load funds, and, to my knowledge, has not been conducted in the existing literature, either published or unpublished. Furthermore, the effects of fund loads have not been employed to investigate the role of brokers and financial advisors in the literature.

In addition to the study of the effects of fund loads on flows into load funds, I also follow Sirri and Tufano (1998) in comparing other determinants of flows into load and no-load funds, and use the observed differences to infer the role played by brokers and financial advisors in the investments into load funds. I also disaggregate load funds according to load types and study their determinants of flows separately.

[4] Sirri and Tufano (1998) also estimate the determinants of flows for load and no-load funds separately. As noted in Section II. D. of Siiri and Tufano (1998), the authors "estimate the models of Table III separately for load and no-load funds" but decide not to report the results. However, fund loads or changes in loads are unlikely to be included in these separate estimations, because they do not appear in Table III. O'Neal (2004) finds that load fund investors base fund-trading decisions on previous performance to a greater extent than do no-load fund investors, but does not study the effects of fund loads, either.

This paper first finds that load funds with higher loads tend to receive higher flows. This finding suggests that brokers and financial advisors exercise a substantial degree of influence on investments into load funds. As a result, fund families have been steadily increasing fund loads since the mid 1990s to presumably make their funds more attractive to brokers and financial advisors. This paper also finds that investments into load funds exhibit similar behaviors as those into no-load funds in chasing past performance (both raw returns and risk-adjusted returns) and investing in fund families with more options. However, load fund investors are more likely to be directed by brokers and financial advisors into smaller funds, which might experience better performance than larger funds exceeding their optimal size, while no-load fund investors flock into larger funds with more visibility.

The remainder of the paper is organized as follows. Section 2 outlines the data, the variables, and the methodology to be used. Section 3 discusses the hypotheses and estimation results. Section 4 concludes.

2. Data, variables, and methodology

2.1 Data

Using the CRSP Survivor-Bias Free US Mutual Fund Database, I create a new data set of quarterly data from the first quarter of 1992 to the third quarter of 2001 of 15,853 open-end mutual funds.[5] The time frame is selected because fund family and 12b-1 fee data are only available after 1992 in the CRSP mutual fund database. The data set

[5] I use quarterly data so that an adequate number of time periods (38 quarters) are available to apply the Fama-MacBeth method as a robustness check. I also use annual data from 1992 to 2000 and find the same qualitative results for all analyses.

covers all equity funds, bond funds, and hybrid funds. Given the rapid growth in international and fixed-income investments, a comprehensive study of the role of brokers and financial advisors in the investments into load funds should include the entire spectrum of fund investment objectives. The current literature on mutual fund flows, with the exception of Zhao (2005), only studies flows into domestic equity funds, giving an incomplete picture of the mutual fund world.[6] As a result, this paper studies the entire mutual fund universe (excluding money market funds). All funds are categorized into 19 investment objectives primarily based on the Investment Company Data, Inc. (ICDI)'s Fund Objective Code, which indicates the fund's investment strategy as identified by Standard & Poor's Fund Services.[7]

The data include fund name, fund family (management company), inception date, fund age (months), quarterly return, NAV (net asset value), expense ratio, turnover ratio, front-end loads, back-end loads, 12b-1 fees, and total assets. More than 60% of the funds are different share classes of a common portfolio.[8] To examine and compare the effects of different types of loads, which are specific to each share class, on flows, following Greene and Hodges (2002), this paper studies flows to each share class instead of each

[6] Domestic equity funds accounted for only 39 and 64% of the total number and total assets of mutual funds (excluding money market funds) at the end of the third quarter of 2001, respectively.

[7] Among all ICDI's Fund Objectives, Money Market Funds and Special Funds, which are primarily currency funds, are excluded. Exchange Traded Funds (ETFs) are also excluded. Utility Funds are combined into Sector Funds. To be consistent with most mutual fund research (see, e.g., Pastor and Stambaugh, 2002; Jayaraman, Khorana, and Nelling, 2002), I also create a separate Small Company Growth Funds objective using the SCG (Small Company Growth Funds) Strategic Insight Fund Objective Code. For a list of all fund objectives and their description, please refer to Appendix A to the CRSP Survivor-Bias Free US Mutual Fund Database Guide.

[8] For example, the following four funds — Dreyfus Premier Aggressive Growth Fund A, Dreyfus Premier Aggressive Growth Fund B, Dreyfus Premier Aggressive Growth Fund C, and Dreyfus Premier Aggressive Growth Fund R — share the same portfolio, that of Dreyfus Premier Aggressive Growth Fund. Each of these funds has the same portfolio manager and the same pool of securities. The major difference among the four funds is the varying load structures. Using fund name, NAV, return, and turnover ratio, I identify the portfolio for each fund.

portfolio. The 15,853 funds belong to 615 families. While 126 families have just one portfolio, the remaining 489 families have at least two portfolios.

About 75% of all funds target retail investors, and these retail mutual funds can be disaggregated by load types into no-load funds and three categories of load funds: front-end load funds, back-end load funds, and level-load funds.[9] Front-end load funds charge a front-end load and a 12b-1 fee but not a back-end load; back-end load funds charge a back-end load and a 12b-1 fee but not a front-end load; and, level-load funds generally charge a standard one-percent back-end load and a 12b-1 fee but not a front-end load. No-load funds, on the other hand, charge neither a front-end load nor a back-end load, but may charge a 12b-1 fee (if any) less than 25 basis points.[10] Load funds are generally sold through brokers and financial advisors, while no-load funds largely rely on direct sales to investors.[11] The loads and 12b-1 fees are used primarily to compensate brokers and financial advisors and to pay for distribution expenses.

At the beginning of 1992, as shown in Figure 1, the composition of retail mutual funds was dominated by front-end load funds and no-load funds, accounting for 46% and 39% of all funds, respectively, while back-end load funds and level-load funds had a

[9] Some "all-load" funds charge both a front-end load and a back-end load. Considering that such funds only account for 3.15% of all funds (500 out of 15,853 funds), they are not included in this study.

[10] The definition of no-load funds follows NASD Rule 2830(d).

[11] Even though investment in mutual funds through employer-sponsored retirement accounts (predominantly defined contribution plans such as 401 (k) or 403 (b)) constitutes an additional source of flows for mutual funds, its effect on retail load or no-load funds is still minimal. First, according to the *2002 Mutual Fund Fact Book* by Investment Company Institute, investments through employer-sponsored retirement accounts accounted for only 12% of total mutual fund assets in 1992. The percentage reached 17% in 1995 and since then has been very stable. Second, money through employer-sponsored retirement accounts is most likely not invested in retail funds, either load or no-load. Most fund families (e.g., more than two-thirds of the 30 largest mutual funds families) direct all money through employer-sponsored retirement accounts either to institutional share classes (subject to the total amount of the overall pool for certain families), such as Vanguard, Janus, Putnum (if overall pool is above $150 million), and Oppenheimer (if overall pool is above $50 million), or to a separate retirement share class, such as Templeton.

combined share of only about 15%. However, this situation changed dramatically over the subsequent ten-year period. By the end of the third quarter of 2001, the shares of front-end load funds and no-load funds had dropped to 32% and 25%, respectively, giving ground to back-end load funds and level-load funds, which both enjoyed dramatic growth over the same period. Together, all load fund categories accounted for 75% of total retail funds. In terms of total assets, at the end of the third quarter of 2001, all load fund categories accounted for roughly 60% of total retail fund assets, still dominating no-load funds.[12]

2.2. Related literature and control variables

As noted in the introduction, using a data set of both load funds and no-load funds, Barber, Odean, and Zheng (2005) and Sirri and Tufano (1998) investigate the effects of fund loads and the change in loads on fund flows, respectively. Sirri and Tufano (1998) also find mutual fund investors are fee-sensitive in that funds with higher total fees (expense ratio plus amortized load assuming a seven-year holding period) have lower flows. Using more recent data, Barber, Odean, and Zheng (2005) study the effects of front-end loads, 12b-1 fees, and other operating expenses separately. They find negative relations between front-end loads and fund flows, no relation between total operating expenses and fund flows, as well as positive relations between 12b-1 fees and fund flows. They argue that mutual fund investors are more sensitive to salient in-your-face fees, such as front-end loads, than operating expenses. Wilcox (2003) draws similar

[12] The development of load funds to a large extent can be attributed to the proliferation of funds with multiple share classes. At the end of the third quarter of 2001, 94.92% of load funds (6,507 out of 6,855 funds) are share classes from funds with multiple share classes.

conclusions using a conjoint experiment. Apparently, in addition to fund loads, 12b-1 fees and operating expenses should also be included as control variables.

The determinants of flows into mutual funds have been the subject of a growing literature of academic studies. This literature provides a number of additional control variables to include in the investigation. Gruber (1996), for instance, finds that investors chase past performance. Chevalier and Ellison (1997) and Sirri and Tufano (1998) not only corroborate this finding but also detect the non-linearity in the performance-flow relationship: mutual fund investors flock to funds with the highest recent returns, but fail to flee from poor performers. Sirri and Tufano (1998) and Nanda, Wang, and Zheng (2004) both study the spillover effects — a fund might enjoy higher flows if the fund family it belongs to has larger size or a star fund with superior performance. In addition, the effects of other factors, such as fund size, previous flows, and fund age, have also been studied in the above-mentioned papers and other studies (see, e.g., Jain and Wu, 2000; Del Guercio and Tkac, 2002; Bergstresser and Poterba, 2002).

In addition to the factors already studied in previous research, this paper introduces two new variables to control for the effects of fund families and investment objectives on the flows into a fund. First, this paper includes the number of investment objectives offered in the fund family. This variable is included to capture the spillover effects within a fund family from a different angle. Second, because this paper follows Sirri and Tufano (1998) in measuring fund performance as its percentile performance relative to other funds with the same investment objective in the same period, the asset-weighted average raw return of the corresponding investment objective is also included to control for the effect of investors chasing the absolute performance of an investment objective.

2.3. *Definitions of variables*

Flows

Consistent with the literature, I define *dollar flows* (*FLOW*) as the change in total assets in excess of appreciation.[13] I especially follow Zheng (1999) in also removing the increase in total assets due to merger so that the flow measure clearly represents only net new investments made by investors:[14]

$$FLOW_{i,t} = ASSET_{i,t} - ASSET_{i,t-1}\,(1 + R_{i,t}) - MASSET_{i,t} \tag{1}$$

where $ASSET_{i,t}$ is the total assets of fund i at the end of quarter t, $R_{i,t}$ is the holding period return of fund i during quarter t, and $MASSET_{i,t}$ is the assets added to fund i during quarter t due to acquiring other mutual funds. I also follow Del Guercio and Tkac (2002) in excluding observations from funds closed to new investors, since these funds' flows are artificially restricted.[15]

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[13] Studying new purchases and redemptions separately instead of net flows might provide more insight. However, data limitations preclude such a study of the role of brokers and financial advisors. The only known source of such information is the N-SAR form filed by mutual funds semiannually with the SEC. However, since mutual funds with multiple share classes only file one N-SAR form for each fund, instead of for each share class, they report in item 28 only aggregate new purchases and redemptions from all share classes. Considering that various load funds are primarily different share classes from funds with multiple share classes, studying their new purchases and redemptions becomes infeasible when such information is not available for each share class. This problem is apparent by examining items 28, 72DD, 73A, 74U, 74V, and 87 of the N-SAR form, available at http://www.sec.gov/info/edgar/forms/nsardoc.htm, and confirmed with the Division of Investment Management of the SEC and the Investment Company Institute.

[14] Del Guercio and Tkac (2002) also try to control for any effect to flows due to merger.

[15] As a result, 3,458 observations are excluded, which account for 1.64% of all observations.

I then define *percentage flows* (*PFLOW*) as the asset growth rate of a fund due to dollar flows:

$$PFLOW_{i,t} = FLOW_{i,t} / ASSET_{i,t-1} \tag{2}$$

Loads and Changes in Loads

Previous research largely includes only the level of front-end loads in the analysis. In addition to using a front-end load level variable, *FLOAD*, in the analysis of flows into front-end load funds, I also include a back-end load level variable, *BLOAD*, in the analysis of flows into back-end load and level-load funds.[16] To test if changes in loads have any immediate effect on flows, I also include changes in front-end loads ($\Delta FLOAD$) or back-end loads ($\Delta BLOAD$) in the estimations.

[16] I understand that the front-end load reported in the CRSP mutual fund database is the maximum load a fund may charge, and might differ from the average actual load, due to breakpoints. (Back-end load funds and level-load funds do not offer breakpoints; therefore, this issue does not apply to these funds.) However, using the maximum load should not misrepresent the relative incentives faced by brokers and financial advisors. As shown in Reid and Rea (2003), most front-end load funds follow the same breakpoint schedule, with the first load reduction at $25,000 and additional breakpoints introduced at $50,000, $100,000, $250,000, $500,000, and $1,000,000 for which the front-end load is eliminated altogether. As a result, with the same amount of new investment, the fund family offering a higher maximum load will still offer a higher actual load after breakpoint adjustments. In addition, it is infeasible to obtain average actual load information from either CRSP or the N-SAR form introduced in footnote 13. Although item 30A on the N-SAR form provides the total front-end loads in dollar terms collected for a fund, to obtain the average actual load, which should be calculated as the ratio of total front-end loads and total sales of front-end load shares, we still need information on total sales of front-end load shares. However, as explained in footnote 12, the total new sales reported in item 28 include sales from all share classes, making it infeasible to obtain total sales for just front-end load shares. Considering that load funds are predominantly share classes from funds with multiple share classes, it becomes impossible to calculate average actual load based on data available from the N-SAR form. (Investment Company Institute (ICI) possesses proprietary share-class level sales data, which are collected directly from each fund. However, ICI maintains a policy not to make the data available to the public.)

12b-1 Fees and Operating Expenses

As in Barber, Odean, and Zheng (2005), I subtract 12b-1 fees (*12B*) from the expense ratio to create a new variable, *NON12B*, which only represents operating expenses not related to distribution efforts.

Fund Size

Consistent with the literature, $LASSET_{i,t}$, which is the natural log of $ASSET_{i,t}$, the total net assets of a mutual fund, is used to represent the size of a fund.

Performance

Following Sirri and Tufano (1998), I measure the performance of a fund as its fractional performance rank ($RANK_{i,t}$), which represents the percentile of its raw return (*RAW*) relative to other funds with the same investment objective in the same quarter. To apply a piecewise linear regression to control for the non-linearity in the flow-performance relationship, I continue to follow Sirri and Tufano (1998) to create three performance range variables defined as follows using splines:

$$LOWPERF_{i,t-1} = \min\,[RANK_{i,t-1}, 0.2]$$

$$MIDPERF_{i,t-1} = \min\,[RANK_{i,t-1} - \mathrm{LOWPERF}_{i,t-1}, 0.6]$$

$$HIGHPERF_{i,t-1} = \min\,[RANK_{i,t-1} - \mathrm{LOWPERF}_{i,t-1} - \mathrm{MIDPERF}_{i,t-1}, 0.2] \quad (3)$$

$LOWPERF_{i,t-1}$ represents the bottom performance quintile, $MIDPERF_{i,t-1}$ represents the middle three performance quintiles, and $HIGHPERF_{i,t-1}$ represents the top performance quintile. I also calculate $OAWRET_{i,t-1}$ as the asset-weighted average of the raw holding period returns of all funds with the same investment objective to measure investment objective performance.

Sirri and Tufano (1998) also use the standard deviation of monthly raw returns to measure the risk of a fund and to study its effect on fund net flows. Instead of incorporating this risk measure directly, I measure the risk-adjusted performance of a fund using the Sharpe ratio (*SHARPE*), which is computed as:

$$SHARPE = \frac{\overline{R}_i - \overline{R}_f}{\sigma_i} \qquad (4)$$

where $\overline{R}_i$ and $\overline{R}_f$ are the average monthly raw return of fund *i* and risk-free rate in the past 12 months, respectively, and σ_i is the standard deviation of the monthly raw returns of fund *i* in the past 12 months.[17] Performance ranks and performance range variables — $LOWSHARPE_{i,t-1}$, $MIDSHARPE_{i,t-1}$, and $HIGHSHARPE_{i,t-1}$ — are computed in the same fashion as in Equation (3), and used to study the effect of risk-adjusted performance on flows.

Fund Age

The age of a fund (*AGE*) is also included in the analysis to control for the possibility that fund families might steer more flows into new funds.

[17] Goetzmann and Kumar (2002) calculate the Sharpe ratio in the same fashion.

Number of Investment Objectives in the Fund Family

NUMOBJ represents the number of investment objectives offered in the fund family.

2.4. Summary statistics

I compute the medians and means of various characteristics of funds with different load types and report the results in Table 1. The median front-end load is 4.75%. As expected, the median back-end load of a level-load fund is considerably lower than that of a back-end load fund. No-load funds and front-end load funds have the lowest 12b-1 fees and operating expenses. The median size of a no-load fund ($60.480 million) is almost 50% larger than that of a front-end load fund ($43.039 million), while the median sizes of the relatively younger back-end load funds and level-load funds are only $24.797 million and $5.195 million, respectively. Similar ranks can also be observed for the raw return and the Sharpe ratio, although the difference is not as significant. No-load funds have the highest median dollar flows, while level-load funds have the highest median percentage flows. Regardless of the flow measure, front-end load funds have the lowest flows. For all variables, using means generates the same ranking among different load types as using medians, even though the means of fund size, dollar flows, and percentage flows are all considerably higher than their medians due to some extreme values.

2.5. The statistical model

To investigate the role of brokers and financial advisors, I test the effects of fund loads on fund flows, while controlling for other variables in a multivariate regression framework. Consistent with the literature, I measure fund flows as percentage flows.[18] In addition, since Del Guercio and Tkac (2002) and Zhao (2005) also employ the dollar flows measure, I report results using dollar flows as well as a robustness check.

For front-end load funds, I estimate the following random effects regression using only observations from front-end load funds: [19]

$$PFLOW_{i,t} = \alpha + \beta_1 \bullet FLOAD_{i,t-1} + \beta_2 \bullet \Delta FLOAD_{i,t-1} + \beta_3 \bullet 12B_{i,t-1} + \beta_4 \bullet NON12B_{i,t-1} + \beta_5 \bullet LASSET_{i,t-1} + \beta_6 \bullet PFLOW_{i,t-1} + \beta_7 \bullet LOWPERF_{i,t-1} + \beta_8 \bullet MIDPERF_{i,t-1} + \beta_9 \bullet HIGHPERF_{i,t-1} + \beta_{10} \bullet AGE_{i,t-1} + \beta_{11} \bullet NUMOBJ_{i,t-1} + \beta_{12} \bullet OAWRET_{i,t-1} + u_i + \varepsilon_{i,t} \quad (5)$$

where all variables are as defined in Section 2.3, and u_i is the random disturbance characterizing the i^{th} fund and is constant through time. If $FLOW_{i,t}$ is used as the dependent variable, as in Del Guercio and Tkac (2002), $ASSET_{i,t-1}$ and $FLOW_{i,t-1}$ will be used to represent fund size and flows in the previous quarter instead. $FLOAD_{i,t-1}$ is replaced by $BLOAD_{i,t-1}$ when back-end load and level-load funds are studied, or dropped

[18] The percentage flow variables are winsorized at the 1st and 99th percentiles in these regressions to control for the effects of outliers.

[19] Pairwise correlations (not reported here) are computed for all independent variables and found to be low enough (all less than 0.30, with the vast majority less than 0.15) to eliminate concerns over multicollinearity problems in the regressions. As a matter of fact, in addition to the variables included in the model, some other variables are also considered. However, they are highly correlated to variables already included in the model and therefore dropped. The total assets or the number of funds in a family are both highly correlated to *NUMOBJ*. The total flows into an investment objective are highly correlated to *FLOW*. I also use measures based on Barclay, Pearson, and Weisbach (1998) to compute fund capital gains overhang, which describes the fraction of the total assets of a fund consisting of unrealized capital gains, to test how tax concerns might affect flows. However, the capital gains overhang variable is found to be highly positively correlated to *OAWRET*, and therefore is not included.

when no-load funds are studied, and only the relevant data are used for each load type. $\Delta FLOAD_{i,t-1}$ is also replaced by $\Delta BLOAD_{i,t-1}$ for back-end load funds. $\Delta BLOAD_{i,t-1}$ is not included for level-load funds because about 90% of the back-end loads for level-load funds are a standard 1%. In separate regressions, *LOWPERF*, *MIDPERF*, and *HIGHPERF* are replaced by *LOWSHARPE*, *MIDSHARPE*, and *HIGHSHARPE* as an alternative performance measure. Performance measures based on raw and risk-adjusted returns are not included in the same model because they tend to be highly correlated to each other.

A potential endogeneity concern on the relationship between fund loads and flows might be raised, based on the argument that both *FLOAD* and *BLOAD* are selected by funds and might very well depend on certain fund characteristics, including fund flows. However, this argument does not consider the fact that, although fund flows vary by fund, fund loads are not specific to each fund. As a matter of fact, a fund family generally selects the same *FLOAD* or *BLOAD* for all its relevant funds within the same asset class. For instance, a fund family tends to charge the same front-end load for all its front-end load equity & hybrid funds. As a result, fund loads are not determined at the fund level but at the fund family level, and therefore are not affected by fund specific characteristics, such as fund flows, but by fund family characteristics instead. For a detailed discussion of the determinants of fund loads, please refer to the Appendix. It is worth mentioning that, as shown in the Appendix, fund loads are not significantly associated with family flows. In addition, even if *FLOAD* and *BLOAD* are indirectly affected by fund flows, $FLOAD_{i,t-1}$ and $BLOAD_{i,t-1}$ are still not endogenous in Equation (5), because $FLOAD_{i,t-1}$ and $BLOAD_{i,t-1}$ should only be functions of fund and fund family characteristics from previous time periods (t-2, t-3, etc.) instead of at time t. For $PFLOW_{i,t}$, the dependent variable in Equation (5), $FLOAD_{i,t-1}$ and $BLOAD_{i,t-1}$ are already predetermined.

After studying the effects of loads on flows into load funds and comparing the determinants of flows into each of the four load types of funds, following the literature, I also use the full sample of load and no-load funds to study the effects of fund loads on flows into load funds. I estimate the following random effects panel regression:

$$PFLOW_{i,t} = \alpha + \beta_1 \bullet FLDUMMY_i + \beta_2 \bullet BLDUMMY_i + \beta_3 \bullet LLDUMMY_i + \beta_4 \bullet FLOAD_{i,t-1} + \beta_5 \bullet BLOAD_{i,t-1} + \beta_6 \bullet 12B_{i,t-1} + \beta_7 \bullet NON12B_{i,t-1} + \beta_8 \bullet LASSET_{i,t-1} + \beta_9 \bullet PFLOW_{i,t-1} + \beta_{10} \bullet LOWPERF_{i,t-1} + \beta_{11} \bullet MIDPERF_{i,t-1} + \beta_{12} \bullet HIGHPERF_{i,t-1} + \beta_{13} \bullet AGE_{i,t-1} + \beta_{14} \bullet NUMOBJ_{i,t-1} + \beta_{15} \bullet OAWRET_{i,t-1} + u_i + \varepsilon_{i,t} \quad (6)$$

where the three load fund dummy variables, *FLDUMMY*, *BLDUMMY*, and *LLDUMMY*, take the value of one if the fund is a front-end load fund, back-end load fund, and level-load fund, respectively, and zero otherwise. Both load fund dummy variables and actual load levels are included to control for the possible non-linearity in the effects of fund loads.[20] If $FLOW_{i,t}$ is used as the dependent variable, $ASSET_{i,t-1}$ and $FLOW_{i,t-1}$ are used to represent fund size and flows in the previous quarter instead. In separate regressions, *LOWPERF*, *MIDPERF*, and *HIGHPERF* are replaced by *LOWSHARPE*, *MIDSHARPE*, and *HIGHSHARPE* as an alternative performance measure.

[20] In the corporate finance literature, the magnitude of a variable and a dummy based on the same variable have been both included in the same estimation to test the non-linearity in the effect of the variable. For example, Lie (2005) includes both the level of dividend yield and a dummy variable that takes the value of one if a firm pays dividend to test the non-linear effect of dividend yield on firm payout choices.

The panel regression method is used to account for the fact that observations from the same fund are not independent relative to one another in this time-series cross-sectional (panel) data set. The random effects model is chosen over a fixed effects model due to the existence of the load fund dummy variables. Like the fixed effects, the dummy variables, which take the value of either one or zero for all observations of a specific fund, are time invariant. Consequently, a fixed effects model cannot be estimated with such dummy variables.[21] As a robustness check, I also apply the Fama-MacBeth method in addition to the random effects model and estimate the coefficients for each of the 38 quarters separately. Then I calculate the coefficients and *t*-statistics from the vector of quarterly results, as in Fama and MacBeth (1973). The same qualitative results (not reported) are obtained for almost all of the variables.[22]

3. Hypotheses and estimation results

3.1. Hypotheses

3.1.1. The effects of fund loads

Nanda, Narayanan, and Warther (2000) suggest that different investor clienteles might exist for load and no-load funds, with load funds catering to unsophisticated investors. Various surveys have corroborated that no-load fund investors are more

[21] The fact that a dummy variable takes the same value for all observations of the same load type (e.g. front-end load funds) does not change the fact that the dummy variable is time invariant for all observations of a specific fund, which violates a necessary condition for fixed effects models. For details of random effects and fixed effects models, please refer to Greene (2003). I estimate Equation (5) using random effects model to stay consistent with the method used for Equation (6). I also estimate Equation (5) and Equation (6) without the dummy variables using the fixed effects model and obtain the same qualitative results (not reported) for the remaining variables.

[22] The estimates for *ASSET* and *12B* are insignificant when *FLOW* is used as the dependent variable in Equation (6).

sophisticated and rely primarily on fund prospectuses and financial publications to make independent investment decisions. Load fund investors, on the other hand, are generally viewed as less informed, and they often consider brokers and financial advisors the most important information source. For instance, Capon, Fitzsimons, and Prince (1996) show that 83% of mutual fund investors who seek advice from commission-based advisors do not know whether they own an equity fund or a fixed-income fund. Alexander, Jones, and Nigro (1998) find that no-load fund investors scored much higher than load fund investors in a financial literacy quiz. Investment Company Institute (1997) claims that 87% of mutual fund investors who use advisors either delegate all decisions to the advisor or choose a fund from among several recommended by the advisor. Investment Company Institute (2004) indicates that 81% of investors in funds sold through a sales force assert that "I tend to rely on the advice of a professional financial advisor when making mutual fund purchase and sales decisions". As a result, I would expect that brokers and financial advisors must exercise a substantial degree of influence on investments into load funds, and anticipate a positive relation between fund net flows and both fund loads and changes in loads. The positive effects of loads on fund flows would suggest that the relatively uninformed load fund investors principally follow the instructions of brokers and financial advisors who are motivated by the higher compensation from higher loads.

I hypothesize that higher back-end loads lead to higher flows into back-end load funds, and such a finding should provide especially convincing evidence of the influential role of brokers and financial advisors. For back-end load fund investors, the back-end loads will be reduced by one percentage point for each year that money is left invested in the fund. As a result, if load fund investors made investment decisions on their own, back-end load funds should appeal to long-term investors because the back-end loads will be reduced to zero when they plan to redeem. However, if this scenario were true, the effect of back-end loads should be insignificant as opposed to the significantly positive effect I hypothesize, because the amount of back-end loads should be irrelevant for long-term investors. Nevertheless, if brokers and financial advisors exercise a substantial degree of influence on investments into back-end load funds, higher back-end loads should also provide stronger incentives for the brokers and financial advisors to sell the fund rather than push investors to redeem from the fund, for the reason that, although no load is paid initially by the investors to purchase back-end load funds, the fund families still advance the sales charges to the brokers and financial advisors when they sell the fund (see, e.g., O'Neal, 1999).

I expect the effects of back-end loads on flows into level-load funds to be insignificant, though, because about 90% of the back-end loads for level-load funds are a standard 1% and should not have any effect on flows.

3.1.2. The effects of control variables

According to O'Neal (1999), 12b-1 fees are primarily paid to brokers and financial advisors as a trailing commission. As a result, consistent with Barber, Odean, and Zheng (2005), I conjecture that load funds with higher 12b-1 fees have higher flows. However, the positive relation might not exist for no-load funds, because no-load fund investors might stay away from any funds which are not truly "no-load". (According to NASD Rule 2830(d), funds that charge neither a front-end load nor a back-end load but charge a 12b-1 fee less than 25 basis points are counted as no-load funds.)

Because operating expenses, unlike loads or 12b-1 fees, do not increase the income of brokers and financial advisors, I expect to observe similar effects of operating expenses on fund flows for both load funds and no-load funds. As suggested in Sirri and Tufano (1998) and Barber, Odean, and Zheng (2005), the effect is most likely to be negative or insignificant.

It is generally assumed in the literature that larger funds tend to receive higher net dollar flows (see, e.g., Gruber, 1996). I hypothesize that this should be the case for no-load funds. No-load funds largely rely on direct sales to investors.[23] No-load fund investors rely, to a great extent, on financial media coverage to collect information for their investment decisions. As shown by Sirri and Tufano (1998), larger funds receive higher media coverage. Consequently, larger funds should exhibit more visibility among potential investors and therefore receive higher flows. In addition, larger fund size might also imply a greater number of current shareholders who might make continuing investments into their accounts. On the other hand, the positive relation between fund size and flows might not necessarily hold for load funds. Brokers and financial advisors should understand that fund performance might deteriorate when a fund exceeds its

[23] No-load funds are also available through mutual fund supermarkets, such as Fidelity and Schwab, and discount brokers. If the fund families pay the supermarkets or discount brokers an annual fee of 25 to 35 basis points, the funds can be sold with a No-Transaction-Fees (NTF) status so that investors do not have to pay normal transaction fees to purchase such funds (see LaPlante (2001) for details of NTF arrangements). Selling no-load funds through fund supermarkets or discount brokers, either with NTF status or not, only provides the convenience of not having to deal with each individual fund family; it does not provide financial advice. Therefore, the decision-making process for no-load fund investors should not be in any way different whether the purchase is through fund supermarkets and discount brokers or directly from the fund family. As a matter of fact, both sources are considered a direct market distribution channel by Investment Company Institute (see, e.g., Investment Company Institute, 2004). It should be noted, though, that a small number of (322 out of 3,170) no-load funds are only available through fee-based financial advisors, and are consequently not included in this study in order to confine no-load fund investors to investors who can make independent investment decisions.

optimal size (see, e.g., Perold and Salomon, 1991; Indro et al., 1999), because funds with larger sizes tend to have higher average trading costs as a result of the tremendous adverse market impacts from trading large blocks of stocks (see, e.g., Keim and Madhavan, 1998; Berk and Green, 2004; Chen et al., 2004). As a result, if brokers and financial advisors exercise a substantial degree of influence on investments into load funds, they might direct investors to smaller funds.

As for other control variables, Gruber (1996) and Del Guercio and Tkac (2002) find that fund flows are highly autocorrelated, Chevalier and Ellison (1997) and Sirri and Tufano (1998) both find that mutual fund investors flock to funds with the highest recent returns, but fail to flee from poor performers. I expect these results should hold for both load funds and no-load funds. In addition, regardless of load types, I predict that funds from fund families investing in a greater number of investment objectives should receive higher flows. By offering more investment objectives, the fund family provides investors with greater flexibility to switch among funds and a better opportunity to execute asset allocation strategies.

3.2. The effects of fund loads

Table 2 reports the results of separate random effects panel estimation using both percentage flows and dollar flows for the following four fund load types: front-end load funds, back-end load funds, level-load funds, and no-load funds. Results from estimations using alternative performance measures based on the Sharpe ratio are reported in Table 3.

As expected, both Table 2 and Table 3 show that front-end loads and back-end loads are significantly positively associated with flows into front-end load funds and back-end load funds, respectively.[24] These findings are consistent with the influential role of brokers and financial advisors in the decision making process of investments into load funds.[25] The finding for back-end load funds indicates that, most likely, the brokers and financial advisors might simply manage to sell back-end load funds to unsophisticated investors who are happy to pay the loads at a later time. It should be noted that back-end load funds do not offer breakpoints in loads (see footnote 16) and flows from retirement plans are seldom directed to back-end load funds. These facts make the positive relation between back-end loads and flows especially convincing and valuable.[26]

In terms of the effects of changes in loads on flows, while increases in back-end loads do lead to higher flows, especially when the effects of risk-adjusted performance are controlled, contrary to my hypothesis, increases in front-end loads are not significantly related to higher flows. The difference in the effects of changes in front-end loads and back-end loads might be due to the fact that back-end loads tend to be more narrowly distributed. The difference between the 90th percentile and the 10th percentile is

[24] The estimate of back-end loads for level-load funds is insignificant, which is not a surprise.

[25] It should be noted that, these findings cannot be interpreted out of context to mean that fund families can simply increase flows by increasing loads without any restriction. These findings are obtained with observations of fund loads in their normal range, and are valid only for this range. We would not expect a fund to receive any flows if it charges a ridiculously high load.

[26] On the other hand, the positive relation between front-end loads and flows might be subject to suspicion, because front-end load fund investors do not always pay the maximum front-end load due to breakpoints and because loads are often waived for flows from retirement plan investments. Although, as explained in footnotes 11 and 16, the effects of such data “contaminations” are not believed to be significant, unfortunately, the exact effects cannot be investigated due to data limitations. However, it should be noted that a significantly positive relation between front-end load and flows is also detected in Bergstresser, Chalmers, and Tufano (2005).

only about 1% for back-end loads, but exceeds 2% for front-end loads. As a result, any increase in back-end loads is more likely to be noticed by brokers and financial advisors.

3.3. A comparison of the determinants of flows into funds with different load types

In addition to studying the role of brokers and financial advisors based on the effects of loads, I also use the observed differences in the determinants of flows into load and no-load funds to infer how brokers and financial advisors influence the investments into load funds. In both Table 2 and Table 3, for each variable other than fund loads and changes in loads, following Del Guercio and Tkac (2002) in their comparison of pension fund and mutual fund managers, I test whether the coefficients for each type of load funds are statistically different from the corresponding coefficients in the no-load fund regression, and use ^{a}, ^{b}, and ^{c} to indicate that the coefficients are statistically different at the 1%, 5%, and 10% confidence levels, respectively.

3.3.1. Differences of determinants

It is first noted that, as predicted, the effects of 12b-1 fees on flows are significantly different between no-load funds and load funds. For no-load funds, a one basis point increase in 12b-1 fees might reduce flows by more than 20 basis points, indicating that no-load fund investors are only interested in funds which are truly "no-load". On the contrary, 12b-1 fees are shown to have a statistically and economically significant and positive effect on flows for both front-end load funds and level-load funds.[27] This finding corroborates that 12b-1 fees exert similar effects on load fund flows as fund loads and provides further evidence of the prominent role of brokers and financial advisors.

Although investments into both load funds and no-load funds are shown to be sensitive to operating expenses, the sensitivity of no-load fund investors is significantly higher. While a one basis point increase in operating expenses might reduce flows into a no-load fund by more than five basis points, the same increase only reduces flows into any type of load funds by less than three basis points. This finding might suggest that no-load fund investors are more enthusiastic in saving expenses.

For both front-end load funds and no-load funds, older funds appear to receive higher flows, while the opposite is true for back-end load funds and level-load funds presumably because, as shown in Table 1, back-end load funds and level-load funds are considerably younger than front-end funds and no-load funds.

Up to now, the analysis focuses on the results using percentage flows, while the same qualitative results are obtained using dollar flows for most variables and load types. However, to understand the effect of fund size on flows, the results using percentage flows do not appear to be very informative. Considering that percentage flows are constructed as dollar flows divided by fund size, the effect of (the natural log of) fund size on percentage flows is not surprisingly significantly negative, as shown in both Table 2 and Table 3 across all load types, as well as in the entire literature on fund

[27] It is not surprising to find that the estimate of 12b-1 fees is insignificant for back-end load funds, though. According to O'Neal (1999), for front-end load and level-load funds, 12b-1 fees are almost entirely paid to brokers and financial advisors as trailing commissions; however, for back-end load funds, only around 25% of the 12b-1 fees are paid to brokers and financial advisors, while the rest of the fees are kept by the fund family to recover the sales charges advanced to brokers and financial advisors.

flows.[28] However, these results do not appear to best answer the question whether larger funds receive more investment money. Therefore, I believe, to investigate the effect of fund size on flows, as argued by Del Guercio and Tkac (2002), using dollar flows as the dependent variable while "controlling for a potential size effect in a multiple regression format, rather than by scaling the flows, preserves this information for analysis."

Examining the results using dollar flows, consistent with my hypothesis, I find a clear distinction between load funds and no-load funds in terms of the fund size-dollar flows relationship. While larger no-load funds receive higher dollar flows, larger load funds of each type receive lower dollar flows instead. In other words, smaller load funds receive higher dollar flows. I believe the difference results from the different roles of individual investors in the decision-making processes of investments into no-load and load funds and provides further evidence of the influential role of brokers and financial advisors in the investments into load funds. Presumably, brokers and financial advisors tend to direct investors to smaller funds. Zheng (1999) observes a stronger smart money effect for both load funds and smaller funds. These findings are consistent with such a practice.

3.3.2. Similarities of determinants

In spite of the observed differences, it should also be noted that many factors have similar qualitative effects on the flows of no-load and various load funds. For example, mutual fund flows are highly autocorrelated regardless of load types, as shown by the significantly positive estimates for lagged flow variables. Because Warther (1995) shows that aggregate flows follow an AR (3) process, I also estimate a new model including

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[28] The negative effect is the strongest for no-load funds apparently because, as shown in Table 1, no-load

(P)FLOW$_{i,t-2}$ and *(P)FLOW*$_{i,t-3}$ in the estimation. The estimates are significantly positive for all three lags of flows (not reported). The autocorrelation decreases over time, though, as evidenced by the fact that the coefficient of the third lag is less than one fifth of that of the first lag in magnitude. On the other hand, if lagged flow variables are not included in the estimation, the same qualitative results can still be obtained for all other variables.

The study also reveals that investments into funds with different load types apparently all chase absolute performance, flocking into investment objectives with high average raw returns. Investments into all load types appear to chase relative performance as well, investing disproportionately more in the performance leaders in each investment objective, as shown by the significantly positive and convex relationship between performance percentile ranks and flows. For instance, the estimates from the piecewise regression of the three performance ranges show that, for both front-end load and no-load funds, the same increase in performance percentile ranks leads to almost five times as high percentage flows in the top performance quintile as in the middle three quintiles. As shown in Table 3, the use of alternative performance measures based on the Sharpe ratio, which measures risk-adjusted performance, does not change the conclusions. In fact, the convex and positive relationship between performance percentile ranks and flows becomes even stronger.

Regardless of load types, funds from fund families investing in a greater number of investment objectives all tend to receive higher flows. This positive spillover effect from having more investment objectives in the fund family indicates that investors do value the potential options to switch within the fund family.

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funds are considerably larger than load funds.

3.3.3. High-load funds vs. low-load funds

To test whether the fund flows of high-load funds respond to the determinants differently from those of low-load funds, for both front-end load funds and back-end load funds, I separate each load type into two sub-samples by median *FLOAD* or median *BLOAD* and repeat the estimations in Table 2 and Table 3 for each sub-sample. For each load type, I find the same qualitative results for most variables from both sub-samples, with only a few exceptions. For front-end load funds, flows into high-load funds are more sensitive to *HIGHPERF*, while *AGE* and *NUMOBJ* are not significantly related to flows into low-load funds. As far as back-end load funds are concerned, *NON12B* and *NUMOBJ* do not appear to significantly affect flows into low-load funds. Due to the overwhelming similarities in the relationships between fund flows and the determinants for high-load and low-load funds, I have omitted the extra tables and discussion.

3.4. The changes in loads from 1992 to 2001

Considering that load funds with higher loads are more likely to receive higher flows, it is interesting to examine how fund loads had changed during the data period.

For each year during the ten years from 1992 to 2001, Table 4 presents the average front-end loads and back-end loads for both equity & hybrid funds and bond funds. Equity funds and hybrid funds are combined together because these funds tend to have the same sales loads in most fund families, while the sales loads of bond funds tend to be slightly lower. Although average fund loads decreased in early 1990s, the trend apparently reversed during the mid 1990s, regardless of load types or asset classes. For example, for front-end load equity & hybrid funds, the average load decreased from

4.87% in 1992 to 4.74% in 1993, but started to increase and reached 5.22% in 2001; for back-end load bond funds, the average load decreased from 4.56% in 1992 to 4.27 percent in 1994, but started to increase steadily and reached 4.53% in 2001. These results suggest that fund families might realize that higher loads make their funds more attractive to brokers and financial advisors and have increased their loads accordingly.

This finding seems to contradict a December 2000 (released on January 10, 2001) SEC report on mutual fund fees and expenses, which states that "many funds have decreased or replaced front-end loads with on-going 12b-1 fees". However, we have to understand that, although the SEC report describes a general trend in thirty years since early 1970s when most funds charged a front-end load of 8.5%, it fails to notice that the trend of decreasing loads has reversed since the mid 1990s.

3.5. Full sample analysis

Following the literature, I also use the full sample of load and no-load funds to study the effects of fund loads on flows. I include both load dummies and load levels to control for possible non-linearity in the effects of fund loads. The results are reported in Table 5. Model 1 uses performance measures based on raw returns, while Model 2 uses performance measures based on Sharpe ratios.

All of the load fund dummies are shown to be significantly negative, suggesting that, all else being equal, a no-load fund receives higher flows (both percentage flows and dollar flows) than any type of load fund. After controlling for these load fund dummy variables, *FLOAD* and *BLOAD* exhibit the same positive relationships with fund flows as observed in Table 2 and Table 3 for front-end load and back-end load funds. These findings corroborate the non-linearity in the relationship between fund loads and flows: no-load funds and high-load funds both receive higher flows than low-load funds. If *FLOAD* and *BLOAD* are dropped from the estimation, the coefficients of the three load fund dummy variables are still significantly negative, while the same qualitative results are obtained for other variables.

The finding that a no-load fund receives higher flows than any type of load fund is somewhat surprising, considering that load funds have shown strong market share gains in recent years. According to the Investment Company Institute, the estimated share of new long-term fund sales made directly to retail investors decreased from 23% in 1990 to 15% in 2001. The Boston-based Financial Research Corporation stated that 45% of the money flowing into mutual funds was invested into no-load funds in 1995, but by 2000, this number had dropped to 35%.[29] Even though the numbers from both sources are not necessarily consistent, they reveal the same declining trend in no-load fund market share. Considering that load funds are becoming increasingly popular, one would expect a no-load fund to receive lower flows.

The existence of a better-informed more sophisticated clientele might explain this phenomenon. It is well documented that load funds do not outperform no-load funds before adjusting for loads, and that they ultimately underperform no-load funds after adjusting for loads. As a result, the better-informed investors might stay away from load funds completely and focus instead on no-load funds. In addition, even though the total market share for load funds has been increasing, an increasing number of funds are also

[29] The Wall Street Journal, "Scudder mulls big switch to funds sold by brokers," October 16, 2000, page C1.

competing in the market. As a result, an average no-load fund might still end up receiving higher flows than an average load fund. As evidence, even though the number of no-load funds only accounts for 25% of the total number of retail funds, the total assets in no-load funds still account for about 40% of total retail fund assets.

Table 5 also shows the aggregate effects of the determinants on mutual fund net flows. For determinants with similar effects on flows into funds with different load types, not surprisingly, these effects are also observed for the full sample, such as the performance-chasing behaviors and the autocorrelation of flows. For determinants with similar effects on flows into funds with all but one load types, the dominant effect is also observed in the full sample. For instance, the negative relationship between fund size and dollar flows is apparently driven by the results from three types of load funds, which account for more than 70% of the observations. This also explains why this paper finds a different aggregate fund size-dollar flows relationship for mutual funds from what is found by Del Guercio and Tkac (2002), who use data from 1987 to 1994. As shown in Figure 1, no-load funds account for a much larger proportion of all funds before 1994 than in the years after. The positive relationship between fund size and dollar flows for no-load funds might dominate in their sample.

3.6. Estimation by investment objectives

The data set used in this paper covers not only domestic equity funds, but also international equity funds, bond funds, and hybrid funds. To test whether the relationships found for the entire data set are robust across different fund groups, I repeat the estimations in Table 2, Table 3, and Table 5 for each of the 19 investment objectives.

In results not reported here, I find that the same qualitative results can be obtained for most variables in most of the 19 investment objectives with the following exceptions: high quality municipal bond funds, single state municipal bond funds, high yield municipal bond funds, high yield bond funds, and precious metal funds.

In the literature, Jensen's α based on the single-factor Capital Asset Pricing Model (CAPM) and multiple-factor alpha based on the Fama-French three-factor model or Carhart four-factor model are often used to measure the performance of domestic equity funds, in addition to performance measures based on raw returns and the Sharpe ratio. To be consistent with the literature, for domestic equity funds (excluding precious metal funds and sector funds), I employ both the single-factor Capital Asset Pricing Model (CAPM) and the Carhart four-factor model (see, e.g., Carhart, 1997), which is based on the Fama and French (1993) three-factor model, to evaluate their performance:

$$R_{it} = \alpha_i + \beta_{i1} RMRF_t + \varepsilon_{it} \tag{7}$$

$$R_{it} = \alpha_i + \beta_{i1} RMRF_t + \beta_{i2} SMB_t + \beta_{i3} HML_t + \beta_{i4} UMD_t + \varepsilon_{it} \tag{8}$$

where R_{it} is the fund return in excess of the monthly T-bill return; *RMRF* is the value-weighted return on all NYSE, AMEX, and NASDAQ stocks in excess of the monthly T-bill return; *SMB* (Small Minus Big) is the difference in returns across small and big equity portfolios; *HML* (High Minus Low) is the difference in returns between high and low book-to-market equity portfolios; *UMD* (Up Minus Down) is the difference in returns between equity portfolios with high and low prior returns. *SMB*, *HML*, and *UMD* are incorporated to control for size, value, and momentum effects, respectively.[30] I calculate these measures using monthly returns over the previous 36 months.

After obtaining the estimates for Jensen's α and the Carhart four-factor α, I follow Sirri and Tufano (1998) in generating performance range variables based on these measures in the same fashion as in Equation (3). I repeat the estimation in Table 2 using these new performance range variables and observations from domestic equity funds. In results not reported here, I find a significantly positive and convex relationship between the new performance measures and fund flows for both load funds and no-load funds. For funds with any load type, the same increase in the new performance percentile ranks leads to between three times and five times as high percentage flows in the top performance quintile as in the middle three quintiles. These results suggest that both the relatively sophisticated no-load fund investors and the brokers and financial advisors, who appear to exercise a substantial degree of influence on investments into load funds, base their investment decisions on these advanced performance measures.

4. Conclusion

This paper investigates the role of brokers and financial advisors behind investments into load (front-end load, back-end load, and level-load) mutual funds using a new data set of all mutual funds, including equity funds, bond funds, and hybrid funds, from 1992 to 2001.

[30] In Carhart (1997), the momentum factor, *UMD*, is designated *PR1YR*. I follow Ken French's designation in this paper. Data on all factors are directly downloaded from Ken French's website (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html).

Load funds are primarily sold through brokers and financial advisors, and load fund investors have been shown to be less informed in general. This paper finds that load funds with higher loads and 12b-1 fees, which provide stronger incentives to the brokers and financial advisors, receive higher flows. This finding suggests that brokers and financial advisors exercise a substantial degree of influence on investments into load funds. As a result, fund families have been steadily increasing fund loads since the mid 1990s to presumably make their funds more attractive to brokers and financial advisors. Investments into load funds exhibit similar behaviors as those into no-load funds, though, in chasing past performance (both raw returns and risk-adjusted returns), and investing in fund families with more options. Investments into both load and no-load funds appear to be sensitive to operating expenses, although no-load fund investors seem to be more enthusiastic in saving operating expenses. However, while no-load fund investors flock into larger funds with more visibility, load fund investors are more likely to be directed by brokers and financial advisors into smaller funds, which might experience better performance than larger funds exceeding their optimal size. In addition, I also find that, although no-load funds as a group have lost market share in recent years, a no-load fund still receives higher flows on average than any type of load fund.

The findings in this paper should provide insight to research related to the behaviors of mutual fund investors. In the current literature, for instance, mutual fund investors are often assumed to "choose" funds as if they were all independent decision makers. But, as shown in this paper, the relatively uninformed load fund investors seldom "choose" load funds on their own; in reality, to a significant degree, brokers and financial advisors "sell" the funds to these investors instead. The identification of the role of brokers and financial advisors behind investments into load funds, which account for 75% of total retail mutual funds, might help researchers better understand how investments into mutual funds react to changes in various factors and policies.

With respect to the main findings of this paper, two questions are often raised: (1) Are investors uninformed to that extent? (2) Because there are repeated interactions between the client and the broker and/or financial advisor, is pushing funds with higher loads a viable long-term strategy for brokers and financial advisors? As to the first question, not all investors are uninformed. However, due to self-selection, informed investors will primarily invest in no-load funds. As for load fund investors, various surveys have shown that they are on average fairly uninformed. For example, Capon, Fitzsimons, and Prince (1996) show that 83% of mutual fund investors who seek advice from commission-based advisors do not know whether they own an equity fund or a fixed-income fund. As to the second question, it should be noted that the difference between the 90th percentile and the 10th percentile is only about 1% for back-end loads, and around 2% for front-end loads. Therefore, the difference between "high" loads and median loads will most likely not be large enough for uninformed investors to notice. In addition, even if investors are unhappy with the brokers or financial advisors, their unhappiness has to go beyond a certain threshold for them to fire the broker or financial advisor. The job of the broker and financial advisor should still be safe as long as the threshold is not reached.[31] If data become available, it would be a very interesting topic

[31] As observed in business and daily life, the "firing" standard is always significantly lower than the "hiring" standard. For instance, at stock exchanges, it is always much easier to clear the delisting standards than to meet the listing standards. Also, in marriage, if being in love is a necessary condition for two people to get married, it usually takes a lot more than not being in love anymore for two people to get divorced.

to study the determinants of investors' decisions to hire and fire brokers and financial advisors.

Appendix

The Determinants of Front-end and Back-end Loads

A fund family generally selects the same *FLOAD* or *BLOAD* for all its relevant funds within the same asset class. For instance, a fund family tends to charge the same front-end load for all its front-end load equity & hybrid funds. Therefore, fund loads are determined at the fund family level and depend on fund family characteristics. In addition, if a fund family changes its loads, the loads are generally changed on an annual basis. As a result, to study the determinants of front-end loads, I first estimate the following random effects model (Model 1) using annual data of family-load type-asset class-level variables:

$$FLOAD_{i,j,t} = \alpha + \beta_1 \bullet ACDUMMY_{i,j} + \beta_2 \bullet FAC12B_{i,j,t-1} + \beta_3 \bullet FACNUM_{i,j,t-1} + \beta_4 \bullet FACAGE_{i,j,t-1} + \beta_5 \bullet FACNON12B_{i,j,t-1} + \beta_6 \bullet FACPFLOW_{i,j,t-1} + \beta_7 \bullet FACRETURN_{i,j,t-1} + u_i + \varepsilon_{i,j,t} \quad \text{(A1)}$$

where i, j, and t stand for each fund family, asset class (equity & hybrid funds vs. bond funds), and year, respectively, and u_i is the random disturbance characterizing the i^{th} family and is constant through time. *ACDUMMY* takes the value of one if *FLOAD* indicates the front-end load charged by a fund family for its equity & hybrid funds, and zero for bond funds. *FAC12B* and *FACNON12B* are the asset-weighted average of 12b-1 fees and other operating expenses of all front-end load funds within the same asset class in a fund family, respectively. *FACNUM* gives the number of all front-end load funds within the same asset class in a fund family. *FACAGE* is the age of the first front-end load fund within the corresponding asset class in the family. *FACPFLOW* and *FACRETURN* are the asset-weighted average of the annual percentage flows and the annual objective-adjusted returns of all front-end load funds within the same asset class in a fund family, respectively. The panel regression method is used to account for the fact that observations from the same family are not independent relative to one another in this time-series cross-sectional (panel) data set.

I also estimate another random effects model (Model 2) using annual data of family-level variables:

$$FLOAD_{i,j,t} = \alpha + \beta_1 \bullet ACDUMMY_{i,j} + \beta_2 \bullet F12B_{i,t-1} + \beta_3 \bullet FNUM_{i,t-1} + \beta_4 \bullet FAGE_{i,t-1} + \beta_5 \bullet FNON12B_{i,t-1} + \beta_6 \bullet FPFLOW_{i,t-1} + \beta_7 \bullet FRETURN_{i,t-1} + u_i + \varepsilon_{i,j,t} \qquad \text{(A2)}$$

Except for *ACDUMMY*, all other variables used in Equation (A2) are family-level variables. They are calculated in the same fashion as the variables used in Equation (A1) using all funds in the family (including funds with all load types and asset classes). The matching family-load type-asset class-level and family-level variables, such as *FACNUM* and *FNUM*, are found to be highly correlated to each other. As a result, they are not included in the same regression. In addition, some other variables, such as the total assets of a fund family, are also considered. However, they are found to be highly correlated to other variables, and therefore not included in the final model.

When the determinants of back-end loads are studied, $FLOAD_{i,j,t}$ is replaced by $BLOAD_{i,j,t}$ in both Equation (A1) and Equation (A2). I also recalculate the family-load type-asset class-level variables using data from back-end load funds. Since level load funds almost all charge a standard 1% back-end load, it is not necessary to study its determinants.

The estimation results are reported in Table A1. The coefficients of *ACDUMMY* are shown to be significantly positive for both *FLOAD* and *BLOAD*, indicating that equity & hybrid funds have higher loads than bond funds. The difference ranges from about 80 basis points for front-end loads to about 10 basis points for back-end loads. This result is consistent with the findings in Table 4. In addition, fund families with a greater number of funds or higher operating expenses tend to charge higher front-end and back-end loads. Fund families with higher 12b-1 fees tend to charge lower front-end loads but higher back-end loads. Factors such as age, flows, and performance do not appear to affect the choice of loads.

References

Alexander, G., Jones J., Nigro, P., 1998. Mutual fund shareholders: characteristics, investor knowledge, and sources of information. Financial Services Review 7, 301-316.

Barber, B., Odean, T., Zheng, L., 2005. Out of sight, out of mind: The effects of expenses on mutual fund flows. Journal of Business, forthcoming

Barclay, M., Pearson, N., Weisbach, M., 1998. Open-end mutual funds and capital gains taxes. Journal of Financial Economics 49, 3-43.

Bergstresser, D., Chalmers, J., Tufano, P., 2005. Assessing the costs and benefits of brokers in the mutual fund industry. Unpublished working paper. Harvard University and University of Oregon.

Bergstresser, D., Poterba, J., 2002. Do after-tax returns affect mutual fund inflows? Journal of Financial Economics 63, 381-414.

Berk, J., Green, R., 2004. Mutual fund flows and performance in rational markets. Journal of Political Economy 112, 1269-1295.

Capon, N., Fitzsimons, G., Prince, R., 1996. An individual level analysis of the mutual fund investment decision. Journal of Financial Service Research 10, 59-82.

Carhart, M., 1997. On persistence in mutual fund performance. Journal of Finance 52, 57-82.

Chen, J., Hong, H., Huang, M., Kubik, J., 2004. Does fund size erode mutual fund performance? The role of liquidity and organization. American Economic Review 94, 1276 - 1302

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., 2002. The determinants of the flows of funds of managed portfolios: Mutual funds vs. pension funds. Journal of Financial and Quantitative Analysis 37, 523-557.

Elton, E., Gruber, M., Das, S., Hlavka, M., 1993. Efficiency with costly information: A reinterpretation of evidence from managed portfolios. Review of Financial Studies 6, 1-22.

Fama, E., French, K., 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33, 3-56.

Fama, E., MacBeth, J., 1973. Risk, returns, and equilibrium: Empirical tests. Journal of Political Economy 81, 607-636.

Goetzmann, W., Kumar, A., 2002. Equity portfolio diversification. Unpublished working paper. Yale University and Cornell University.

Greene, J., Hodges, C., 2002. The dilution impact of daily fund flows on open-end mutual funds. Journal of Financial Economics 65, 131-158.

Greene, W., 2003. Econometric Analysis. Prentice Hall, Inc., Upper Saddle River, New Jersey.

Gruber, M., 1996. Another puzzle: The growth in actively managed mutual funds. Journal of Finance 51, 783-810.

Indro, D., Jiang, C., Hu, M., Lee, W., 1999. Mutual fund performance: Does fund size matter? Financial Analysts Journal 55, 74-87.

Investment Company Institute, 1997. Understanding Shareholders' Use of Information and Advisers. Washington, DC.

Investment Company Institute, 2002. 2002 Mutual Fund Fact Book. Washington, DC.

Investment Company Institute, 2004. Profile of Mutual Fund Shareholders. Washington, DC.

Jain, P., Wu, J., 2000. Truth in mutual fund advertising: Evidence on future performance and fund flows. Journal of Finance 55, 937-958.

Jayaraman, N., Khorana, A., Nelling, E., 2002. An analysis of the determinants and shareholder wealth effects of mutual fund mergers. Journal of Finance 57, 1521-1551.

Keim, D., Madhavan, A., 1998. The cost of institutional equity trades. Financial Analysts Journal 54, 50-69.

LaPlante, M., 2001. Influences and trends in mutual fund expense ratios. Journal of Financial Research 24, 45-63.

Lie, E., 2005. Financial flexibility, performance, and the corporate payout choice. Journal of Business, forthcoming.

Morey, M., 2003, Should you carry the load? A comprehensive analysis of load and no-load mutual fund out-of-sample performance. Journal of Banking and Finance 27, 1245-71.

Nanda, V., Narayanan, M., Warther, V., 2000. Liquidity, investment ability, and mutual fund structure. Journal of Financial Economics 57, 417-43.

Nanda, V., Wang, Z., Zheng, L., 2004. Family values and the star phenomenon. Review of Financial Studies 17, 667-698.

O'Neal, E., 1999, Mutual fund share classes and broker incentives. Financial Analysts Journal 55, 76-87.

O'Neal, E., 2004. Purchase and redemption patterns of US equity mutual funds. Financial Management 33, 5-32.

Pastor, L., Stambaugh, R., 2002. Mutual fund performance and seemingly unrelated assets. Journal of Financial Economics 63, 315-349.

Perold, A., Salomon Jr., R., 1991. The right amount of assets under management. Financial Analysts Journal 47, 31-39.

Reid, B., Rea, J., 2003. Mutual fund distribution channels and distribution costs. Investment Company Institute Perspective 9, 1-19.

The Securities & Exchange Commission, 2000 (released in 2001). Report on mutual fund fees and expenses. http://www.sec.gov/news/studies/feestudy.htm

Sirri, E., Tufano, P., 1998. Costly search and mutual fund flows. Journal of Finance 53, 1589-1622.

Warther, V., 1995. Aggregate mutual fund flows and security returns. Journal of Financial Economics 39, 209-235.

Wilcox, R., 2003. Bargain hunting or star gazing? Investors' preferences for stock mutual funds. Journal of Business 76, 645-63.

Zhao, X., 2005. The determinants of flows into retail bond funds. Financial Analysts Journal 61, 47-59

Zheng, L., 1999. Is money smart? A study of mutual fund investors' fund selection ability. Journal of Finance 54, 901-933.

Table 1
Summary statistics of load and no-load funds

This table reports the medians and means of various characteristics of funds with different load types. *FLOAD* and *BLOAD* measure the front-end load level and back-end load level of a fund, respectively. *12B* represents the 12b-1 fees of a fund, while *NON12B* is created by subtracting 12b-1 fees from expense ratio to represent operating expenses not related to distribution efforts. *ASSET* is the total assets of a fund. *RAW* is the raw quarterly return of a fund. *SHARPE* stands for Sharpe ratio, a measure of risk-adjusted performance, which is calculated as average monthly return in excess of T-bill return divided by standard deviation of monthly returns in the past 12 months. *FLOW* measures *dollar flows*, and is defined as change in total assets in excess of appreciation and assets added through acquisition. *PFLOW* measures *percentage flows* and is defined as the asset growth rate of a fund due to dollar flows. *PFLOW* is winsorized at the 1st and 99th percentiles to control for the effects of outliers. *AGE* represents the age of a fund.

Fund Characteristics	All Retail Funds	Front-end Load Funds	Back-end Load Funds	Level-load Funds	No-load Funds
Panel A: Medians					
FLOAD (%)	N/A	4.750	N/A	N/A	N/A
BLOAD (%)	N/A	N/A	5.000	1.000	N/A
12B (%)	0.250	0.250	1.000	1.000	0.000
NON12B (%)	0.930	0.900	0.970	1.000	0.900
ASSET ($ million)	32.697	43.039	24.797	5.195	60.498
RAW (%)	1.724	1.782	1.558	1.364	1.933
SHARPE (%)	14.028	15.113	10.725	7.917	17.692
FLOW ($ million)	0.108	0.010	0.221	0.103	0.235
PFLOW (%)	1.099	-0.013	2.665	4.352	1.038
AGE (months)	44	57	36	29	47
Panel B: Means					
FLOAD (%)	N/A	4.581	N/A	N/A	N/A
BLOAD (%)	N/A	N/A	4.622	1.030	N/A
12B (%)	0.395	0.208	0.904	0.871	0.023
NON12B (%)	0.992	0.981	1.024	1.065	0.943
ASSET ($ million)	329.970	383.384	208.126	44.780	490.864
RAW (%)	1.661	1.685	1.333	1.063	2.144
SHARPE (%)	13.067	13.912	8.979	6.222	18.115
FLOW ($ million)	4.675	2.331	3.300	2.329	9.628
PFLOW (%)	16.902	11.465	21.879	29.345	14.068
AGE (months)	70.970	91.564	48.867	36.396	79.095

Table 2
Determinants of flows into retail mutual funds with different load types

For front-end load funds, I estimate the following random effects regression using only observations from front-end load funds, while excluding observations from funds closed to new investors:

$$PFLOW_{i,t} = \alpha + \beta_1 \bullet FLOAD_{i,t-1} + \beta_2 \bullet \Delta FLOAD_{i,t-1} + \beta_3 \bullet 12B_{i,t-1} + \beta_4 \bullet NON12B_{i,t-1} + \beta_5 \bullet LASSET_{i,t-1} + \beta_6 \bullet PFLOW_{i,t-1} + \beta_7 \bullet LOWPERF_{i,t-1} + \beta_8 \bullet MIDPERF_{i,t-1} + \beta_9 \bullet HIGHPERF_{i,t-1}$$

$$+ \beta_{10} \bullet AGE_{i,t-1} + \beta_{11} \bullet NUMOBJ_{i,t-1} + \beta_{12} \bullet OAWRET_{i,t-1} + u_i + \varepsilon_{i,t}$$

PFLOW measures *percentage flows*, and is defined as the asset growth rate of a fund due to dollar flows. *FLOAD* measures the front-end load level. *ΔFLOAD* measures the change in front-end load. *12B* represents the 12b-1 fees of a fund, while *NON12B* is created by subtracting 12b-1 fees from expense ratio to represent operating expenses not related to distribution efforts. *LASSET* is the natural log of *ASSET*, the total assets of a fund. Following Sirri and Tufano (1998), I measure the performance of a fund as its fractional performance rank ($RANK_{i,t}$), which represents the percentile of its raw return relative to other funds with the same investment objective in the same quarter, and create three performance range variables defined as follows using splines: $LOWPERF_{i,t} = \min [RANK_{i,t}, 0.2]$, $MIDPERF_{i,t} = \min [RANK_{i,t} - LOWPERF_{i,t}, 0.6]$, and $HIGHPERF_{i,t} = \min [RANK_{i,t} - LOWPERF_{i,t} - MIDPERF_{i,t}, 0.2]$. *LOWPERF* represents the bottom performance quintile, *MIDPERF* represents the middle three performance quintiles, and *HIGHPERF* represents the top performance quintile. *AGE* represents the age of a fund. *NUMOBJ* represents the number of investment objectives offered in the fund family. *OAWRET* is the asset-weighted average of the raw holding period returns of all funds with the same investment objective. u_i is the random disturbance characterizing the i^{th} fund and is constant through time. *FLOAD* is replaced by *BLOAD*, which measures the back-end load level, when back-end load and level-load funds are studied, or dropped when no-load funds are studied, and only the relevant data are used for each load type. *ΔFLOAD* is also replaced by *ΔBLOAD* for back-end load funds. If *FLOW*, which measures *dollar flows*, the change in total assets in excess of appreciation and assets added through acquisition, is used as the dependent variable, *ASSET* and *FLOW* (t-1) will be used to represent fund size and flows in the previous quarter instead. The percentage flow variable is winsorized at the 1st and 99th percentiles to control for the effects of outliers. *p*-values are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% confidence levels, respectively. [a], [b], and [c] indicate that the coefficients for each type of load funds are statistically different from the corresponding coefficients in the no-load fund regression at the 1%, 5%, and 10% confidence levels, respectively.

Table 2 (Continued)
Determinants of flows into retail mutual funds with different load types

Variables	Front-end Load Funds Percentage Flows	Front-end Load Funds Dollar Flows	Back-end Load Funds Percentage Flows	Back-end Load Funds Dollar Flows	Level-load Funds Percentage Flows	Level-load Funds Dollar Flows	No-load Funds Percentage Flows	No-load Funds Dollar Flows
FLOAD (t-1)	1.334***	0.419**						
	(0.000)	(0.028)						
BLOAD (t-1)			1.261***	0.714**	2.491	-0.131		
			(0.006)	(0.014)	(0.181)	(0.757)		
ΔFLOAD/ ΔBLOAD (t-1)	-0.417	-0.005	0.975	1.116				
	(0.289)	(0.994)	(0.121)	(0.142)				
12B (t-1)	2.471*, a	2.678**, b	0.244 a	3.180***, a	5.921***, a	2.078***, b	-21.309***	-1.831
	(0.057)	(0.028)	(0.878)	(0.004)	(0.002)	(0.000)	(0.000)	(0.692)
NON12B (t-1)	-2.232***, a	0.198	-0.883**, a	-0.460	-2.654***, b	-0.312*	-5.398***	-0.541
	(0.000)	(0.567)	(0.036)	(0.186)	(0.001)	(0.089)	(0.000)	(0.599)
LASSET (t-1)	-6.082***, a		-6.860***, a		-7.978***, a		-9.622***	
	(0.000)		(0.000)		(0.000)		(0.000)	
ASSET (t-1)		-1.197***, a		-6.786***, a		-2.866***, a		0.859***
		(0.000)		(0.000)		(0.000)		(0.000)
PFLOW (t-1)	0.138***, a		0.194***, a		0.157***, a		0.069***	
	(0.000)		(0.000)		(0.000)		(0.000)	
FLOW (t-1)		0.700***, a		0.736***, a		0.633***, a		0.483***
		(0.000)		(0.000)		(0.000)		(0.000)
LOWPERF (t-1)	0.067**	0.077	0.064*	0.059	0.009	0.011	0.034	0.049
	(0.047)	(0.134)	(0.090)	(0.187)	(0.905)	(0.612)	(0.423)	(0.713)
MIDPERF (t-1)	0.053***	0.091***, a	0.068***	0.095***, a	0.115***, a	0.038***, a	0.042***	0.242***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
HIGHPERF (t-1)	0.251***	0.136***, b	0.456***, a	0.175***, b	0.702***, a	0.092***, b	0.209***	0.378***
	(0.000)	(0.004)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.002)
AGE (t-1)	0.011***, a	0.003*, a	-0.061***, a	-0.013***	-0.083***, a	-0.011***	0.009**	-0.021***
	(0.000)	(0.074)	(0.000)	(0.000)	(0.000)	(0.000)	(0.024)	(0.000)
NUMOBJ (t-1)	0.123***, a	0.104***, a	0.123*, b	0.204***	0.166*	0.028 b	0.274***	0.352***
	(0.004)	(0.009)	(0.072)	(0.000)	(0.100)	(0.226)	(0.000)	(0.000)
OAWRET (t-1)	0.211***	0.244***, a	0.279***, a	0.251***, a	0.331***, a	0.105***, a	0.168***	0.554***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
INTERCEPT	-25.609***	-8.558***	-27.238***	-10.544***	-37.825***	-2.080***	-21.907***	-8.380***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.007)	(0.000)	(0.002)
Number of observations	75,653	75,653	44,225	44,227	27,637	27,637	59,371	59,371
Overall R^2	0.1036	0.4932	0.2508	0.5673	0.1601	0.4220	0.0638	0.2338

Table 3
The effect of alternative performance measure on the flows into retail mutual funds with different load types

In this table, performance range variables based on the Sharpe ratio, *LOWSHARPE* $_{i,t}$, *MIDSHARPE* $_{i,t}$, and *HIGHSHARPE* $_{i,t}$, which are computed in the same fashion as the percentage variables based on raw returns, are used instead as an alternative performance measure. Sharpe ratio measures the risk-adjusted performance of a fund, and is calculated as average monthly return in excess of T-bill return divided by standard deviation of monthly returns in the past 12 months. As a result, to study the determinants of percentage flows for front-end load funds, I estimate the following random effects regression using only observations from front-end load funds, while excluding observations from funds closed to new investors:

$$PFLOW_{i,t} = \alpha + \beta_1 \bullet FLOAD_{i,t-1} + \beta_2 \bullet \Delta FLOAD_{i,t-1} + \beta_3 \bullet 12B_{i,t-1} + \beta_4 \bullet NON12B_{i,t-1} + \beta_5 \bullet LASSET_{i,t-1} + \beta_6 \bullet PFLOW_{i,t-1} + \beta_7 \bullet LOWSHARPE_{i,t-1} + \beta_8 \bullet MIDSHARPE_{i,t-1} + \beta_9 \bullet HIGHSHARPE_{i,t-1} + \beta_{10} \bullet AGE_{i,t-1} + \beta_{11} \bullet NUMOBJ_{i,t-1} + \beta_{12} \bullet OAWRET_{i,t-1} + u_i + \varepsilon_{i,t}$$

PFLOW measures *percentage flows*, and is defined as the asset growth rate of a fund due to dollar flows. *FLOAD* measures the front-end load level. *ΔFLOAD* measures the change in front-end load. *12B* represents the 12b-1 fees of a fund, while *NON12B* is created by subtracting 12b-1 fees from expense ratio to represent operating expenses not related to distribution efforts. *LASSET* is the natural log of *ASSET*, the total assets of a fund. Following Sirri and Tufano (1998), I measure the performance of a fund as its fractional performance rank (*RANK* $_{i,t}$), which represents the percentile of its Shape ratio relative to other funds with the same investment objective in the same quarter, and create three performance range variables defined as follows using splines: *LOWSHARPE* $_{i,t}$ = min [*RANK* $_{i,t}$, 0.2], *MIDSHARPE* $_{i,t}$ = min [*RANK* $_{i,t}$ - *LOWSHARPE* $_{i,t}$, 0.6], and *HIGHSHARPE* $_{i,t}$ = min [*RANK* $_{i,t}$ - *LOWSHARPE* $_{i,t}$ - *MIDSHARPE* $_{i,t}$, 0.2]. *LOWSHARPE* represents the bottom performance quintile, *MIDSHARPE* represents the middle three performance quintiles, and *HIGHSHARPE* represents the top performance quintile. *AGE* represents the age of a fund. *NUMOBJ* represents the number of investment objectives offered in the fund family. *OAWRET* is the asset-weighted average of the raw holding period returns of all funds with the same investment objective. u_i is the random disturbance characterizing the i^{th} fund and is constant through time. *FLOAD* is replaced by *BLOAD*, which measures the back-end load level, when back-end load and level-load funds are studied, or dropped when no-load funds are studied, and only the relevant data are used for each load type. *ΔFLOAD* is also replaced by *ΔBLOAD* for back-end load funds. If *FLOW*, which measures *dollar flows*, the change in total assets in excess of appreciation and assets added through acquisition, is used as the dependent variable, *ASSET* and *FLOW* (t-1) will be used to represent fund size and flows in the previous quarter instead. The percentage flow variable is winsorized at the 1st and 99th percentiles to control for the effects of outliers. *p*-values are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% confidence levels, respectively. [a], [b], and [c] indicate that the coefficients for each type of load funds are statistically different from the corresponding coefficients in the no-load fund regression at the 1%, 5%, and 10% confidence levels, respectively.

Table 3 (Continued)
The effect of alternative performance measure on the flows into retail mutual funds with different load types

	Front-end Load Funds		Back-end Load Funds		Level-load Funds		No-load Funds	
Variables	Percentage Flows	Dollar Flows	Percentage Flows	Dollar Flows	Percentage Flows	Dollar Flows	Percentage Flows	Dollar Flows
FLOAD (t-1)	1.187***	0.324*						
	(0.000)	(0.097)						
BLOAD (t-1)			1.237***	0.618**	1.657	-0.101		
			(0.005)	(0.040)	(0.308)	(0.816)		
ΔFLOAD/ ΔBLOAD (t-1)	-0.419	0.110	1.334**	1.243				
	(0.261)	(0.860)	(0.016)	(0.107)				
12B (t-1)	2.444^{*,a}	3.208^{**,a}	-2.217^{a}	2.947^{**,a}	4.817^{***,a}	2.222^{***,a}	-17.156***	0.116
	(0.054)	(0.011)	(0.141)	(0.011)	(0.005)	(0.000)	(0.000)	(0.981)
NON12B (t-1)	-1.758^{***,b}	0.575	-0.936^{**,a}	-0.647*	-1.455**	-0.411**	-4.149***	0.254
	(0.000)	(0.108)	(0.017)	(0.072)	(0.035)	(0.032)	(0.000)	(0.812)
LASSET (t-1)	-5.715^{***,c}		-6.238^{***,a}		-6.648^{***,a}		-8.006***	
	(0.000)		(0.000)		(0.000)		(0.000)	
ASSET (t-1)		-1.241^{***,a}		-6.976^{***,a}		-3.030^{***,a}		0.865***
		(0.000)		(0.000)		(0.000)		(0.000)
PFLOW (t-1)	0.122^{***,a}		0.187^{***,a}		0.138^{***,a}		0.056***	
	(0.000)		(0.000)		(0.000)		(0.000)	
FLOW (t-1)		0.697^{***,a}		0.728^{***,a}		0.624^{***,a}		0.476***
		(0.000)		(0.000)		(0.000)		(0.000)
LOWSHARPE (t-1)	0.213^{***,a}	-0.036	0.105***	-0.065	0.101	-0.043	0.046	-0.118
	(0.000)	(0.512)	(0.002)	(0.151)	(0.150)	(0.052)	(0.308)	(0.417)
MIDSHARPE (t-1)	0.066***	0.118^{***,a}	0.102^{***,b}	0.122^{***,a}	0.181^{***,a}	0.062^{***,a}	0.068***	0.265***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
HIGHSHARPE (t-1)	0.459***	0.227^{***,a}	0.685^{***,a}	0.315^{***,a}	1.234^{***,a}	0.054^{***,a}	0.389***	0.791***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.051)	(0.000)	(0.000)
AGE (t-1)	0.010^{***,a}	0.004^{**,a}	-0.064^{***,a}	-0.013***	-0.065^{***,a}	-0.009***	0.003	-0.020***
	(0.000)	(0.030)	(0.000)	(0.000)	(0.000)	(0.003)	(0.387)	(0.000)
NUMOBJ (t-1)	0.119^{***,c}	0.104^{**,a}	0.104	0.208***	0.191**	0.024^{b}	0.203***	0.348***
	(0.004)	(0.011)	(0.106)	(0.000)	(0.032)	(0.321)	(0.001)	(0.001)
OAWRET (t-1)	0.207***	0.256^{***,a}	0.272^{***,a}	0.265^{***,a}	0.368^{***,a}	0.110^{***,a}	0.173***	0.559***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
INTERCEPT	-27.818***	-7.753***	-24.208***	-8.183***	-35.674***	-1.632**	-18.939***	-8.269***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.038)	(0.000)	(0.004)
Number of observations	73,807	73,807	42,506	42,508	26,588	26,684	57,456	57,550
Overall R^2	0.0875	0.4941	0.2147	0.5657	0.1571	0.4206	0.0526	0.2341

Table 4
The changes in average loads from 1992 to 2001

Average front-end loads and back-end loads are reported for each year from 1992 to 2001. Equity funds and hybrid funds are combined together because these funds tend to have the same sales loads in most fund families, while the sales loads of bond funds tend to be slightly lower.

	Average Front-end Loads (%)		Average Back-end Loads (%)	
Year	Equity & Hybrid Funds	Bond Funds	Equity & Hybrid Funds	Bond Funds
1992	4.87	4.24	4.76	4.56
1993	4.74	4.03	4.65	4.36
1994	4.90	4.03	4.66	4.27
1995	4.86	3.97	4.66	4.29
1996	4.90	3.96	4.67	4.40
1997	5.00	4.02	4.71	4.43
1998	5.02	4.02	4.76	4.48
1999	5.13	4.09	4.79	4.50
2000	5.19	4.10	4.80	4.52
2001	5.22	4.11	4.83	4.53

Table 5

An analysis using the full sample of load and no-load funds

Model 1 estimates the following random effects panel regression using the full sample of retail mutual funds excluding observations from funds closed to new investors:

$$PFLOW_{i,t} = \alpha + \beta_1 \bullet FLDUMMY_i + \beta_2 \bullet BLDUMMY_i + \beta_3 \bullet LLDUMMY_i + \beta_4 \bullet FLOAD_{i,t-1} + \beta_5 \bullet BLOAD_{i,t-1} + \beta_6 \bullet 12B_{i,t-1}$$
$$+ \beta_7 \bullet NON12B_{i,t-1} + \beta_8 \bullet LASSET_{i,t-1} + \beta_9 \bullet PFLOW_{i,t-1} + \beta_{10} \bullet LOWPERF_{i,t-1} + \beta_{11} \bullet MIDPERF_{i,t-1} + \beta_{12} \bullet HIGHPERF_{i,t-1} + \beta_{13} \bullet$$
$$AGE_{i,t-1} + \beta_{14} \bullet NUMOBJ_{i,t-1} + \beta_{15} \bullet OAWRET_{i,t-1} + u_i + \varepsilon_{i,t}$$

PFLOW measures *percentage flows*, and is defined as the asset growth rate of a fund due to dollar flows. *FLDUMMY*, *BLDUMMY*, and *LLDUMMY*, take the value of one if the fund is a front-end load fund, back-end load fund, and level-load fund, respectively, and zero otherwise. *FLOAD* and *BLOAD* measure the levels of front-end loads and back-end loads, respectively. Both load fund dummy variables and actual load levels are included to control for the possible non-linearity in the effects of fund loads. *12B* represents the 12b-1 fees of a fund, while *NON12B* is created by subtracting 12b-1 fees from expense ratio to represent operating expenses not related to distribution efforts. *LASSET* is the natural log of *ASSET*, which is the total assets of a fund. Following Sirri and Tufano (1998), I measure the performance of a fund as its fractional performance rank ($RANK_{i,t}$), which represents the percentile of its raw return relative to other funds with the same investment objective in the same quarter, and create three performance range variables defined as follows using splines: $LOWPERF_{i,t}$ = min [$RANK_{i,t}$, 0.2], $MIDPERF_{i,t}$ = min [$RANK_{i,t}$ - $LOWPERF_{i,t}$, 0.6], and $HIGHPERF_{i,t}$ = min [$RANK_{i,t}$ - $LOWPERF_{i,t}$ - $MIDPERF_{i,t}$, 0.2]. *LOWPERF* represents the bottom performance quintile, *MIDPERF* represents the middle three performance quintiles, and *HIGHPERF* represents the top performance quintile. *AGE* represents the age of a fund. *NUMOBJ* represents the number of investment objectives offered in the fund family. *OAWRET* is the asset-weighted average of the raw holding period returns of all funds with the same investment objective. u_i is the random disturbance characterizing the i^{th} fund and is constant through time. If *FLOW*, which measures *dollar flows*, the change in total assets in excess of appreciation and assets added through acquisition, is used as the dependent variable, *ASSET* and *FLOW*(t-1) will be used to represent fund size and flows in the previous quarter instead. The percentage flow variable is winsorized at the 1^{st} and 99^{th} percentiles to control for the effects of outliers. Model 2 uses alternative performance range variables based on the Sharpe ratio, $LOWSHARPE_{i,t}$, $MIDSHARPE_{i,t}$, and $HIGHSHARPE_{i,t}$, which are computed in the same fashion as the performance range variables based on raw returns. Sharpe ratio measures the risk-adjusted performance of a fund, and is calculated as average monthly return in excess of T-bill return divided by standard deviation of monthly returns in the past 12 months. *p*-values are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% confidence levels, respectively.

Table 5 (Continued)

An analysis using the full sample of load and no-load funds

Variables	Percentage Flows Model 1	Percentage Flows Model 2	Dollar Flows Model 1	Dollar Flows Model 2
FLDUMMY	-8.454***	-7.509***	-6.507***	-6.051***
	(0.000)	(0.000)	(0.000)	(0.000)
BLDUMMY	-9.585***	-9.307***	-8.780***	-7.442***
	(0.000)	(0.007)	(0.001)	(0.006)
LLDUMMY	-10.576***	-8.970***	-5.845***	-5.159***
	(0.000)	(0.000)	(0.000)	(0.000)
FLOAD (t-1)	1.068***	0.923***	0.670***	0.579***
	(0.000)	(0.000)	(0.009)	(0.000)
BLOAD (t-1)	1.520***	1.590***	0.778	0.596
	(0.002)	(0.001)	(0.148)	(0.283)
12B (t-1)	-1.679*	-1.298	2.463**	2.864***
	(0.066)	(0.128)	(0.023)	(0.010)
NON12B (t-1)	-2.903***	-2.062***	-0.076	0.212
	(0.000)	(0.000)	(0.811)	(0.520)
LASSET (t-1)	-8.349***	-7.222***		
	(0.000)	(0.000)		
ASSET (t-1)			-0.603***	-0.643***
			(0.000)	(0.000)
PFLOW (t-1)	0.138***	0.125***		
	(0.000)	(0.000)		
FLOW (t-1)			0.562***	0.555***
			(0.000)	(0.000)
LOWPERF (t-1)	0.049**		0.060	
	(0.023)		(0.166)	
MIDPERF (t-1)	0.062***		0.128***	
	(0.000)		(0.000)	
HIGHPERF (t-1)	0.299***		0.244***	
	(0.000)		(0.000)	
LOWSHARPE (t-1)		0.134***		-0.068
		(0.000)		(0.132)
MIDSHARPE (t-1)		0.091***		0.162***
		(0.000)		(0.000)
HIGHSHARPE (t-1)		0.550***		0.449***
		(0.000)		(0.000)
AGE (t-1)	0.006***	0.002	-0.009***	-0.008***
	(0.007)	(0.226)	(0.000)	(0.000)
NUMOBJ (t-1)	0.183***	0.173***	0.207***	0.205***
	(0.000)	(0.000)	(0.000)	(0.000)
OAWRET (t-1)	0.242***	0.245***	0.316***	0.330***
	(0.000)	(0.000)	(0.000)	(0.000)
INTERCEPT	-22.542***	-22.699***	-4.141***	-4.126***
	(0.000)	(0.000)	(0.000)	(0.000)
Number of observations	206,890	200,361	206,892	200,816
Overall R^2	0.1235	0.1063	0.3114	0.3115

Table A1
The determinants of front-end and back-end loads

To study the determinants of front-end loads, I first estimate the following random effects model (Model 1) using annual data of family-load type-asset class-level variables:

$$FLOAD_{i,j,t} = \alpha + \beta_1 \bullet ACDUMMY_{i,j} + \beta_2 \bullet FAC12B_{i,j,t-1} + \beta_3 \bullet FACNUM_{i,j,t-1} + \beta_4 \bullet FACAGE_{i,j,t-1} + \beta_5 \bullet FACNON12B_{i,j,t-1} + \beta_6 \bullet FACPFLOW_{i,j,t-1} + \beta_7 \bullet FACRETURN_{i,j,t-1} + u_i + \varepsilon_{i,j,t}$$

where *i*, *j*, and *t* stand for each fund family, asset class (equity & hybrid funds vs. bond funds), and year, respectively, and u_i is the random disturbance characterizing the i^{th} family and is constant through time. *ACDUMMY* takes the value of one if *FLOAD* indicates the front-end load charged by a fund family for its equity & hybrid funds, and zero for bond funds. *FAC12B* and *FACNON12B* are the asset-weighted average of 12b-1 fees and other operating expenses of all front-end load funds within the same asset class in a fund family, respectively. *FACNUM* gives the number of all front-end load funds within the same asset class in a fund family. *FACAGE* is the age of the first front-end load fund within the corresponding asset class in the family. *FACPFLOW* and *FACRETURN* are the asset-weighted average of the annual percentage flows and the annual objective-adjusted returns of all front-end load funds within the same asset class in a fund family, respectively. The panel regression method is used to account for the fact that observations from the same family are not independent relative to one another in this time-series cross-sectional (panel) data set.

I also estimate another random effects model (Model 2) using annual data of family-level variables:

$$FLOAD_{i,j,t} = \alpha + \beta_1 \bullet ACDUMMY_{i,j} + \beta_2 \bullet F12B_{i,t-1} + \beta_3 \bullet FNUM_{i,t-1} + \beta_4 \bullet FAGE_{i,t-1} + \beta_5 \bullet FNON12B_{i,t-1} + \beta_6 \bullet FPFLOW_{i,t-1} + \beta_7 \bullet FRETURN_{i,t-1} + u_i + \varepsilon_{i,j,t}$$

Except for *ACDUMMY*, all other variables used in Model 2 are family-level variables. They are calculated in the same fashion as the variables used in Model 1 using all funds in the family (including funds with all load types and asset classes).

When the determinants of back-end loads are studied, $FLOAD_{i,j,t}$ is replaced by $BLOAD_{i,j,t}$ in both Model 1 and Model 2. I also recalculate the family-load type-asset class-level variables using data from back-end load funds. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% confidence levels, respectively.

	FLOAD				BLOAD			
	Model 1		Model 2		Model 1		Model 2	
Variables	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
ACDUMMY	0.765***	0.000	0.801***	0.000	0.085***	0.001	0.121***	0.000
FAC12B (t-1)	-0.340***	0.007			0.362***	0.000		
FACNUM (t-1)	0.003*	0.075			0.002	0.317		
FACAGE (t-1)	0.000	0.187			0.000	0.208		
FACNON12B (t-1)	0.059**	0.015			0.043	0.255		
FACPFLOW (t-1)	0.000	0.968			0.000	0.315		
FACRETURN (t-1)	0.071	0.544			0.010	0.929		
F12B (t-1)			-0.319***	0.007			0.281***	0.001
FNUM (t-1)			0.003***	0.003			0.003***	0.004
FAGE (t-1)			0.000	0.653			0.000	0.551
FNON12B (t-1)			0.056**	0.024			0.110***	0.039
FPFLOW (t-1)			0.001	0.626			0.014	0.145
FRETURN (t-1)			0.094	0.402			0.019	0.867
INTERCEPT	4.844***	0.000	4.826***	0.000	4.297***	0.000	4.242***	0.000
Number of observations	2,336		2,405		1,095		1,201	
Overall R^2	0.1970		0.1867		0.0352		0.0464	

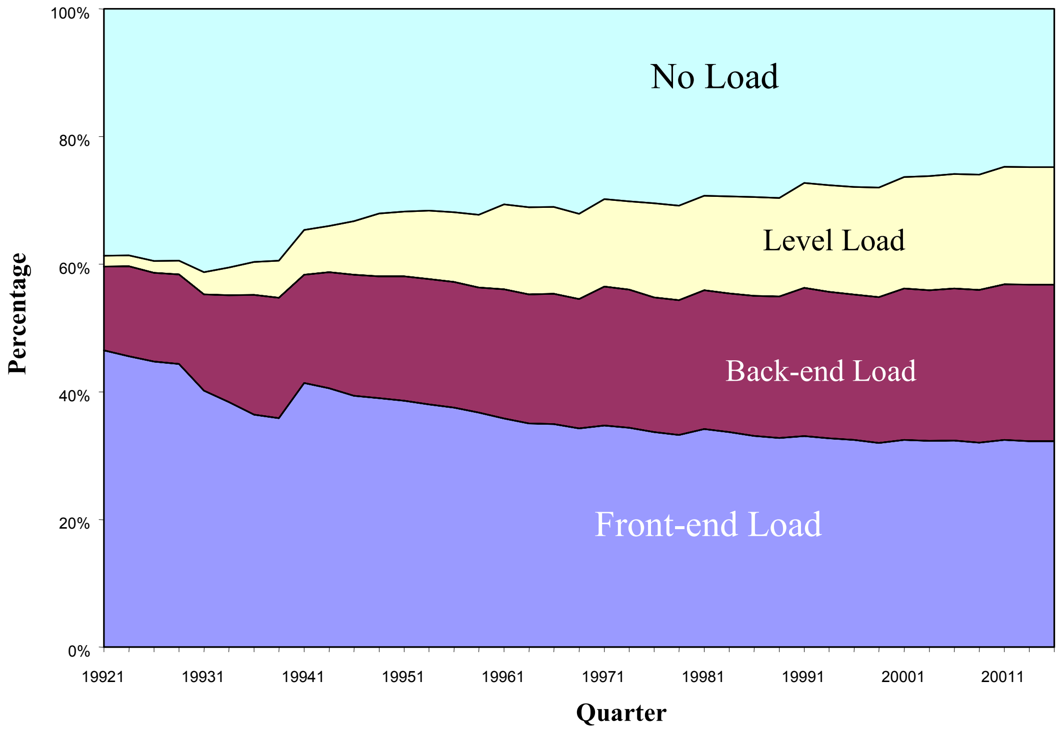

Fig. 1. The Distribution of Retail Mutual Funds among Different Load Types. Retail mutual funds can be disaggregated into four categories by load types: front-end load funds, back-end load funds, level-load funds, and no-load funds. Front-end load funds charge a front-end load and a 12b-1 fee but not a back-end load; back-end load funds charge a back-end load and a 12b-1 fee but not a front-end load; level-load funds generally charge a standard one-percent back-end load and a 12b-1 fee but not a front-end load; and no-load funds charge neither a front-end load nor a back-end load, but might charge a 12b-1 fee (if any) less than 25 basis points. Load funds are generally sold through brokers and financial advisors, while no-load funds largely rely on direct sales to investors. The loads and 12b-1 fees are used primarily to compensate brokers and financial advisors and to pay for distribution expenses.