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ABSTRACT

Mutual Fund Flows and Liquidity

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This dissertation is a comprehensive study on mutual fund flows and the portfolio liquidity of mutual funds. The dissertation is organized into three chapters. In the first chapter, I consider the problem of aligning the incentives between the mutual fund investor and the mutual fund manager. I show that the investor reduces the overall risk of the portfolio by threatening to lower the allocation of future wealth to the mutual fund manager. The model predicts that the flow-performance relationship is sensitive to the riskiness of the funds, the riskiness of the underlying asset, and the fee structure of the fund. In the second chapter, I perform an empirical analysis on mutual fund flows. The objective of the study is to improve the understanding of the sensitivity of future mutual fund flows to past fund performance, in particular, how individual fund characteristics influence the mutual fund flow-performance relationship. I test the empirical predictions of the model presented in Chapter 1 and find supporting evidence that the flow-performance relationship is sensitive to the load fees of the mutual fund. In the third chapter, I study the implication of liquidity on fund portfolio management. I focus on two types of liquidity

events specific to mutual funds: events of extreme anticipated fund flow and events of extreme unanticipated fund flow. I show that mutual fund managers, in anticipation of high expected outflow, increase the fund portfolio liquidity to avoid the forced sale of assets. Moreover, fund managers optimize their portfolios to reduce the trading cost of illiquid assets during unexpected bad times.

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To my parents

Anna and Norman

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CHAPTER 1

Strategic Investor in a Dynamic Setting: Implications on Mutual Fund Flows

1.1. Introduction

In a static model, a small investor without bargaining power on the delegation contract can be forced into a contract with suboptimal outcome. Obviously, if the issue is caused by information asymmetry, information disclosure may resolve the problem. However, disclosure of information and regulations are usually costly. In this paper, I provide insights on an alternative vehicle to improve the current situation of the investor.

A prime example of the above scenario is an investor who invests in mutual funds. Although the investor is unable to specify the desired contractual form given the structure of the mutual fund industry, the investor is not as passive as predicted in a static setup. By using future income streams as a threat in a dynamic setting, the investor can implicitly alter the incentive of the mutual fund manager. In this model, I show that the investor is better off behaving strategically in the dynamic setup than to passively invest. By doing so, the investor levels the playing field in delegated portfolio management, without monitoring and revelation of additional information. I also study the implications of having an aggregate economy of these investors, in particular, I derive predictions for the flow-performance relationship in the mutual fund industry.

There are two main purposes of this work. First, by using a 3 period model, I study the behavior of investors that participate in the financial market dynamically and their optimal investment flow strategy. The investor's optimal strategy is highly sensitive to his degree of risk aversion; moreover, the strategy also depends on the asset characteristics. In the aggregated industry level, I show that the existing empirical asymmetric flow-performance relationship (See Chevalier and Ellison (1997) for details) can be produced by an economy of strategic investors.

In the model, the manager has superior ability in picking stocks as compared to the investor, who lacks the knowledge and expertise. Instead of focusing on the issue of identifying the best manager, I assume the existence and common knowledge of the manager's skills and investigate the behavior of a strategic investor during the portfolio delegation process.

It is important to understand the driving force behind the observed flow-performance relationship, since the true incentives of the mutual fund manager is not simply to optimize the wealth of the investors. Manager compensation does not only depend on the structure of single-period fees, but also on the asset growth over time. As shown in Chevalier and Ellison (1997), mutual fund flow-performance relationship has a significant impact on the incentive and the risk-taking behavior of mutual fund managers. This paper aims to improve the understanding of the flow-performance relationship in mutual funds, by studying how the investor's optimal flow strategy is chosen and how the flow-performance relationship changes with respect to different mutual fund characteristics such as the risk level, the compensation scheme and the fund size.

1.1.1. Relation to the Literature

The paper touches several different areas such as agency theory, delegated portfolio theory and mutual fund flows. A closely related paper in the asset pricing literature is Carpenter (2000), which focuses on the risk-taking behavior of the manager in a continuous-time framework. The paper investigates the optimal dynamic investment policy of a risk averse fund manager who is compensated by a contract with a call option type feature. Her model illustrates the risk incentive created by a specific contract in a single evaluation period. Similar to her approach, I also take the contract between the two parties as given, however, the major deviation from Carpenter (2000) and the other related asset pricing literature is that I introduce the feature of repeated interaction. The investor has multiple evaluation periods which can be used as a strategic device.[1]

The principal-agent relationship is studied extensively in the contract theory literature. It is common to assume that the agent enjoys some informational advantage over the principal. The principal chooses an optimal compensation contract, taking into accounts the adverse effects and informational constraints. However, this assumption may not hold when an individual investor delegates portfolio management. In the real world when an investor tries to hire a financial advisor or invest in a mutual fund, the investor cannot choose the contractual form. At best, the investor could compare services offered by different mutual fund companies and pick the best option out of the set of predetermined contracts.

Therefore, I assume that the investor has no bargaining power with respect to the contractual terms in the model. Essentially, the investor faces a decision that has the flavor of a take-it-or-leave-it offer by the mutual fund industry. I find that even when the information is imperfect and the investor is unable to choose the contract, the investor can align the incentive with the agent by utilizing his future income as a threat.

The model studies the dynamic interaction between the investor and the mutual fund manager that is contractually bounded by a linear compensation contract. There are two main reasons behind the choice of linearity in the compensation scheme. First, as

[1]Other related research on risk-taking, money manager incentives and delegated portfolio theory include Bhattacharya and Pfleiderer (1985), Das and Sandaram (2002), Goetzmann et al. (2003), Grinblatt and Titman (1989), Heinkel and Stoughton (1994), Kockesen and Ok (2004), Ou-Yang (2003), Ross (2004) and Stoughton (1993).

discussed in Holmstrom and Milgrom (1987), real world incentive schemes appear to be simpler than the ones predicted by theory. Moreover, they find that in various settings, the optimal compensation scheme is a linear function of the argument. Second, linear contracts are commonly observed in real-life situations and in order to understand more complicated forms of compensation schemes, it is important to study the impact of repeated dynamic interaction between the investor and the fund manager with linear compensation as the benchmark case. Finally, as in many other models that move away from the static paradigm towards an intertemporal setting, tractability becomes an issue. By keeping the structure of the compensation scheme simple, I focus the investigation on the impact of a strategically behaved investor in a repeated interaction setting.

As shown in Chevalier and Ellison (1997), the manager's compensation does not only depend on the structure of the one-period fees, but also on how the dollar fees and assets grow over time. With the knowledge that the flow-performance relationship has an economic impact on the risk-taking behavior of mutual fund managers, it is important to understand the driving force behind the flow-performance relationship. Although there are models that try to incorporate the mutual fund flow-performance relationship, little work has focused on the flow-performance relationship. It remains unclear how the flow-performance relationship changes in different environments.[2] Imagine if we want to study the risk-taking behavior of a manager of an aggressive growth fund. Without the knowledge on how the flow-performance relationship of an aggressive growth fund differs from the flow-performance relationship of an income fund, one could at best assume the flow-performance relationship to be the same in the two cases. However, if aggressive

[2] For example of papers that study fund flows theoretically, see Basak et al. (2004) and Berk and Green (2004).

growth fund has a more sensitive flow-performance relationship, our assumption results in an over estimation of the risk-taking behavior by the manager.

Berk and Green (2004) derive a rational model with active portfolio management in which they explain two observed behaviors in the mutual fund industry: flows are responsive to performance and performance is not persistent. In contrast to my work, their players use past history to form their beliefs of a manager's ability, which is not known to both the investor and the manager. Although Berk and Green (2004) successfully form a rational model that explains the flow-performance relationship without performance persistent, they fail to replicate the nonlinearity observed in the flow-performance relationship. However, with strategic investors as described in this paper, the predicted flow of funds is a nonlinear function of the lagged fund return as shown in Chevalier and Ellison (1997).

Finally, I incorporate the possibility of front load fee in the model. Mutual fund investors usually have to pay a fixed percentage of their investment to the mutual fund company. This charge does not reoccur if the money is reinvested, however, it will be incurred once again if the investors decide to withdraw their money from the fund and reallocate it to another mutual fund. This creates a cost of shifting money between two identical funds, and thus the front load fee acts as a switching cost to the investors. The fee structure influences the behavior of repeated investors. This observation relates the paper to the literature in industrial organization, especially in the area of switching costs.[3]

[3]For references, see Beggs and Klemperer (1992), Klemperer (1995), Farrell and Shapiro (1988), Farrell and Shapiro (1989) and more.

1.2. Modeling Details

In this section, I present the basic setup of the model. I assume that the investor and the manager live in a two assets world. The first asset is a riskfree asset with a known, deterministic payoff of $R_{b,t}$ in time t. The second asset traded in the market is a risky asset with uncertain payoff $R_{s,t}$ at time t. I assume that the stock return, $R_{s,t}$, is normal distributed with mean μ and variance σ^2, i.e. $R_{s,t} \sim \mathcal{N}(\mu, \sigma^2)$, and the return on the riskfree asset is lower than the mean return on the risky asset , i.e. $R_{b,t} < \mu$ for all time t. In this chapter, $R(.)$ is used to denote cumulative return and return is in gross terms unless stated otherwise.

At time 0 and time 1, the investor receives income w_0 and w_1 dollars in each period respectively. The income is invested for future consumption. At time 2, the investor no longer receives any income and consumes his payoff from prior investment. At time 0, the investor has the choice between investing in the riskfree asset, or investing in a mutual fund and paying management fees to the mutual fund company. By investing in the mutual fund, the investor can participate in the stock market. The investor either invests the entire time 0 income w_0 in the mutual fund or the entire time 0 income w_0 in the outside option, which is the riskfree asset. The investor cannot allocate a fraction of his income in the mutual fund and the remaining in the outside option.

Let $R_p(\alpha_0)$ be the cumulative return of the mutual fund in the first period. If the investor invests in the mutual fund, the resulting wealth at time 1 from the time 0 investment before fees is $w_0 R_p(\alpha_0)$. At time 1, the investor allocates his time 1 wealth, which is the sum of the time 1 income w_1 and the cumulative return of the time 0 investment net of any fees, among the original mutual fund, another mutual fund with similar characteristics and the riskfree asset. Similar to the initial period time 0, the investor cannot infinitesimally split his investment between the three choices. Instead, he chooses to allocate a fixed portion of his time 1 wealth into the three options. The details are described in a latter section.

In this paper, the form of compensation is assumed to be linear[4] and the investor does not have influences over the contractual form between the fund manager and himself. I assume that the investor is unable to observe the portfolio weights the manager chooses if he delegates the portfolio management. Only the realized portfolio return is revealed to the investor when the compensation fee is due. This information asymmetry places the investor in a vulnerable situation. However, in this paper, I show that by acting strategically, the investor can discourage the fund manager from investing in an overly risky portfolio allocation.

The current fee structure in the model is exogenously determined. I view the setup as a simplification of the fee structure commonly found in the mutual fund industry. The fee structure is assumed to be constant over time. The fund manager's compensation contract and the fee structure are the same in the initial mutual fund MF_I and the alternative fund MF_{II}. The management fee in both cases, denoted by $x \in (0, 1)$, is a fixed percentage of the assets under management. In both mutual funds MF_I and MF_{II}, there is an additional fixed percentage initial sales charge. Let B denotes the percentage net of the initial sales charge. For example, for a fund with 5% initial sales charge, B is equal to 0.95. I also assume that the manager does not get a separate compensation contract with the mutual fund company, thus the manager's compensation is the total fees paid by all

[4]As discussed in the introduction, linear compensation contract is an important benchmark to study. For references, please see Holmstrom and Milgrom (1987).

investors invested in the mutual fund. The manager does not receive any of the initial sales charge paid by the investor. The following example should help to illustrate the fee structure of the mutual fund in the model. For an investor who invests 100 dollars in a mutual fund with 2% management fee and 5% initial sales charge, 5% of the 100 dollars is taken off at the beginning as the initial sales charge and 95 dollars is under the management of the fund manager. Lets suppose that the return of the portfolio in the following period is 10%, the manager receives a compensation of $\$95 \times 1.1 \times 2\% = \$2.09$ and the investor retains the rest.

The manager is assumed to be a risk averse individual with negative exponential utility, thus his utility has the following form: $u_A(\tilde{c}_A) = -\exp\{-\delta_A \tilde{c}_A\}$, where $\tilde{c}_A$ is the stochastic consumption of the manager. The manager is assumed to have an intertemporal discount rate of $\beta \in [0, 1]$. The manager's objective at time t is to maximize his expected discounted utility at time t. Thus the manager maximizes $u_A(\tilde{c}_1) + \beta u_A(\tilde{c}_2)$ in the three period model at time 0.

For simplification, the manager does not incur any effort cost during portfolio management. Therefore, the manager's utility is solely a function of the compensation received. If the manager is not awarded with the delegation contract from the investor, his reservation utility is denoted by v. In every period, the manager learns the return distribution of the risky asset and participates in the financial market freely.

I focus on the relationship among 1 fund manager and N symmetric investors. The fund manager manages the investment from a group of investors with the same characteristics, in terms of the utility form, the risk aversion parameter and the outside options. Hence, if all of the investors decide to invest through portfolio delegation, the manager's compensation is N times the individual compensation from each contract. The size of the potential pool of investors, N, is assumed to be exogenous. The fund manager does not have any outside income in addition to the compensation from the portfolio management. All in all, the manager optimizes the total compensation fee from the portfolio management of all potential investors.

1.2.1. Incentive and Strategies of the Investor

In the model, the investor has an incentive to invest in the mutual fund because he is unable to directly participate in the risky asset market. There are two motivations behind this setting. First of all, the typical size of a mutual fund is large, compared to the wealth of an individual investor. As shown in Brennan and Hughes (1991)[5], mutual funds receive discounts on transaction cost and benefit from transaction cost savings through brokerage and other securities services, which are unavailable to individual investors.

Although the lower transaction cost of the mutual funds is not explicitly modeled, one could view the current setup as an investor incurring high transaction costs in acquiring the risky asset, thus limiting participation in the risky asset market. Secondly, I would like to capture a manager who has the ability to pick stocks as compared to an investor with little knowledge of the financial markets and assets. It is unlikely that an investor with time constraints is able to gain sufficient knowledge about the markets to make sound financial decisions. Therefore, he invests into the financial markets through the mutual fund. Although the investor does not have direct access to the risky asset market, the investor does know the distribution of the risky asset return. By using this information

[5] In Brennan and Hughes (1991), they document that the brokerage commissions decrease with the size of the transaction.

strategically, the investor can alter the incentive of the fund manager to better align the incentives between the two parties.

A time constrained individual investor is also unable to regularly monitor his portfolio and investment. It is unlikely that the individual has the time and energy to optimize his behavior frequently. Instead, the investor is more likely to examine his portfolio performance periodically. Therefore, in the model, I assume that the investor optimizes and forms his strategy once at the beginning of the game. At time 0, the investor optimizes his strategic move for the next two periods, taking into account the best response of the fund manager. At time 1, the investor behaves according to the predetermined strategy with respect to the realized time 0 portfolio return.[6]

The investor's objective is to maximize his terminal wealth at time 2 in the three period model. The investor is assumed to be a risk averse individual with negative exponential utility as follows,

$$u_I(\tilde{c}) = -\exp\{-\delta_I \tilde{c}\}, \text{where } \tilde{c} \text{ is the stochastic consumption of the investor.}$$

Let the risk aversion parameter of the N symmetric investors be denoted by δ_I and the risk aversion parameter of the manager be denoted by δ_A where $\delta_A = \theta\delta_I$ and $\theta \leq 1$.

In the initial period, the investor chooses to invest in either the riskfree asset or in a mutual fund. Let the mutual fund selected at time 0 be denoted by MF_I and let the portfolio choice of the manager at time 0, which is the weight allocated to the risky asset at time 0, be denoted by α_0.

[6]The investor is essentially behaving as if there is a commitment device that binds him to the predetermined strategy at time 1.

The investor is unable to observe the manager's risky asset allocation in both periods 0 and 1. The investor's knowledge of the manager's performance is reflected only by the realized portfolio return of the mutual fund. Although the investor knows the return of the riskfree asset, the investor does not know the realized return of the risky asset, and thus cannot infer the composition of the portfolio by studying the realized portfolio return. When the realized return of the portfolio is extremely low, the investor can infer that either the manager took on a very risky allocation or the return of the risky asset was extremely low, resulting in a low portfolio return even though the manager did not overload on the risky asset.

At time 1, the portfolio return from $R_p(\alpha_0)$ is realized, where $R_p(\alpha_0) = R_b(1-\alpha_0) + \alpha_0 R_{s,0} =$ the weighted average return of the two assets. In the model, I focus the attention on simple trigger strategies with 4 thresholds $\eta = \{\eta_1, \eta_2, \eta_3, \eta_4\}$, where $\eta_1 \leq \eta_2 \leq \eta_3 \leq \eta_4$. The investor's trigger strategy creates 5 response regions with respect to the realized portfolio return, which are $R_p < \eta_1$, $\eta_1 \leq R_p < \eta_2$, $\eta_2 \leq R_p < \eta_3$, $\eta_3 \leq R_p < \eta_4$ and $R_p \geq \eta_4$ respectively.

The investor observes $R_p(\alpha_0)$ at time 1 and takes one of the following three actions at time 1. First, the investor can decide to withdraw the entire amount from MF_I and allocate the sum of the realized portfolio return and current income to the alternative options, which include another mutual fund, MF_{II}, or the riskfree asset. Secondly, the investor can reinvest the existing MF_I investment with MF_I and allocate the current income with the same alternative options as in the first case. Last but not least, the investor can reinvest the existing investment and the current income with MF_I. I denote the above cases as case 1, 2 and 3, respectively.[7] The alternative fund at time 1, MF_{II}, is assumed to have the same fund characteristics as MF_I. This means that both of the mutual fund managers face the same investment opportunity set and the same number of potential investors, and both of the managers have the same utility, the same level of risk aversion and the same effort cost.

In order to understand how the investor uses his mutual fund investment flows to change the manager's implicit compensation, I first analyze the incentive of the investor. On one hand, the investor would like to discourage the manager from choosing an overly risky portfolio allocation. On the other hand, the investor would like to encourage the manager to hold a portfolio with a reasonable amount of risk.

Therefore, I focus on the strategies where the investor chooses to terminate his relationship with the manager of MF_I when the realized portfolio return is extreme. An extreme realized return can be viewed as a signal of a high allocation on the risky asset. If the manager has only placed a low allocation on the risky asset, the probability of an extreme realized portfolio return is low. Using the model, I show that an investor utilizing the four thresholds trigger strategy can indirectly alter the manager's compensation such that the portfolio weights chosen by the manager is closer to the investor's ideal portfolio weight.

Formally, let η_1 be the threshold in which the investor terminates the relationship when the realized portfolio return is below η_1 and let η_4 be the threshold in which the investor terminates the relationship when the realized portfolio return is above η_4. The termination of the relationship with the manager of MF_I at time 1 is denoted as case 1.

[7]For the graphically representation of the timeline of the model, please see figure 1.5.

Figure 1.1: A graphic illustration of threats levels η_1, η_4 and the outflow region.

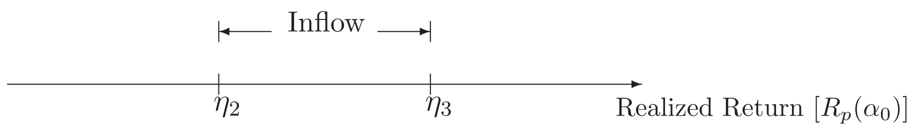


Figure 1.2: A graphic illustration of threats levels η_2, η_3 and the inflow region.

When the investor observes the time 1 realization of the portfolio return $R_p(\alpha_0)$ to be above η_4 or below η_1, the investor withdraws the entire existing investment from MF_I and allocates the time 1 wealth in the alternative options. Therefore, case 1 occurs when the realized time 0 portfolio return is within set A_1 where $A_1 = \{R_p : R_p < \eta_1 \text{ and } R_p \geq \eta_4\}$. Region A_1 is also referred as the outflow region since the investor withdraws the current investment from the mutual fund when $R_p(\alpha_0) \in A_1$. See figure 1.1.

With similar intuition, in order to encourage the fund manager to choose the right amount of risk, the investor would like to increase the funds into MF_I when the realized portfolio return at time 1 reflects desired portfolio choice. Let $A_3 = \{R_p : \eta_2 \leq R_p < \eta_3\}$ be the set of values in which the investor chooses case 3 and allocates all of his time 1 wealth into MF_I. When the realized portfolio return is within the bounds of η_2 and η_3, there is an inflow of funds into the initial mutual fund MF_I, thus region A_3 is also referred as the inflow region. See figure 1.2.

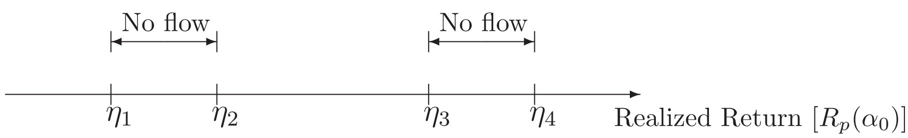


Figure 1.3: A graphic illustration of all threats levels and the no-flow region

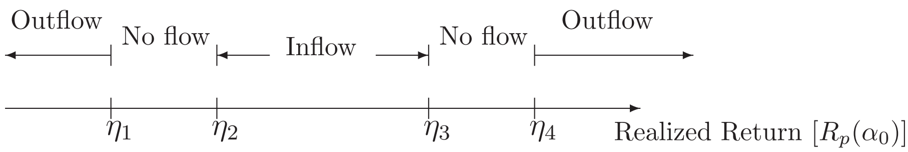


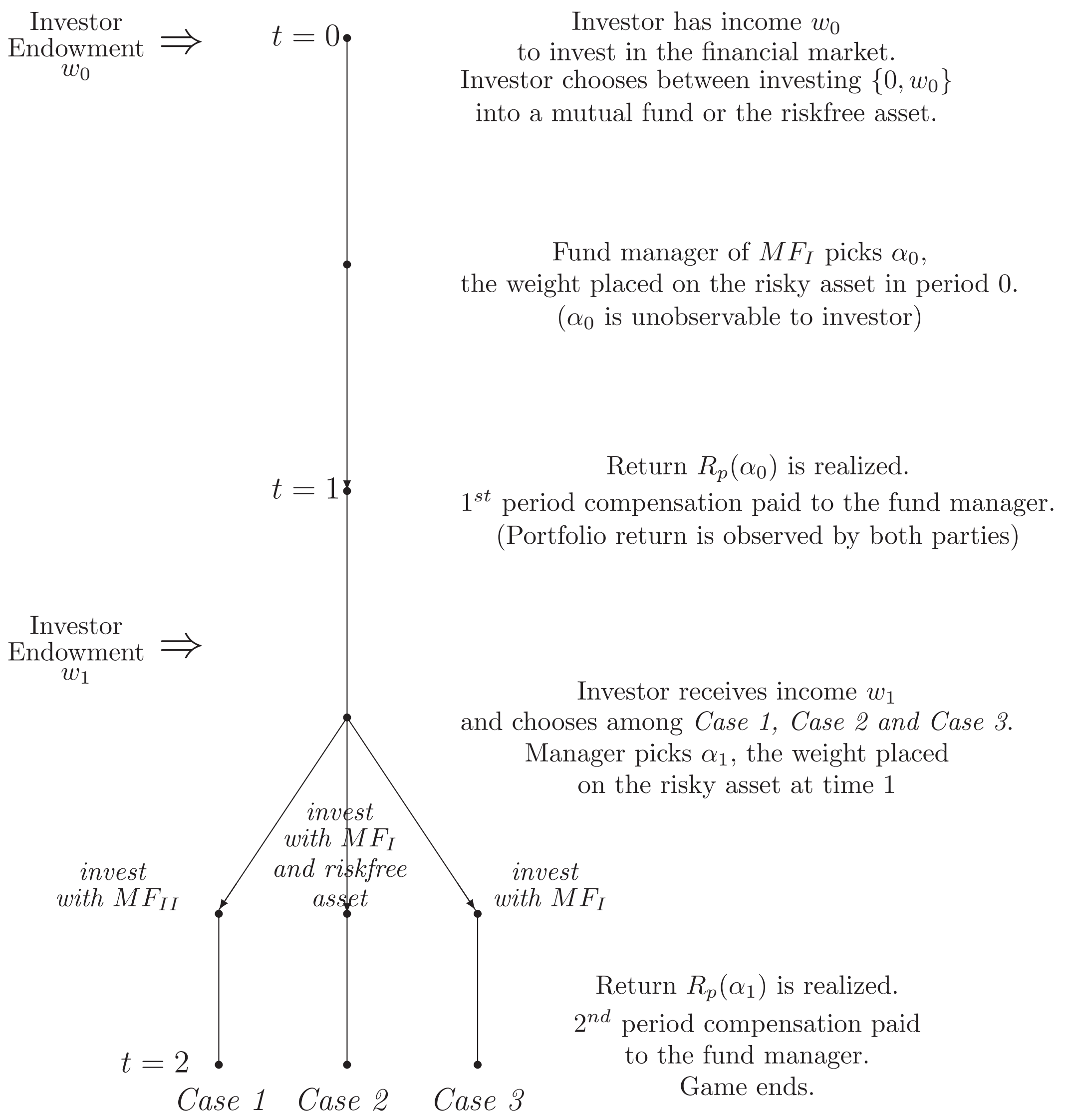
Figure 1.4: A graphic illustration of overall threats levels $\eta = \{\eta_1, \eta_2, \eta_3, \eta_4\}$, with all three flow regions.

For the remaining values of the realized portfolio return in set A_2, where $A_2 = \{R_p : \eta_1 \leq R_p < \eta_2 \text{ and } \eta_3 \leq R_p < \eta_4\}$, the investor only reinvests the portfolio from time 0 in MF_I and allocates the current income w_1 with an alternative financial instrument. Region A_2 is also referred as the no-flow region since no additional capital enter or exit the initial mutual fund MF_I. See figure 1.3.

All in all, the investor has a strategy set as shown in figure 1.4 in the model. I do not claim that the strategy is the optimal strategy for the investor. Instead, I constrain the attention to the aforementioned strategy set, with the intuitions discussed in this section, and study the optimal threshold $\eta^* = \{\eta_1^*, \eta_2^*, \eta_3^*, \eta_4^*\}$ chosen by the investor.

In the model, it is implicitly assumed that the investor is fully committed at the time 0 strategy. The modeling assumption is supported by the following two scenarios. First of all, if the investor is time constrained and does not have sufficient time to monitor the manager and maximize his portfolio allocation every period, the investor chooses his strategy at time 0 and follows the strategy for the entire duration of the game and does not deviate at time 1 under any circumstances. The second scenario is that a second maximization at time 1 is costly. In this case, it is worth considering a change in the investment strategy only if the expected gain is sufficiently large to recover the cost of maximization. But if the investor's payoffs in the three cases are less than the cost of re-optimization, the investor does not have an incentive to review his strategy and reallocate the portfolio in a different manner at time 1. In both cases, the investor does not deviate from the strategy optimized at time 0.

Strategic Delegation Game:



Case 1: Invest entire portfolio with MF_{II}.
Case 2: Reinvest the initial portfolio with MF_I and w_1 into the riskfree asset.
Case 3: Invest entire portfolio with MF_I.

Figure 1.5: A graphic illustration of the timing of the game

1.3. Maximization of the Investor and the Manager

In this section, I formally setup the objective functions of the investor and the mutual fund manager. Since the model is a three period model and w_1 is the last income of the investor, the investor is unable to form further future threats at time 1. Therefore, the fund manager chooses the same portfolio allocation weight as in a static model at time 1. In order to compute the time 0 expected value of the objective functions for both players, I first determine the last period portfolio weight chosen by the manager, α_1^*. Then by substituting the optimal time 1 portfolio allocation weight α_1^* into the time 0 expectation of the objective functions, the objective functions of the investor and the manager are re-expressed in terms of the fundamentals in the model, i.e. the riskfree rate, the mean and the variance of the risky asset, the rate of compensation and the fund size.

1.3.1. Manager Maximization at Time 1

In the following section, I compute the optimal second period portfolio allocation in the various cases. MF_I is the mutual fund with the initial investment at the beginning of the game, and MF_{II} is the alternative mutual fund in the second period. The managers can choose any real number as the allocation in the risky asset, i.e. $\alpha_t \in \mathbb{R}$, for each period $t = 0, 1$.

Let F^{ij} be the fund size of MF_i in case j, after the compensation fee for the first period fund management, where i=I,II and j=1,2,3. In general, F^{ij} is a function of the portfolio choice α_0 from the initial period. For the portfolio choice at time 1, let α_1^{ij} be the weight placed on the risky asset at time 1 by the mutual fund manager of MF_i in case j, where i=I,II and j=1,2,3.[8] Let c_1 be the total compensation fund manager of MF_I receives at time 1. Let c_2^{ij} be the total compensation fund manager of MF_i receives in case j at time 2. Note that c_2^{ij} is a function of the size of the fund at time 1, F^{ij}. Therefore,

- Case 1: Complete withdrawal

$$\begin{aligned} F^{11} &= MF_I\text{'s fund value in case } 1 = 0 \\ F^{21} &= MF_{II}\text{'s fund value in case } 1 = \left[w_1 + BR_p\left(\alpha_0\right)\left(1-x\right)w_0\right]NB \end{aligned}$$

- Case 2: Reinvest principal and dividends only

$$\begin{aligned} F^{12} &= MF_I\text{'s fund value in case } 2 = \left[R_p\left(\alpha_0\right)w_0\left(1-x\right)\right]NB \\ F^{22} &= MF_{II}\text{'s fund value in case } 2 = w_1 NB \end{aligned}$$

- Case 3: Additional inflow

$$\begin{aligned} F^{13} &= MF_I\text{'s fund value in case } 3 = \left[w_1 + R_p\left(\alpha_0\right)w_0\left(1-x\right)\right]NB \\ F^{23} &= MF_{II}\text{'s fund value in case } 3 = 0 \end{aligned}$$

The payoff of the mutual fund manager of MF_I in the first period is dependent on the compensation rate x, the portfolio choice variable at time 0, α_0, and the realization of the risky asset return at time 1. The second period payoff of the mutual fund manager of MF_I

[8]For simplicity, the notation α_1^{ij} is defined for both fund managers in case 1, 2 and 3, however, there are exceptions. In case 1, the manager of MF_I does not get any fund and similarly in case 3 for the manager of MR_{II}. Therefore, in these two cases, the managers consume their outside option and do not pick α_1. The calculations for α_1^{ij} do not apply in these two cases.

under the three different cases is a function of the compensation rate x, the portfolio choice variable at time 1, α_1, the realization of the risky asset return at time 2 and the size of the fund. Since the size of the fund is determined by the time 0 portfolio choice variable and the realization of the risky asset return at time 1, the overall payoff of the fund manager of MF_I is dependent on the compensation rate x, the portfolio choice variable at time 0 and 1, the realization of the risky asset return at time 1 and 2. Mathematically,

Case 1 (Complete withdrawal). *At time 1, all funds are withdrawn and invested into an alternative instrument. The fund manager of MF_I receives the following compensation,*

$$\textit{For manager of } MF_I := \begin{cases} \textit{Manages } w_0NB \textit{ at time 0 and receives } w_0NBxR_p(\alpha_0) \textit{ at time 1} \\ \textit{Manages 0 at time 1 and receives } 0 \textit{ at time 2} \end{cases}$$

Case 2 (Reinvest time 0 portfolio). *At time 1, all of the funds from the time 0 portfolio are reinvested in MF_I and the income at time 1 is invested elsewhere. The fund manager of MF_I receives the following compensation,*

$$\textit{For manager of } MF_I := \begin{cases} \textit{Manages } w_0NB \textit{ at time 0 and receives } w_0NBxR_p(\alpha_0) \textit{ at time 1} \\ \textit{Manages } \left[R_p\left(\alpha_0\right)\right]\left(1-x\right)Bw_0N \textit{ at time 1} \\ \textit{and receives } \left[R_p\left(\alpha_0\right)\right]\left(1-x\right)Bw_0NxR_p(\alpha_1) \textit{ at time 2} \end{cases}$$

Case 3 (Additional Inflow). *At time 1, all of the funds from the time 0 portfolio are reinvested in MF_I, together with the time 1 income of the investor. The fund manager of MF_I receives the following compensation,*

$$\textit{For manager of } MF_I := \begin{cases} \textit{Manages } w_0NB \textit{ at time 0 and receives } w_0NBxR_p(\alpha_0) \textit{ at time 1} \\ \textit{Manages } \left[w_1 + R_p\left(\alpha_0\right)\left(1-x\right)w_0\right]BN \textit{ at time 1} \\ \textit{and receives } \left[w_1 + R_p\left(\alpha_0\right)\left(1-x\right)w_0\right]BNxR_p(\alpha_1) \textit{ at time 2} \end{cases}$$

Since there is no further threat on the future fund allocation, both of the fund managers choose the portfolio α_1^{ij} in period 1 as follows:

$$\max_{\alpha_1^{ij}} E_1 u_A \left[c_2^{ij}\right] \text{ where } c_2^{ij} = xF^{ij} R_p\left(\alpha_1^{ij}\right)$$

$$\begin{aligned}
&\Leftrightarrow \max_{\alpha_1^{ij}} u_A \left\{ E_1\left(c_2^{ij}\right) - \frac{1}{2}\delta_A Var\left(c_2^{ij}\right) \right\} \Leftrightarrow \max_{\alpha_1^{ij}} E_1\left(c_2^{ij}\right) - \frac{1}{2}\delta_A Var\left(c_2^{ij}\right) \\
&\Leftrightarrow \max_{\alpha_1^{ij}} xF^{ij} E_1\left[R_p\left(\alpha_1^{ij}\right)\right] - \frac{1}{2}\delta_A\left(xF^{ij}\alpha_1^{ij}\right)^2\sigma^2 \text{ where } E_1\left[R_p\left(\alpha_1^{ij}\right)\right] = \left(\mu - R_b\right)\alpha_1^{ij} + R_b \\
&\Leftrightarrow \max_{\alpha_1^{ij}} xF^{ij}\left[\left(\mu - R_b\right)\alpha_1^{ij} + R_b\right] - \frac{1}{2}\delta_A\left(xF^{ij}\alpha_1^{ij}\right)^2\sigma^2
\end{aligned}$$

By differentiating with respect to α_1^{ij}, we have the following FOC

$$\left(\mu - R_b\right) - \delta_A xF^{ij}\sigma^2\alpha_1^{ij} = 0$$

Hence, at time 1, the fund manager of MF_i chooses α_1^{ij*} in case j where

$$\alpha_1^{ij*} = \frac{\mu - R_b}{\delta_A xF^{ij}\sigma^2}$$

In order to compute the expected utility of the investor and manager, I first calculate the probability of each case given the investor's strategy $\eta = \{\eta_1, \eta_2, \eta_3, \eta_4\}$. Since the portfolio return distribution is dependent on the portfolio weight on the risky asset, the probability of the future threats is a function of both the threat threshold, η, and the distribution of the portfolio return $R_p(\alpha_0)$. Let A_j denotes the set of realized portfolio values in which case j occurs at $t = 1$. The set of values for the three different cases and the corresponding probability values are as follows,

$$
\begin{aligned}
A_1 &= \{R_p : R_p < \eta_1 \text{ and } R_p \geq \eta_4\} \\
A_2 &= \{R_p : \eta_1 \leq R_p < \eta_2 \text{ and } \eta_3 \leq R_p < \eta_4\} \\
A_3 &= \{R_p : \eta_2 \leq R_p < \eta_3\}
\end{aligned}
$$

The portfolio return distribution with the risky asset weight α_0 at time 0 is normal distributed, $R_p(\alpha_0) \sim \mathcal{N}(\mu_p(\alpha_0), \sigma_p^2(\alpha_0)) = \mathcal{N}(\alpha_0\mu + (1-\alpha_0)R_b, \alpha_0^2\sigma^2)$. By defining $s(\alpha_t, \eta) = \frac{\eta - \alpha_t\mu - (1-\alpha_t)R_{b,t}}{\alpha_t\sigma}$, the probability of the portfolio return below a threshold η becomes

$$
\Pr(R_p(\alpha_0) \leq \eta) = \Phi[s(\alpha_0, \eta)]
$$

Therefore,

$$
\begin{aligned}
\Pr(case1) &= \Pr(R_p(\alpha_0) \in A_1) \\
&= \Pr(R_p(\alpha_0) \leq \eta_1) + 1 - \Pr(R_p(\alpha_0) \leq \eta_4) \\
&= \Phi[s(\alpha_0, \eta_1)] + 1 - \Phi[s(\alpha_0, \eta_4)]
\end{aligned}
$$

$$
\begin{aligned}
\Pr(case2) &= \Pr(R_p(\alpha_0) \in A_2) \\
&= \Pr(R_p(\alpha_0) \leq \eta_2) - \Pr(R_p(\alpha_0) \leq \eta_1) + ... \\
&\quad \Pr(R_p(\alpha_0) \leq \eta_4) - \Pr(R_p(\alpha_0) \leq \eta_3) \\
&= \Phi[s(\alpha_0, \eta_2)] - \Phi[s(\alpha_0, \eta_1)] + \Phi[s(\alpha_0, \eta_4)] - \Phi[s(\alpha_0, \eta_3)]
\end{aligned}
$$

$$
\begin{aligned}
\Pr(case3) &= \Pr(R_p(\alpha_0) \in A_3) \\
&= \Pr(R_p(\alpha_0) \leq \eta_3) - \Pr(R_p(\alpha_0) \leq \eta_2) \\
&= \Phi[s(\alpha_0, \eta_3)] - \Phi[s(\alpha_0, \eta_2)]
\end{aligned}
$$

1.3.2. Manager Maximization at Time 0

In this section, I calculate the objective function value of the fund manager of MF_I with negative exponential utility. There are two steps in solving for the optimal behavior in the model. Step 1 solves for the optimal portfolio weights the manager chooses given the threat level η. From previous calculations, we know the manager's choice of the portfolio weights at time 2 given the realized portfolio return and investor's strategy at time 1. The manager maximizes the time 0 expected discounted utility from the compensation in period 1 and the compensation under the three scenarios A_1, A_2 and A_3 in period 2. The derivation of the expected utility is similar for the investor and the manager. In case 1 when the investor completely withdraws his investment, the manager does not have any fund to manage. Therefore, the manager's consumption is his outside option. The outside option is assumed to be less attractive than the compensations from the portfolio management in case 2 and case 3.

Mathematically, in case 2 when the investor reinvests the existing investment,

$$\begin{aligned} & Eu_A\left[c_2^{1,2} \mid R_p(\alpha_0) \in A_2\right] \\ = \; & Eu_A\left[xF^{1,2}R_b + (R_s - R_b)\frac{\mu - R_b}{\delta_A \sigma^2} \middle| R_p(\alpha_0) \in A_2 \right] \end{aligned}$$

$$\begin{aligned} \text{With } R_p(\alpha_0) &= \alpha_0 R_s + (1-\alpha_0) R_b, \\ R_p(\alpha_0) &\leq \eta_i \Leftrightarrow \alpha_0 R_s + (1-\alpha_0) R_b \leq \eta_i \\ &\Leftrightarrow \; R_s \leq \frac{\eta_i - (1-\alpha_0) R_b}{\alpha_0} \end{aligned}$$

$$\begin{aligned} \text{Let } \tilde{\eta}_i &= \frac{\eta_i - (1-\alpha_0) R_b}{\alpha_0}, \forall i = 1,2,3,4. \\ \text{and define } \tilde{A}_1 &= \{R_s : R_s < \tilde{\eta}_1 \text{ and } R_s \geq \tilde{\eta}_4\} \\ \tilde{A}_2 &= \{R_s : \tilde{\eta}_1 \leq R_s < \tilde{\eta}_2 \text{ and } \tilde{\eta}_3 \leq R_s < \tilde{\eta}_4\} \\ \tilde{A}_3 &= \{R_s : \tilde{\eta}_2 \leq R_s < \tilde{\eta}_3\} \end{aligned}$$

where $\tilde{A}_j$ is the set of the realized risky asset return in which case j occurs at $t = 1$, given the asset allocation α_0. The expected utility of the manager in case 2 can be rewritten as

$$\begin{aligned} & Eu_A\left[c_2^{1,2} \mid R_p(\alpha_0) \in A_2\right] \\ = \; & Eu_A\left[xF^{1,2}R_b + (R_s - R_b)\frac{\mu - R_b}{\delta_A \sigma^2} \middle| R_s \in \tilde{A}_2 \right] \\ = \; & Eu_A\left[x\left[R_p(\alpha_0) w_0 (1-x)\right] NBR_b + (R_s - R_b)\frac{\mu - R_b}{\delta_A \sigma^2} \middle| R_s \in \tilde{A}_2 \right] \end{aligned}$$

$$\begin{aligned}
\text{Let } b_{A2} &= \exp\left\{-\delta_A R_b \left[x R_b \left(1-\alpha_0\right) w_0 \left(1-x\right) NB - \frac{\mu - R_b}{\delta_A \sigma^2}\right]\right\} \\
z_{A2} &= x\alpha_0 w_0 \left(1-x\right) NBR_b + \frac{\mu - R_b}{\delta_A \sigma^2}
\end{aligned}$$

$$\begin{aligned}
& Eu_A \left[x\left[R_p\left(\alpha_0\right) w_0 \left(1-x\right)\right] NBR_b + \left(R_s - R_b\right) \frac{\mu - R_b}{\delta_A \sigma^2} \middle| \, R_s \leq \tilde{\eta} \right] \\
= \; & -b_{A2} E\left\{ \exp\left[-\delta_A z_{A2} R_s\right] \middle| \, R_s \leq \tilde{\eta} \right\} \\
= \; & -b_{A2} \exp\left\{-\frac{1}{2} v_{A2}\right\} \Phi\left[\frac{\tilde{\eta} - \tilde{\mu}_{A2}}{\sigma}\right]
\end{aligned}$$

$$\begin{aligned}
\text{where } v_{A2} &= 2\delta_A \mu z_{A2} - \delta_A^2 z_{A2}^2 \sigma^2 \\
\tilde{\mu}_{A2} &= \mu - \delta_A z_{A2} \sigma^2
\end{aligned}$$

Thus, the expected utility of the manager in case 2 is

$$\begin{aligned}
& Eu_A \left[c_2^{1,2} \mid R_p\left(\alpha_0\right) \in A_2\right] \\
= \; & -b_{A2} \exp\left\{-\frac{1}{2} v_{A2}\right\} \left(\Phi\left[\frac{\tilde{\eta}_2 - \tilde{\mu}_{A2}}{\sigma}\right] - \Phi\left[\frac{\tilde{\eta}_1 - \tilde{\mu}_{A2}}{\sigma}\right] + \Phi\left[\frac{\tilde{\eta}_4 - \tilde{\mu}_{A2}}{\sigma}\right] - \Phi\left[\frac{\tilde{\eta}_3 - \tilde{\mu}_{A2}}{\sigma}\right] \right)
\end{aligned}$$

Mathematically, in case 3 when the investor invests the sum of the existing investment and the current income with MF_I, the expected utility of the manager is

$$
\begin{aligned}
& Eu_A\left[c_2^{1,3} \mid R_p(\alpha_0) \in A_3\right] \\
= \; & Eu_A\left[xF^{1,3}R_b + (R_s - R_b)\frac{\mu - R_b}{\delta_A \sigma^2} \middle| R_p(\alpha_0) \in A_3 \right] \\
= \; & Eu_A\left[\begin{array}{c} [w_1 + R_p(\alpha_0) w_0 (1-x)] NBR_b x + \\ (R_s - R_b)\left[\frac{\mu - R_b}{\delta_A \sigma^2}\right] \end{array} \middle| R_p(\alpha_0) \in A_3 \right] \\
= \; & Eu_A\left[\begin{array}{c} [w_1 + R_p(\alpha_0) w_0 (1-x)] NBR_b x + \\ (R_s - R_b)\left[\frac{\mu - R_b}{\delta_A \sigma^2}\right] \end{array} \middle| R_s \in \tilde{A}_3 \right]
\end{aligned}
$$

$$
\begin{aligned}
\text{Let } b_{A3} &= \exp\left\{-\delta_A\left[(w_1 + R_b(1-\alpha_0) w_0 (1-x)) NBR_b x - R_b\left[\frac{\mu - R_b}{\delta_A \sigma^2}\right]\right]\right\} \\
\text{and } z_{A3} &= \alpha_0 w_0 (1-x) NBR_b x + \frac{\mu - R_b}{\delta_A \sigma^2}
\end{aligned}
$$

$$
\begin{aligned}
& Eu_A\left[c_2^{1,3} \mid R_s \leq \tilde{\eta}\right] = -b_{A3} E\left\{\exp\left[-\delta_A z_{A3} R_s\right] \mid R_s \leq \tilde{\eta}\right\} \\
= \; & -b_{A3} \exp\left\{-\frac{1}{2} v_{A3}\right\} \Phi\left[\frac{\tilde{\eta} - \tilde{\mu}_{A3}}{\sigma}\right]
\end{aligned}
$$

$$
\begin{aligned}
\text{where } v_{A3} &= 2\delta_A \mu z_{A3} - \delta_A^2 z_{A3}^2 \sigma^2 \\
\tilde{\mu}_{A3} &= \mu - \delta_A z_{A3} \sigma^2
\end{aligned}
$$

Thus, the expected utility of the manager in case 3 is

$$\begin{aligned} & Eu_A\left[c_2^{1,3} \mid R_p(\alpha_0) \in A_3\right] \\ = & -b_{A3}\exp\left\{-\frac{1}{2}\upsilon_{A3}\right\}\left(\Phi\left[\frac{\tilde{\eta}_3-\tilde{\mu}_{A3}}{\sigma}\right]-\Phi\left[\frac{\tilde{\eta}_2-\tilde{\mu}_{A3}}{\sigma}\right]\right)\end{aligned}$$

Overall, the manager of MF_I maximizes the following objective function at time 0:

$$\max_{\alpha_0} Eu(c_1)+\sum_{j=1}^{3}\beta E\left[u\left(c_2^{I,j}\right) \mid R_p(\alpha_0)\in A_j\right]\Pr\left(R_p(\alpha_0)\in A_j\right)$$

$$\begin{aligned} &\Leftrightarrow \max_{\alpha_0} u\left\{xNw_0B\mu_p(\alpha_0)-\frac{1}{2}\delta\left[xNw_0B\right]^2\sigma_p^2(\alpha_0)\right\} \\ &+\beta\left\{\Phi\left[s(\alpha_0,\eta_1)\right]+1-\Phi\left[s(\alpha_0,\eta_4)\right]\right\}\upsilon \\ &-\beta\left\{\begin{array}{c}\left(\Phi\left[s(\alpha_0,\eta_2)\right]-\Phi\left[s(\alpha_0,\eta_1)\right]+\Phi\left[s(\alpha_0,\eta_4)\right]-\Phi\left[s(\alpha_0,\eta_3)\right]\right) \\ b_{A2}\exp\left\{-\frac{1}{2}\upsilon_{A2}\right\}\left[\Phi\left(\frac{\tilde{\eta}_2-\tilde{\mu}_{A2}}{\sigma}\right)-\Phi\left(\frac{\tilde{\eta}_1-\tilde{\mu}_{A2}}{\sigma}\right)+\Phi\left(\frac{\tilde{\eta}_4-\tilde{\mu}_{A2}}{\sigma}\right)-\Phi\left(\frac{\tilde{\eta}_3-\tilde{\mu}_{A2}}{\sigma}\right)\right]\end{array}\right\} \\ &-\beta\left\{\Phi\left[s(\alpha_0,\eta_3)\right]-\Phi\left[s(\alpha_0,\eta_2)\right]\right\}b_{A3}\exp\left\{-\frac{1}{2}\upsilon_{A3}\right\}\left[\Phi\left(\frac{\tilde{\eta}_3-\tilde{\mu}_{A3}}{\sigma}\right)-\Phi\left(\frac{\tilde{\eta}_2-\tilde{\mu}_{A3}}{\sigma}\right)\right]\end{aligned}$$

1.3.3. Investor Maximization at Time 0

As discussed in the previous section, there are two steps in solving for the optimal behavior in the model. Step 1 solves for the optimal portfolio weights the manager chooses given a certain level of threat, η. Using backward induction, the objective function of the manager is rewritten to be a function of the first period risky asset allocation. The optimal time 0 portfolio weight $\alpha_0^*(\eta)$ is obtained by the maximizing the manager's objective function at time 0.

In this section, I compute the objective function value of the investor and solve for the optimal investor threat η^* given the manager's best response to the different values of η. The investor optimizes his time 2 terminal wealth from his prior investments at time 0 and time 1. The investor receives the sum of the two portfolios in MF_I and MF_{II}, $W^j = \frac{(1-x)}{N}\left[F^{1j}R_p\left(\alpha_1^{1j*}\right) + F^{2j}R_p\left(\alpha_1^{2j*}\right)\right]$ in case j at time 2.

The following calculations show how the investor's expected payoff in the various cases is rewritten as a function of the fundamentals. The approaches for all three cases are similar. First, I expand the expression of the investor's wealth in case j into two parts, $j = 1, 2, 3$. The first component contains terms that depend on the risky asset return. The second component is the collection of all other terms which are independent of the risky asset return in the first period. Since the second component is independent of the realization of the risky asset return, it is taken out of the conditional expectation. The two components are separately evaluated and combined in the last step.

For the first component, the expression is fully expanded into integrals and the investor's utility is expressed in exponential form. I rewrite the expression in terms of another normal distribution with mean $\tilde{\mu}$ and variance σ, using the probability density function of the normal distribution. Finally, I combine all the expressions to get the desired expected utility of the investor in terms of the fundamentals.

Case 1: Complete withdrawal

The investor's expected utility in case 1 given the manager's choice of portfolio weights is,

$$
\begin{aligned}
& Eu\left[W^1 \mid R_p(\alpha_0) \in A_1\right] \text{ where } W^1 \text{ is the investor's wealth in case 1} \\
= \; & Eu\left[\frac{(1-x)}{N} F^{2,1} R_p\left(\alpha_1^{2,1}\right) + 0 \middle| R_p(\alpha_0) \in A_1\right] \text{ by substituting the fund size in case 1} \\
= \; & Eu\left[\frac{(1-x)}{N}\left(F^{2,1} R_b + (R_s - R_b)\frac{\mu - R_b}{\delta_A x \sigma^2}\right) \middle| R_p(\alpha_0) \in A_1\right] \\
= \; & Eu\left\{\frac{(1-x)}{N}\left[\left[w_1 + BR_p(\alpha_0)(1-x) w_0\right] NBR_b + (R_s - R_b)\frac{\mu - R_b}{\delta_A x \sigma^2}\right] \middle| R_p(\alpha_0) \in A_1\right\}
\end{aligned}
$$

$$
\begin{aligned}
\text{With } R_p(\alpha_0) &= \alpha_0 R_s + (1-\alpha_0) R_b, \\
R_p(\alpha_0) &\leq \eta_i \Leftrightarrow \alpha_0 R_s + (1-\alpha_0) R_b \leq \eta_i \\
&\Leftrightarrow R_s \leq \frac{\eta_i - (1-\alpha_0) R_b}{\alpha_0}
\end{aligned}
$$

$$
\begin{aligned}
\text{Let } \tilde{\eta}_i &= \frac{\eta_i - (1-\alpha_0) R_b}{\alpha_0}, \forall i = 1,2,3,4. \\
\text{and define } \tilde{A}_1 &= \{R_s : R_s < \tilde{\eta}_1 \text{ and } R_s \geq \tilde{\eta}_4\} \\
\tilde{A}_2 &= \{R_s : \tilde{\eta}_1 \leq R_s < \tilde{\eta}_2 \text{ and } \tilde{\eta}_3 \leq R_s < \tilde{\eta}_4\} \\
\tilde{A}_3 &= \{R_s : \tilde{\eta}_2 \leq R_s < \tilde{\eta}_3\}
\end{aligned}
$$

where $\tilde{A}_j$ is the set of the realized risky asset return in which case j occurs at $t = 1$, given the asset allocation $\alpha_{0.}$ Thus the expectation can be rewritten as

$$\begin{aligned}
& Eu\left[W^1 \mid R_p(\alpha_0) \in A_1\right] \\
= \;& Eu\left\{\frac{(1-x)}{N}\left[\left[w_1 + BR_p(\alpha_0)(1-x)w_0\right]NBR_b + (R_s - R_b)\frac{\mu - R_b}{\delta_A x\sigma^2}\right]\middle| R_s \in \tilde{A}_1\right\} \\
= \;& b_{I1}Eu\left\{\frac{(1-x)}{N}R_s\left[B^2(1-x)w_0NR_b\alpha_0 + \frac{\mu - R_b}{\delta_A x\sigma^2}\right]\middle| R_s \in \tilde{A}_1\right\} \\
= \;& -b_{I1}E\left[\exp\{-\delta z_{I1}R_s\}\middle| R_s \in \tilde{A}_1\right]
\end{aligned}$$

where

$$\begin{aligned}
b_{I1} &= \exp\left\{-\delta\frac{(1-x)}{N}\left[NBR_b\left(w_1 + BR_b(1-\alpha_0)(1-x)w_0\right) - R_b\frac{\mu - R_b}{\delta_A x\sigma^2}\right]\right\} \\
z_{I1} &= \frac{(1-x)}{N}\left[B^2(1-x)w_0NR_b\alpha_0 + \frac{\mu - R_b}{\delta_A x\sigma^2}\right] \\
v_{I1} &= 2\delta\mu z_{I1} - \delta^2 z_{I1}^2\sigma^2 \\
\tilde{\mu}_1 &= \mu - \delta z_{I1}\sigma^2
\end{aligned}$$

Since

$$
\begin{aligned}
& Eu\left\{\left.\frac{(1-x)}{N}R_s\left[B^2(1-x)\,w_0NR_b\alpha_0+\frac{\mu-R_b}{\delta_A x\sigma^2}\right]\right| R_s\leq\tilde{\eta}\right\} \\
= & \int_{-\infty}^{\tilde{\eta}}-\exp\left\{-\delta z_{I1}y\right\}\frac{1}{\sigma\sqrt{2\pi}}\exp\left[-\frac{(y-\mu)^2}{2\sigma^2}\right]dy \text{ as } R_s\sim N\left(\mu,\sigma^2\right) \\
= & -\frac{1}{\sigma\sqrt{2\pi}}\int_{-\infty}^{\tilde{\eta}}\exp\left\{-\left[\frac{(y-\mu)^2+\delta z_{I1}y2\sigma^2}{2\sigma^2}\right]\right\}dy \\
= & -\frac{1}{\sigma\sqrt{2\pi}}\int_{-\infty}^{\tilde{\eta}}\exp\left\{-\left[\frac{(y-\tilde{\mu}_1)^2+2\delta\mu z_{I1}\sigma^2-\left(\delta z_{I1}\sigma^2\right)^2}{2\sigma^2}\right]\right\}dy \\
= & -\frac{1}{\sigma\sqrt{2\pi}}\int_{-\infty}^{\tilde{\eta}}\exp\left\{-\frac{(y-\tilde{\mu}_1)^2}{2\sigma^2}\right\}\exp\left\{-\frac{1}{2}v_{I1}\right\}dy \\
= & -\exp\left\{-\frac{1}{2}v_{I1}\right\}\Phi\left[\frac{\tilde{\eta}-\tilde{\mu}_1}{\sigma}\right]
\end{aligned}
$$

Substituting all of the above expressions,

$$
\begin{aligned}
& Eu\left[W^1\mid R_p(\alpha_0)\in A_1\right] \\
= & -b_{I1}\exp\left\{-\frac{1}{2}v_{I1}\right\}\left(1+\Phi\left[\frac{\tilde{\eta}_1-\tilde{\mu}_1}{\sigma}\right]-\Phi\left[\frac{\tilde{\eta}_4-\tilde{\mu}_1}{\sigma}\right]\right)
\end{aligned}
$$

Case 2: Reinvest time 0 portfolio in MF_I and invest time 1 income w_1 in the outside option

$Eu\left[W^2 \mid R_p(\alpha_0) \in A_2\right]$ where W^2 is the investor's wealth in case 2

$$= \begin{cases} Eu\left(\begin{array}{c} \frac{(1-x)}{N} F^{1,2} R_p\left(\alpha_1^{1,2}\right) + \\ \frac{(1-x)}{N} F^{2,2} R_b \end{array} \middle| R_p(\alpha_0) \in A_2 \right) & \text{if invest } w_1 \text{ in the riskfree asset} \\ \\ Eu\left(\begin{array}{c} \frac{(1-x)}{N} F^{1,2} R_p\left(\alpha_1^{1,2}\right) + \\ \frac{(1-x)}{N} F^{2,2} R_p\left(\alpha_1^{2,2}\right) \end{array} \middle| R_p(\alpha_0) \in A_2 \right) & \text{if invest } w_1 \text{ in } MF_{II} \end{cases}$$

$$\begin{aligned} & Eu\left[W^2 \mid R_p(\alpha_0) \in A_2\right] \text{ when } w_1 \text{ is invested in the riskfree asset} \\ = \; & Eu\left[\frac{(1-x)}{N} F^{1,2} R_p\left(\alpha_1^{1,2}\right) + \frac{(1-x)}{N} F^{2,2} R_b \middle| R_p(\alpha_0) \in A_2\right] \\ = \; & Eu\left[\frac{(1-x)}{N}\left[F^{1,3}\right] R_b + \frac{(1-x)}{N}(R_s - R_b)\left[\frac{\mu - R_b}{\delta_A x \sigma^2}\right] \middle| R_p(\alpha_0) \in A_2\right] \\ = \; & Eu\left[\frac{(1-x)}{N}\left(\begin{array}{c} \left[w_1 + R_p(\alpha_0) w_0 (1-x)\right] NBR_b + \\ (R_s - R_b)\left[\frac{\mu - R_b}{\delta_A x \sigma^2}\right] \end{array} \right) \middle| R_p(\alpha_0) \in A_2\right] \end{aligned}$$

$$\text{where } F^{1,3} = F^{1,2} + F^{2,2} = \left[w_1 + R_p(\alpha_0) w_0 (1-x)\right] NB$$

$$\begin{aligned} \text{Let } b_{I2} &= \exp\left\{ -\delta \frac{(1-x)}{N} \left[\begin{array}{c} \left(w_1 + R_b (1-\alpha_0) w_0 (1-x)\right) NBR_b + \\ -R_b \left[\frac{\mu - R_b}{\delta_A x \sigma^2}\right] \end{array} \right] \right\} \\ \text{and } z_{I2} &= \frac{(1-x)}{N}\left[\alpha_0 w_0 (1-x) NBR_b + \frac{\mu - R_b}{\delta_A x \sigma^2}\right] \end{aligned}$$

$$
\begin{aligned}
& Eu\left[W^2 \mid R_p\left(\alpha_0\right) \in A_2\right] \\
= \; & b_{I2} Eu\left[\frac{(1-x) R_s}{N}\left[\alpha_0 w_0 (1-x) NBR_b + \frac{\mu - R_b}{\delta_A x \sigma^2}\right] \middle| \, R_s \in \tilde{A}_2\right] \\
= \; & b_{I2} Eu\left[z_{I2} R_s \mid R_s \in \tilde{A}_2\right]
\end{aligned}
$$

And since

$$
\begin{aligned}
& Eu\left[\frac{(1-x) R_s}{N}\left[\alpha_0 w_0 (1-x) NBR_b + \frac{\mu - R_b}{\delta_A x \sigma^2}\right] \middle| \, R_s \leq \tilde{\eta}\right] \\
= \; & \int_{-\infty}^{\tilde{\eta}} -\exp\left\{-\delta z_{I2} y\right\} \frac{1}{\sigma\sqrt{2\pi}} \exp\left[-\frac{(y-\mu)^2}{2\sigma^2}\right] dy \text{ as } R_s \sim N\left(\mu, \sigma^2\right) \\
= \; & -\exp\left\{-\frac{1}{2} v_{I2}\right\} \Phi\left[\frac{\tilde{\eta} - \tilde{\mu}_2}{\sigma}\right]
\end{aligned}
$$

$$
\begin{aligned}
\text{where } v_{I2} &= 2\delta\mu z_{I2} - \delta^2 z_{I2}^2 \sigma^2 \\
\tilde{\mu}_2 &= \mu - \delta z_{I2} \sigma^2
\end{aligned}
$$

Therefore,

$$
\begin{aligned}
& Eu\left[W^2 \mid R_p\left(\alpha_0\right) \in A_2\right] \text{ when } w_1 \text{ is invested in the riskfree asset} \\
= \; & -b_{I2} \exp\left\{-\frac{1}{2} v_{I2}\right\}\left(\Phi\left[\frac{\tilde{\eta}_2 - \tilde{\mu}_2}{\sigma}\right] - \Phi\left[\frac{\tilde{\eta}_1 - \tilde{\mu}_2}{\sigma}\right] + \Phi\left[\frac{\tilde{\eta}_4 - \tilde{\mu}_2}{\sigma}\right] - \Phi\left[\frac{\tilde{\eta}_3 - \tilde{\mu}_2}{\sigma}\right]\right)
\end{aligned}
$$

Similarly,

$$
\begin{aligned}
& Eu\left[W^2 \mid R_p\left(\alpha_0\right) \in A_2\right] \text{ when } w_1 \text{ is invested in the alternative } MF_{II} \\
= \; & -\hat{b_{I2}} \exp\left\{-\frac{1}{2} \hat{v_{I2}}\right\}\left(\Phi\left[\frac{\tilde{\eta}_2 - \hat{\mu}_2}{\sigma}\right] - \Phi\left[\frac{\tilde{\eta}_1 - \hat{\mu}_2}{\sigma}\right] + \Phi\left[\frac{\tilde{\eta}_4 - \hat{\mu}_2}{\sigma}\right] - \Phi\left[\frac{\tilde{\eta}_3 - \hat{\mu}_2}{\sigma}\right]\right)
\end{aligned}
$$

$$
\begin{aligned}
\text{where } \hat{b_{I2}} &= \exp\left\{-\delta\frac{(1-x)}{N}\left[\begin{array}{c}(w_1+R_b(1-\alpha_0)w_0(1-x))NBR_b+\\ -2R_b\left[\frac{\mu-R_b}{\delta_A x\sigma^2}\right]\end{array}\right]\right\} \\
\text{and } \hat{z_{I2}} &= \frac{(1-x)}{N}\left[\alpha_0 w_0(1-x)NBR_b+2\frac{\mu-R_b}{\delta_A x\sigma^2}\right] \\
\text{and } \hat{v_{I2}} &= 2\delta\mu\hat{z_{I2}}-\delta^2\hat{z_{I2}}^2\sigma^2 \\
\text{and } \hat{\mu}_2 &= \mu-\delta\hat{z_{I2}}\sigma^2
\end{aligned}
$$

Case 3: Additional Inflow into MF_I

$$
\begin{aligned}
& Eu\left[W^3 \mid R_p(\alpha_0)\in A_3\right] \text{ where } W^3 \text{ is the investor's wealth in case 3} \\
= \; & Eu\left[\frac{(1-x)}{N}F^{1,3}R_p\left(\alpha_1^{1,3}\right)\middle| R_p(\alpha_0)\in A_3\right] \\
= \; & E\left\{u\left[\frac{(1-x)}{N}\left(F^{1,3}R_b+(R_s-R_b)\frac{\mu-R_b}{\delta_A x\sigma^2}\right)\right]\middle| R_p(\alpha_0)\in A_3\right\} \\
= \; & E\left\{u\left[\frac{(1-x)}{N}\left(F^{1,3}R_b+(R_s-R_b)\frac{\mu-R_b}{\delta_A x\sigma^2}\right)\right]\middle| R_s\in \tilde{A}_3\right\}
\end{aligned}
$$

Following the steps as in case 1 and case 2, we obtain

$$
\begin{aligned}
& Eu\left[W^3 \mid R_p(\alpha_0)\in A_3\right] \\
= \; & -b_{I2}\exp\left\{-\frac{1}{2}v_{I2}\right\}\left(\Phi\left[\frac{\tilde{\eta}_3-\tilde{\mu}_2}{\sigma}\right]-\Phi\left[\frac{\tilde{\eta}_2-\tilde{\mu}_2}{\sigma}\right]\right)
\end{aligned}
$$

Overall, the investor maximizes the following objective function,

$$\max_{\{\eta_1,\eta_2,\eta_3,\eta_4\}} Eu\left[W\right] \Leftrightarrow \max_{\{\eta_1,\eta_2,\eta_3,\eta_4\}} \sum_{j=1}^{3} Eu\left[W^j \mid R_p\left(\alpha_0\right) \in A_j\right] \Pr\left(R_p\left(\alpha_0\right) \in A_j\right)$$

where $A_j =$ the set of realized portfolio values in which case j occurs in period 2.

1.4. Results and Empirical Predictions

In this paper, I focus on the case of over allocation in the risky asset and study the impact of strategic investors that use threats on future wealth as a tool to align incentives. Although it is possible that mutual fund managers are too risk averse and choose a risky asset allocation lower than the allocation desired by the investors, this seems not to be the case in the real world. The prohibition on the use of performance fees in mutual funds under section 205(a)(1) of the Investment Advisers Act of 1940 reflects the need to discourage the risk-taking behavior of mutual fund managers.

In the model, the manager has incentive to over allocate into the risky asset when his risk aversion is low or when the manager's compensation is too small, either because of a small fund size or a low compensation rate or both. In these cases, the manager prefers a high risky asset allocation in order to increase the chance of receiving a high payoff. This results in a portfolio risk level higher than the level desired by the investor. Therefore, given the linear compensation contract, the investor alters the incentives of the manager by concavifying the payoff strategically. By decreasing the flow when performance is poor and increasing the flow when performance is good, the manager has fewer incentives to take overly risky allocation. The investor benefits from the strategy since the weight on the risky asset is reduced and is closer to the investor's optimal risky asset allocation.

1.4.1. Numerical Methods and Model Calibration

With the objective functions of the manager and the investor expressed in terms of the fundamentals, I use numerical methods to maximize the manager's objective function values given various levels of η. The manager's maximization with respect to α_0 is solved numerically by using the constraint maximization function from MATLAB. The bound of α_0 is set to be sufficiently large such that a corner solution does not occur. The objective function value is maximized over $\alpha_0 \in [0.00001, 2]$.

Given the manager's best response $\alpha_0^*(\eta)$, I maximize the investor's objective function value. A grid search of the investor's objective function value is performed over different values of $\eta = \{\eta_1, \eta_2, \eta_3, \eta_4\}$. The current grid size of each η_i is 0.01 and the search is performed for η_i between 0.6 and 2, where $i = 1, 2, 3, 4$[9]. As a result, I obtain numerically the set of optimal threat strategy of the investor with risk aversion parameter from 1.5 to 5.5, given the manager's best response portfolio weight α_0 at time 0.

The parameters of the numerical calibration are described as follows. The numerical result from the set of parameters in table 1.1 is considered to be the base case. I first analyze the findings in the base case, especially the optimal investor's strategy η^*. Other variations are then contrasted to the base case for analysis. The variations include changes in the financial market characteristics such as the distribution of the risky asset, changes in the initial sales charge and changes in the rate of compensation for the manager. In the model, I use $R(.)$ to denote gross return. Return is in gross terms unless stated otherwise.

[9]The optimization is repeated for each risk aversion parameter $\delta = \{1.5, 1.6, ..., 5.4, 5.5\}$.

Description of Variable	Symbol	Value
Risk aversion parameter	δ	1.5-5.5
Mean return of the risky asset	μ	10%
Standard deviation of the risky asset	σ	0.25
Return on the riskfree asset	R_b	3%
Intertemporal discount rate	β	0.95
Initial sales charge	1-B	5%
Rate of compensation	x	2%
Size of the fund	N	30
Relative risk aversion	θ	0.5

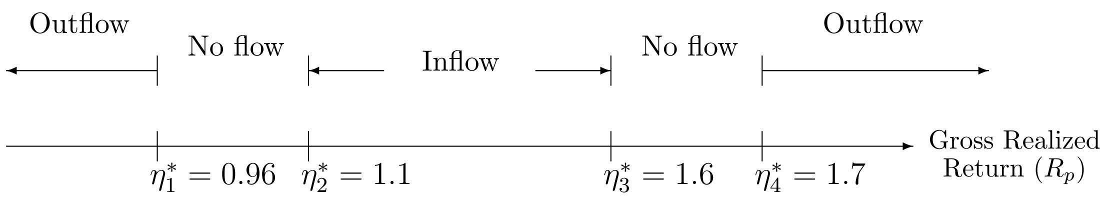
Table 1.1: **The parameter values in the base case.**
The numerical result from this set of parameters is considered to be the base case. Other variations are contrasted to this set of parameters for analysis. For graphical representation of the result in the base case, please see figure 1.6.

The overall results are analyzed in two levels of details. At the individual level, I investigate the optimal strategy of the investor and its effect on the portfolio weight chosen by the manager. With the optimal strategy η^* of the investors with different risk aversion level, I aggregate the individual capital flows and study the predictions on the industry level mutual fund flows with an economy of strategic investors.

1.4.2. Individual Investor Level

With the specifications in table 1.1, an investor with risk aversion parameter $\delta = 3.5$ has the optimal strategy $\eta^* = \{0.96, 1.1, 1.6, 1.7\}$. The interpretation of the result is that an investor with risk aversion parameter of 3.5 withdraws from the initial mutual fund when the time 1 gross realized portfolio return is below 0.96. The investor also withdraws his money when the fund performance is extremely high (gross realized portfolio return above 1.7). By threatening outflow when the realized gross return is extreme, the investor discourages overly risky portfolio allocation. The investor withdraws when the fund beats the riskfree asset return by 67%. When the realized gross portfolio return is between [0.96,1.1] and [1.6,1.7], the investor reinvests the initial portfolio with the first mutual fund MF_I but does not place any additional funds into the mutual fund. Finally, when the realized gross portfolio return is between 1.1 and 1.6, the investor invests all of the time 1 wealth in MF_I.

Concerned with the investor's optimal flow strategy with respect to the realized portfolio return, the manager lowers the risky asset allocation weight from 1.1228 to 0.5917. Although the risky asset allocation remains higher than the investor's desired level, which is 0.3368, the flow strategy is effective in altering the incentive of the manager as the weight on the risky asset drops. The fund manager's incentive to overload on the risky asset is reduced due to the strategic behavior of the investor. See the following diagram for a graphical illustration of the optimal threats in this setting.



It is interesting to note that in the optimal flow strategy $\eta^* = \{\eta_1^*, \eta_2^*, \eta_3^*, \eta_4^*\}$, η_1^* and η_2^* have the strongest impact on the manager's incentive. With the mean of the portfolio return distribution around 1.1, the probability of case 1, case 2 and case 3 are highly dependent on the value of η_1^* and η_2^*. On the other hand, η_3^* and η_4^* are in the range of 1.6 to 1.7. The probability that the gross realized portfolio return exceeds η_3^* or η_4^* is very low, thus the threat η_3^* and η_4^* has minimal impact on the manager's incentive. This overall pattern is observed for all of the optimal investor strategy studied in the paper.

In the analysis that follows, I focus on the more important component of the optimal flow strategy, the cutoff strategy η_1^* and the inflow strategy η_2^*.

Let's turn our attention to how the optimal investor strategy changes with different level of risk aversion, as shown in figure 1.6. There are five major results on the behavior of the optimal investor strategy η^*:

(1) The optimal η_3^* and η_4^* are far from the noticeable region. The η_3^* and η_4^* thresholds occur at very extreme positive performance, at gains of at least 50% and up to 100% for less risk averse investors. Although η_3^* and η_4^* do decrease with increasing risk aversion, the thresholds remain in the region of extreme positive performance.

(2) η_1^* is increasing in the risk aversion parameter δ.

(3) η_2^* is decreasing in the risk aversion parameter δ.

(4) At the individual level, the increases and decreases in η_1^* and η_2^*, is not linear with respect to δ, the risk aversion parameter. This is due to the fact that the investor's desired portfolio allocation in the risky asset decreases with the shape of $\frac{1}{\delta}$. For illustration purposes only, imagine how the optimal portfolio weight changes with respect to δ for an investor with mean-variance preference. The optimal risky asset allocation in this setting has the form of $\frac{\mu - R_b}{\delta c}$ for some $c \in \mathbb{R}$ and the decrease in the optimal risky asset allocation with respect to δ is nonlinear. For low values of δ, the decrease is steep and the rate of change drops with increasing δ.

Back to the optimal investor strategy in the model, as a result of the increasing η_1^* and the decreasing η_2^* with the risk aversion parameter δ, the more risk averse the investor, the more narrow is the no-flow region which is the band between η_1^* and η_2^*.

(5) Although both the cutoff strategy η_1^* and the inflow strategy η_2^* changes with respect to δ, the changes of the two strategies is not symmetric. The changes in the cutoff strategy η_1^* is more sensitive to the changes in the risk aversion parameter δ. The increase in the cutoff strategy η_1^* is larger than the decreases in the inflow strategy η_2^* given the same increase in the investor's risk aversion level.

One of the reasons behind this behavior is that the withdrawal strategy is more costly than the inflow strategy. At the beginning of the game, the investor pays 5% as the initial sales charge to MF_I. When the investor decides to withdraw the invested capital from MF_I, the investor incurs another initial sales charge when entering the alternative mutual fund MF_{II}. This switching cost is only prevalent in the withdrawal case. In the case when inflow takes place, the investor needs to pay the initial sales charge no matter if he invests in MF_I or MF_{II}. Therefore, the initial sales charge gives the investor different incentives when choosing between the inflow and the outflow strategy, thus creating the asymmetry in the rate of change of η_1^* with respect to δ and the rate of change of η_2^* with respect to δ. If the initial sales charge is the cause of the asymmetry in the relationship, mutual funds with no initial sales charge should have a symmetric relationship between the rate of change of η_1^* with respect to δ and the rate of change of η_2^* with respect to δ. This conjecture is verified when I study the investor's optimal flow strategy in an economy with no load funds.

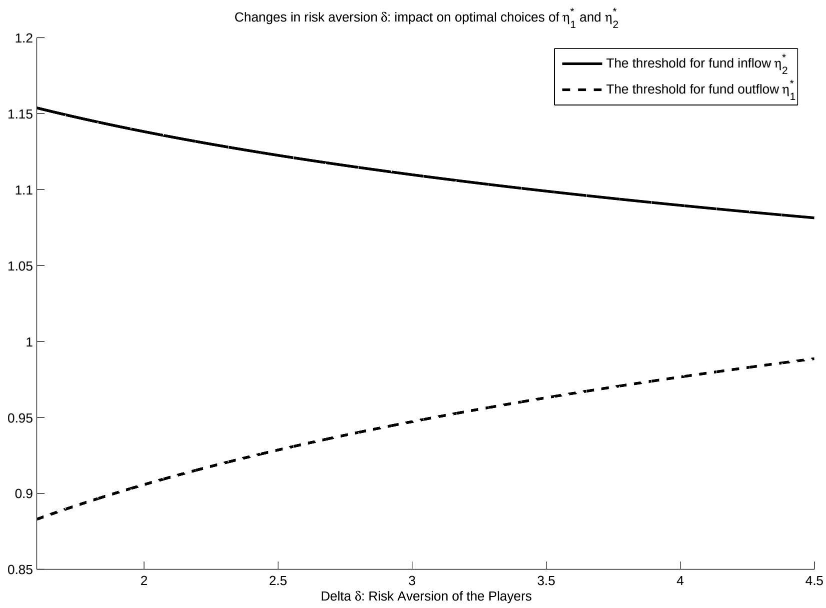


Figure 1.6: The investor's optimal threats η_1^* and η_2^* in the base case economy. The region above the series of η_2^* is the region of fund inflow. The region below the series of the η_1^* is the region of fund outflow. The remaining region is the no-flow region. Please see table 1.1 for the parameter values in the base case.

1.4.3. Mutual Fund Industry Level

Equipped with the understanding on how the individual investor's optimal strategy changes with the risk aversion parameter δ, I turn the attention to the aggregate effect of an economy of strategic investors. The economy is formed by assuming a discrete uniform distribution of investors with risk aversion parameter from $\delta \in \{1.5, 1.6, ...5.4, 5.5\}$ and that there are $N \times \frac{(5.5-1.5)}{0.1}$ investors in the aggregate economy. Individually, they maximize their personal terminal wealth at time 2 by choosing the optimal flow strategy as discuss in the previous sections.

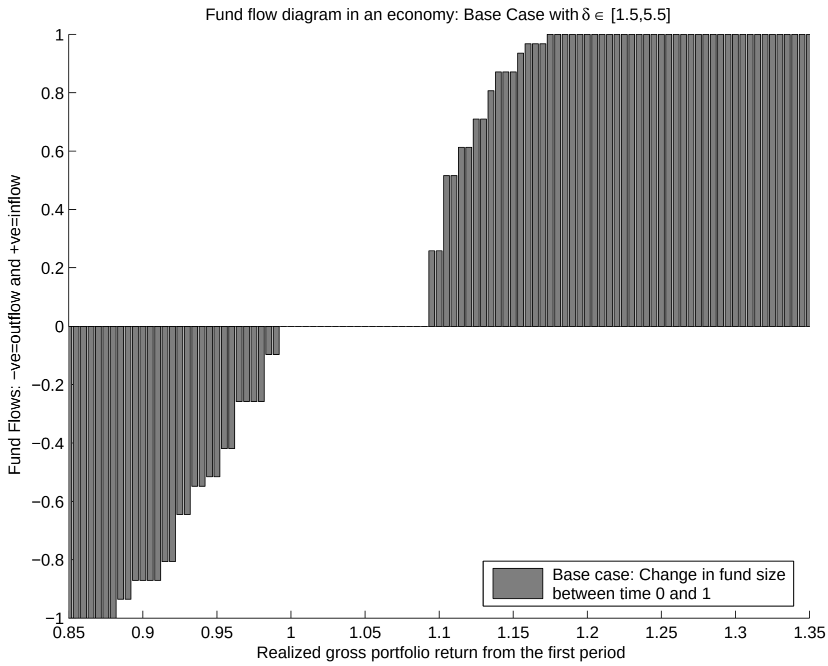


Figure 1.7: The predicted fund flows in the base case economy.

With the formation of an economy of strategic investors and managers, the individual flow strategy is aggregated to an industry level. The resulting base case mutual fund flow-performance relationship is shown in figure 1.7. Figure 1.7 graphically illustrates the relationship between the realized gross portfolio return from time 0 and the aggregate mutual fund flows from a group of strategic investors at time 1.

In the base case economy, the outflow region which is the region with negative flow of funds at the aggregate level, is less sensitive to the realized portfolio return than the inflow region which is the region with positive flow of funds. The rate of investors' capital inflow is higher than the rate of investors' outflow of funds in the mutual fund industry. This is a result of the asymmetry in the changes of η_1^* and η_2^* with respect to the risk aversion parameter δ at the individual level. The model predicts an inactive region where no funds are withdrawn from the initial mutual fund MF_I and no additional funds are added to the mutual fund. This corresponds to the common area between η_1^* and η_2^* of all investors. In other words, the lowest optimal inflow strategy η_2^* in the economy is greater than the highest optimal outflow strategy η_1^* in the economy, and thus an inactive region is formed. Similar features are observed in the predicted mutual fund flow-performance relationship in the various settings. However, the sensitivity and the curvature of the mutual fund flow-performance relationship, and the size of the inactive region vary with the structure of the financial market.

1.4.4. Empirical Predictions of the Model

In order to study the different empirical implications on mutual fund flows, I solve the model under different settings and parameter values. The resulting mutual fund flows predictions are compared to the mutual fund flow-performance relationship in the base economy. I study five scenarios in depth. They are (1) the flow-performance relationship in an economy with less risk averse investors versus the flow-performance relationship in an economy with more risk averse investors, (2) the flow-performance relationship in an economy with no front load fee, (3) the flow-performance relationship in an economy with high variance in the risky asset return distribution, (4) the optimal threat strategy of investors with low income at time 0 and high income at time 1, (5) the optimal threat strategy of investors with high income at time 0 and low income at time 1.

Case 1. ***Flow-performance relationship of an economy with less risk averse investors versus the flow-performance relationship of an economy with more risk averse investor:***

In order to study the mutual fund flows of two economies with different risk aversion level, I form two groups of investors by sorting on their risk aversion level δ. Investors with risk aversion parameter $\delta \in [3.5, 5.5]$ are considered as the more risk averse group, whereas the investors with $\delta \in [1.5, 3.4]$ are considered the less risk averse group. See figure 1.8 for the comparison between the flow of funds in the base case economy and the economy with a subset of less risk averse investors. And see figure 1.9 for the comparison between the flow of funds in the base case economy and the economy with a subset of more risk averse investors. For the comparison between the risky subset of the economy and the less risky subset of the economy, one could focus on how the mutual fund flows differ from the base case economy in figure 1.8 and figure 1.9.

In the economy with more risk averse investors and mutual fund managers, the sensitivity of the mutual fund flow to the realized return is high. The slope of the flow-performance diagram is steeper for both the poor performance region and the good performance region compared to an economy with less risk averse investors. This is due to the nonlinear decrease in η_2^* with respect to the realized gross portfolio return and the nonlinear increase in η_1^* with respect to the realized gross portfolio return at the individual level. Since more risk averse investors prefer lower allocation weight in the risky asset, the investors are more active in the flow strategy, increasing the probability of case 1 and the probability of case 3. As shown in figure 1.6, the group of investors with high level of risk aversion tend to have a tight strategy set at the individual level. The difference between the optimal η_1^* and η_2^* is small for more risk averse investor, resulting in a relatively small inaction region.

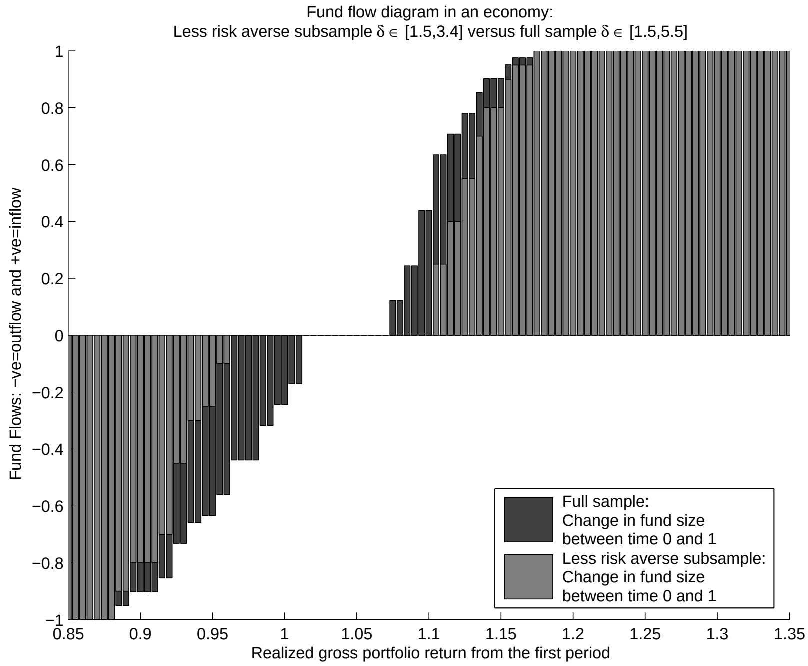


Figure 1.8: The predicted fund flows in the base case versus a population subset with less risk averse investors and managers.

Similar argument applies for the economy with less risk averse mutual fund managers and their investors. The investors' optimal threat threshold η_1^* and η_2^* are spread wider apart at the individual level, and thus the overall mutual fund flows for these type of funds are less sensitive to past returns. The inaction region also widens in this case.

Case 2. ***Flow-performance relationship of an economy with no front load fee mutual funds:***

For the comparison between the base case and the no initial sales charge case, please see figure 1.10. In both the base case and the no initial sales charge case, the investor's cutoff strategy, η_1^*, is increasing in the risk aversion parameter, and the inflow strategy, η_2^*, is decreasing in the risk aversion parameter. As argued previously, the asymmetry in

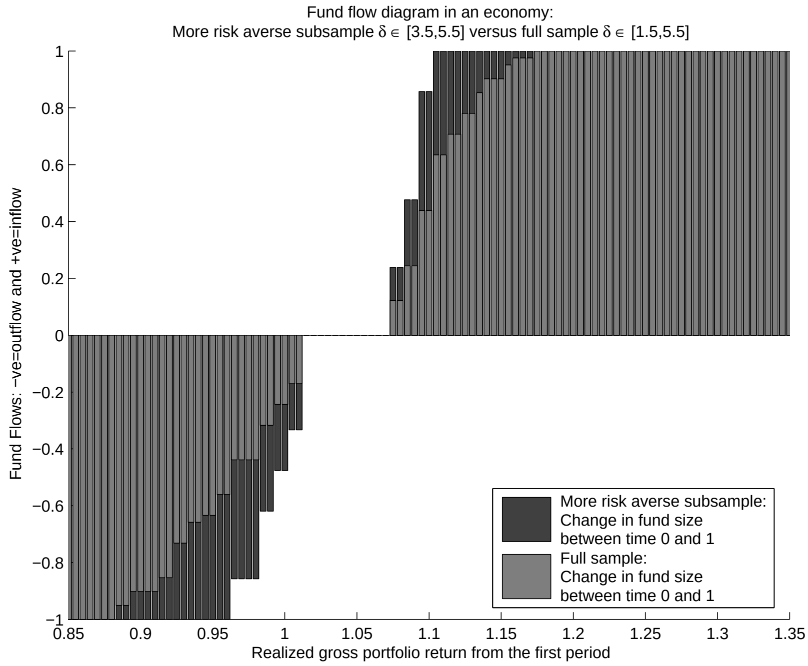


Figure 1.9: The predicted fund flows in the base case versus a population subset with more risk averse investors and managers.

the change of the optimal flow strategy with respect to δ in the base case is partially due to the positive initial sales charge incurred by the investor.

With a positive initial sales charge, the withdrawal strategy is more costly than the inflow strategy to the investor, since the investor incurs another sales charge when the money is withdrawn and placed in an alternative mutual fund. It is obvious that without the initial sales charge, the investor will be more willing to threaten withdraw from the initial mutual fund. Therefore, the corresponding optimal investor strategy η_1^* for each risk aversion level in the no load fee economy is higher, compared to the optimal investor strategy η_1^* in an economy with a positive initial sales charge. This creates the upward shift in the optimal η_1^* at the individual level observed in figure 1.10.

Since the initial sales charge is a percentage of the initial investment, the assets under management increase when there is no initial sales charge in the mutual fund. The incentive of the managers in the economy with no front load fee differs from the incentive of the managers in the base case economy, although, the initial sales charge is not paid to the fund managers as compensation.

The incentive of the managers is indirectly affected by the change in the fund size. When the initial charge varies, the first period fund size also varies. Therefore, the incentive of the managers and the power of the threat by the investors changes accordingly. This means that the reduction in the initial sales charge does not shift the optimal η_1^* strategy in a linear fashion. As shown in figure 1.10, the optimal η_1^* strategy in the economy with no initial sales charge is less sensitive to the changes in the risk aversion parameter δ compared to the base case economy, resulting in a slightly flatter relationship between η_1^* and δ.

Implications on the mutual fund flow-performance relationship: The inflow region of a no load fund should be similar to the inflow region of a fund with positive load fees, as η_2^* is almost equivalent in both cases except the slight curvature difference with respect to δ. However, the outflow region in the flow-performance diagram of a no load fund should be steeper compared to the flow-performance diagram in the base case. Moreover, the flat/inactive region should be smaller in the mutual funds with no initial sales charge. See figure 1.11 for the predicted differences in the mutual fund flow-performance relationship between a no load fund and a fund with positive front load fees. The model suggests that the future mutual fund flows of a no load fund is more sensitive

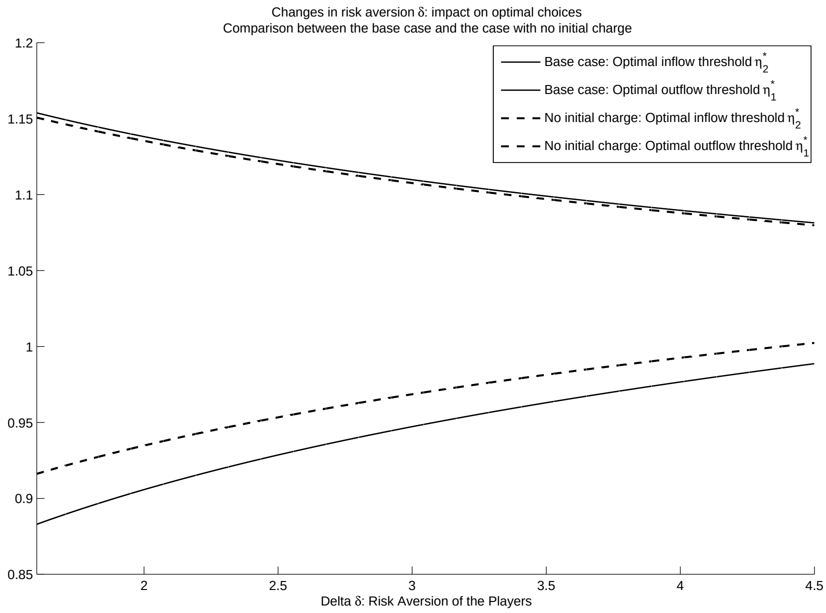


Figure 1.10: Investor optimal threats η_1^* and η_2^* in the case with no initial sales charge, contrasted to the base case. The region above the series of η_2^* is the region of fund inflow. The region below the series of η_1^* is the region of fund outflow. The remaining region is the no-flow region.

to past poor performance, since more investors withdraw their capital when the fund underperforms.

Case 3. ***Flow-performance relationship of an economy with high variance in the risky asset distribution:***

When the variance of the risky asset distribution increases, the optimal threat level η_1^* shifts up and η_2^* shifts down for all of the investors. However, the changes in the optimal η_1^* and η_2^* are not uniform. The changes in the threat level are larger in absolute term for less risk averse players with low values of δ, than for more risk averse players. See figure 1.12. Although the absolute change of the optimal η_1^* and η_2^* strategy is higher for low δ,

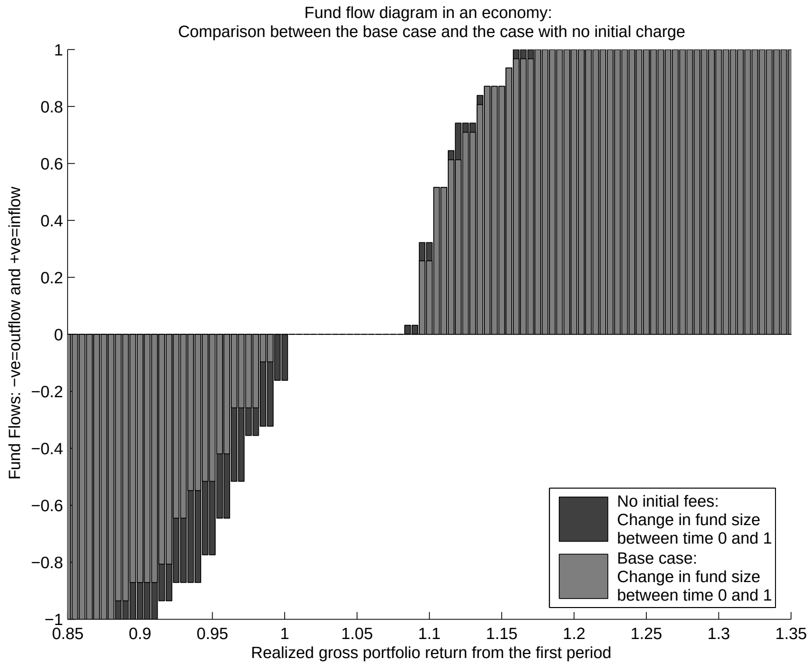


Figure 1.11: The predicted fund flows in the case with no initial sales charge, contrasted to the base case with 5% initial sales charge.

in the economy with highly risky asset, the proportional change is larger for the investors with high δ.

There are two reasons behind the changes in the threat region. First of all, with higher variance in the risky asset return, (other variables remain the same), the investor's desired risky asset allocation drops. Thus the threat level between η_1^* and η_2^* tightens to reflect the lower desired allocation weight. Secondly, with higher variance in the risky asset distribution, the signal from the realized portfolio return weakens as the noise of the portfolio return increases and the power of the inference falls. As shown in figure 1.12, the decrease in the desire portfolio weight has a stronger impact on the optimal threat strategy than the noise created by the higher variance, resulting in the reduction of the threat region.

Implications on mutual fund flow-performance relationship: Controlling for the fee structure and other fund characteristics, the model predicts that if the variance of the underlying asset is higher, the inflow and outflow region of the mutual fund flow-performance diagram should be slightly steepen. Unfortunately, the curvature difference between the two flow-performance diagrams is very small. A more testable implication can be formed with respect to the size of the inactive region. When the variance of the underlying asset increases, the difference between η_1^* and η_2^* for all of the investors shrink at the individual level, resulting in a much smaller flat/inactive region. See figure 1.13 for detail.

Case 4. ***Optimal threat strategy of investors with low income at time 0 and high income at time 1 (low-high compensation case):***

In this specification, the wage of the investors in the first period is halved and the wage in the second period remains the same. This has two impacts in the players' behavior. For the manager, his compensation is lower in the first period compared to the second period, and hence, the power of the threat changes. With lower compensation in the first period and the same compensation in the second period, in the eyes of the manager, the current size of the pie is relatively small compared to the size of the pie in the future. The future compensation becomes the more important component of his overall two period compensation. Therefore the manager puts more weight in the future when he maximizes his expected utility and the power of the investor's threat increases. If the investor uses the same strategy as in the base case, the investor's threat is able to alter the incentive more in the low-high compensation case. As a result, the investor widens the threat regions between η_1^* and η_2^* to decrease the power of the threat in the low-high compensation case. In short, the power of threat increases and thus the threat region widens.

Another reason behind the increase in the threat levels is that the investor has less income in the first period and is willing to take more chance for hopes of a good payoff in the future. The investor's increased optimal portfolio weight also decreases the need of a strong threat. Therefore, the corresponding threat levels widen. See figure 1.14.

Case 5. *Optimal threat strategy of investors with high income at time 0 and low income at time 1 (high-low compensation case):*

In this specification, the wage of the investor in the first period remains the same and the wage in the second period is halved. The manager has a smaller income in the future and the power of the threat lowers, since less future compensation is under the investor's threat. For the investor, the second period income does not have a strong impact in the desired first period portfolio holdings. As seen in figure 1.16, the lower income at time 1 has little impact on the optimal threat strategy η_1^* and η_2^*. Only minor changes are observed compared to the base case economy. Although the investor's inflow threshold is lower in the base case, the manager is equally concerned about the outflow threat as before. The overall optimal threat levels η_1^* and η_2^* in the two cases are very similar.

1.4.4.1. Robustness Checks. As robustness check, I varied more settings to study the corresponding optimal behavior in the model[10]. The variations include a case with higher mean return on both the risky asset and the riskfree asset, a case with higher riskfree

[10]For the parameter values of the various analysis, see table 1.2.

asset mean return and a case with low but positive initial sales charge. In these three cases, the results are as expected.

i. **Higher mean return on both assets:** When both of the assets mean return increase, keeping the difference between the mean return of the two assets the same, the shape and the curvature of the threats with respect to the realized gross portfolio return do not change. The only noticeable change is the upward shift of the η_1^* and η_2^* correspondingly. See figure 1.18.

ii. **Higher riskfree rate:** With the higher riskfree rate, the threat level η_1^* shifts up as one would predict. The desired risky asset allocation drops slightly as the higher riskfree rate narrows the gap with the risky asset mean return. This is reflected in the slight drop in η_2^*. The more sizeable impact is on the optimal η_1^*. Since the investor infers the riskiness of the portfolio by comparing the realized gross portfolio return with the return on the riskfree asset, the reference point is shifted upwards in the economy with the higher riskfree rate. Therefore, the corresponding threat level η_1^* is increased.

iii. **Low initial sales charge:** The initial sales charge in this case is set to be 2.5%, instead of 5% in the base case and 0% in the no initial fee case. The results are similar to the case with no initial charge, but with different magnitude of change. The optimal η_1^* is shifted upwards and the slope of η_1^* is flatter than the base case but steeper than the no fee case. See figure 1.20.

Table 1.2: **The parameter values in the comparative statics analysis.**
The table contains the parameter values used in the various scenarios, including the base case. The differences between the various cases compared to the base case are as follows: (1) *No initial fees*, the initial sales charge is set to be zero instead of 5%. (2) *Low initial fees*, the initial sales charge is set to be 2.5% instead of 5%. (3) *High risky asset variance* σ^2, the standard deviation of the risky asset is set to be 0.4 instead of 0.25. (4) *High riskfree asset return*, the riskfree asset return is set to be 8% instead of 5%. (5) *High risky and high riskfree asset mean return (High means)* the mean return of the risky asset is set to be 15% instead of 10% and the return of the risk-free asset is set to be 8% instead of 3%.

Description of Variable	**Symbol**	**Base**	**Low δ**	**High δ**
Risk aversion parameter	δ	1.5-5.5	1.5-3.4	3.5-5.5
Mean return of the risky asset	μ	10%	10%	10%
Standard deviation of the risky asset	σ	0.25	0.25	0.25
Return on the riskfree asset	R_b	3%	3%	3%
Intertemporal discount rate	β	0.95	0.95	0.95
Initial sales charge	1-B	5%	5%	5%
Rate of compensation	x	2%	2%	2%
Size of the fund	N	30	30	30

Description of Variable	**No initial fees**	**Low initial fees**
Risk aversion parameter	1.5-4.5	1.5-4.5
Mean return of the risky asset	10%	10%
Standard deviation of the risky asset	0.25	0.25
Return on the riskfree asset	3%	3%
Intertemporal discount rate	0.95	0.95
Initial sales charge	0%	2.5%
Rate of compensation	2%	2%
Size of the fund	30	30

Description of Variable	**High σ^2**	**High R_b**	**High means**
Risk aversion parameter	1.5-4.5	1.5-4.5	1.5-4.5
Mean return of the risky asset	10%	10%	15%
Standard deviation of the risky asset	0.4	0.25	0.25
Return on the riskfree asset	3%	8%	8%
Intertemporal discount rate	0.95	0.95	0.95
Initial sales charge	5%	5%	5%
Rate of compensation	2%	2%	2%
Size of the fund	30	30	30

1.5. Concluding Comments

In the model, the incentive issue between the investor and the manager arises from the different objectives of the two players. With a predetermined contractual form in the mutual fund industry, the investor does not have the choice to personalize the contractual terms. Generally, the manager chooses the best allocation for himself. Only in the case when the payoff and the preference of the investor and the manager are equivalent, do their optimal allocations coincide.

In this chapter, I consider the problem of aligning the mutual fund manager's incentive with the incentive of the investor. By using future investment as a threat, the investor reduces the fund manager's incentive to take overly risky portfolio allocation. The investor has three options: to reinvest his existing funds, withdraw his existing funds or reinvest with additional funds, and strategically chooses among the three options. I analyze a three period model of portfolio delegation with a strategic investor. I show that (i) by threatening to lower the allocation of future wealth to the fund manager, the investor reduces the risk of the portfolio chosen by the manager; (ii) the realized return can serve as a signal to infer past behavior and facilitates the investor's strategy to align incentives; (iii) the strategic delegation game is a Pareto improvement compared to the single period delegation game; (iv) the model generates a fund flow-performance relationship which is asymmetric and nonlinear, similar to the ones in Chevalier and Ellison (1997); (v) the model predicts that the flow-performance relationship is sensitive to several factors such as the riskiness of the funds, the riskiness of the underlying asset, as well as the fee structure.

With the investor decreasing the capital flow when the performance is poor and increasing the capital flow when the performance is good, the manager has fewer incentives to take overly risky allocation. Essentially, the investor alters the incentive of the manager by concavifying the payoff. The investor benefits from the strategy as the weight on the risky asset is reduced to a level closer to his desired allocation.

One of the features in the model is that the initial sales charge discourages the investors to withdraw their invested capital. Since the load fees could be seen as a switching cost incurred by the investor, the model could be generalized to investigate how competition affects the equilibrium fee structure in the industry. The model may serve as a tool to explore the optimal fee structure in the mutual fund industry. Methodologies in the theoretical switching cost literature may be adapted in combination with the specific features in the mutual fund industry, to study the trade-off between attracting new mutual fund investors with low load fees versus the use of load fees to lock-in the existing mutual fund investors.

CHAPTER 2

Disentangling Mutual Fund Flows - the Role of Fund Characteristics

2.1. Introduction

In this chapter, I perform an empirical analysis on mutual fund flows with the objective to improve the understanding of the factors that affect the sensitivity of the relationship between future fund flows and past fund performance. In particular, I focus on how fund characteristics, e.g. the fee structure and the investment style, influence mutual fund flows.

Chevalier and Ellison (1997) is one of the earlier studies that focuses on the relationship between past mutual fund performance and future flows of funds. They propose a semiparametric model for the estimation of the flow-performance relationship. Their main result is that the relationship between past fund performance and future capital flows is nonlinear and asymmetric, which justifies the semiparametric model specification. Chevalier and Ellison (1997) show that the age of the fund is another important determinant of the flow-performance relationship. They find that future mutual fund flows of young mutual funds are more sensitive to the past fund performance than the future fund flows of old mutual funds.

Sirri and Tufano (1998) is another empirical study on the fund flow-performance relationship. Using a linear regression model, they find that the mutual fund flows of U.S. equity funds are asymmetric, with a disproportionately high capital inflows when the mutual funds perform well. The asymmetry of the estimated flow-performance relationship is consistent with the findings of Chevalier and Ellison (1997). Moreover, Sirri and Tufano (1998) find that fund flows are affected by the search cost the investors incur for obtaining and processing information such as the past fund performance, the fee structure and other fund characteristics.

In this chapter, I extend the empirical estimations on the mutual fund flow-performance relationship by Chevalier and Ellison (1997) and Sirri and Tufano (1998). It is important to deepen the understanding of the mutual fund flow-performance relationship for two reasons. First, the mutual funds industry grew tremendously over the last decade. The increase in the number of funds may alter the mutual fund investors' behavior and their investment strategies, resulting in a different flow-performance relationship. The increased popularity in mutual fund investments may also affect the aggregate capital flows into the mutual fund industry, which has been shown to be an important factor in the flow-performance relationship. Using US equity mutual fund data for the period from 1980 to 2005, I study if there has been any significant changes in the flow-performance relationship from the period studied by Chevalier and Ellison (1997)[1]. The second reason behind the exploration in mutual fund flows is the limited understanding of how individual fund characteristics interact with the flow-performance relationship. Contrary to Sirri and Tufano (1998), who study how load fees and the expense ratio affect the level of mutual fund capital flows, I investigate how individual fund characteristics affect the curvature and the shape of the flow-performance relationship.

One of the fund characteristics I examine is mutual fund investment style. Investors with different utilities, different wealth and different levels of risk aversion may have different preferences on the mutual fund investment style. Investors may also favor funds or fund styles with significant media coverage. Cooper et al. (2005) show that fund managers choose to change the name of the fund to incorporate a popular investment style. They find that changes in the fund names result in an averaged 28% increase in abnormal

[1]The sample period of Chevalier and Ellison (1997) is from 1983 to 1993.

fund inflow. Since the mutual fund flow-performance relationship is dependent on the investment styles of the funds, mutual fund investment styles should be incorporated in the flow-performance analysis. Therefore, in addition to studying the changes in the sensitivity of the mutual fund flows with respect to the mutual fund fee structure, I study the changes in the sensitivity of the mutual fund flows with respect to the mutual fund investment styles.

I first present the original Chevalier and Ellison (1997) model and discuss the different modifications on the semiparametric model. The results from the Chevalier and Ellison (1997) model, the benchmark model, are then compared to the results from the modified mutual fund flow-performance models. In section 2.3.2, I test the empirical implications on the mutual fund flow-performance relationship from Chapter 1. Finally, I propose an investment style specific mutual fund flow-performance model and compare the estimated flow-performance relationship with the estimated flow-performance relationship from Chevalier and Ellison (1997).

2.2. Data and Methodology

To estimate the flow-performance relationship, I use the Center for Research in Security Prices (CRSP) Survivor-Bias Free US Mutual Fund Database, developed by Carhart (1997), for the period from 1980 to 2005.

I will briefly describe the data cleaning criterions used. I remove funds existed for less than 2 years at the end of the calender year. The objective of removing these funds is to filter funds that may experience abnormal level of inflow, independent of fund characteristics. Similarly, funds with low total net asset value may also experience abnormal mutual fund flows relative to the average sized fund. Therefore, I enforce the minimum end of year total net asset value of the mutual fund to be 10 million dollars. Since this study focuses on the inflows and outflows of mutual funds, mutual funds which are closed to new investors are excluded. Finally, any fund identified as an institutional fund or a funds-of-funds is removed from the entire sample[2].

Should two funds merge, or should a fund split, the annual return of the resulting fund(s) may be misrepresented. I use the *merge_icdi* and the *split_icdi* variable to identify any funds that participated in a merger or a split. The identified funds are dropped from the sample for the event year.

Funds are removed from the sample if they are identified as international funds, bond funds, balanced funds, etc. I start by filtering the entire fund sample as suggested by Pástor and Stambaugh (2002)[3]. Then, the data sample is filtered again using more recent variables available for the period after 2003. Funds identified to have a US market focus using the Standard & Poor area code[4] and funds that are identified to have an equity focus using the Standard & Poor style codes remain in the database. In the period after 2003, only funds with the following Standard & Poor style codes remain in the database: equity all cap growth (ACG), equity all cap value (ACV), equity large cap blend (LCB), equity large cap growth (LCG), equity large cap value (LCV), equity mid cap blend (MCB),

[2]The institutional funds and funds-of-funds are identified by using the *inst_fund* and the *fund_of_funds* variables in the database.

[3]As in Pástor and Stambaugh (2002), funds are filtered out of the sample if the *policy* variable = (B & P, Bal, Bonds, C & I, GS, Hedge, Leases, MM, Pfd, TF, TFE, TFM), *obj* = (AAL, BAL, CBD, CHY, GOV, GPM, IBD, IFL, INT, MBD, MHY, MMF, MSS, MTG, TFM, TMM), or if *icdi_obj* = (BL, BQ, BY, GB, GE, GM, GS, IE, MF, MG, MQ, MS, MT, MY, PM, SP, TR).

[4]In order to filter out funds outside the geographic area of the United States, funds with *sp_area_cd* not equal to NAU are taken out of the sample.

equity mid cap growth (MCG), equity mid cap value (MCV), equity small cap blend (SCP), equity small cap growth (SCG), and equity small cap value (SCV).

Finally, in order to filter any remaining potential data errors and outliers, any observation with a fund flow greater than 200% or a turnover greater than 3 is removed from the sample.

I use the CRSP value weighted market index as the measure for annual market return. The CRSP value weighted market index includes the end of year value of all securities traded in the NYSE, AMEX and NASDAQ. The age of a fund is defined as the difference between the calendar year and the year when the fund was first offered. For example, the age of a mutual fund first offered on 12 Feb 1982 is zero at the end of year 1982, since the fund is in existence for less than 12 months.

I follow the methodology of Sirri and Tufano (1998) and Chevalier and Ellison (1997) in constructing the mutual fund flow,

$$Flow_{it+1} = \frac{TNA_{it+1} - TNA_{it}}{TNA_{it}} - r_{it+1}$$

where TNA_{it} is the total net asset of fund i in year t, and r_{it+1} is the annual return of fund i in year $t+1$. Hence, mutual fund flow is the proportional growth in the total asset under management, net of internal growth, reinvestment of dividends and distribution.

2.2.1. A Semiparametric Model of the Flow-Performance model

Chevalier and Ellison (1997) is one of the first studies that uses a semiparametric mutual fund flow-performance model. They use the past performance of mutual funds, the size of the mutual fund industry and other relevant economic factors, to explain the level of mutual fund flow. Their primary focus is the effect of year t excess returns on the investment flows in year $t+1$.

$$
\begin{aligned}
(2.1) \quad Flow_{it+1} &= \sum \gamma_k Agek_{it} f\left(r_{it} - rm_t\right) + \sum \delta_k Agek_{it} \\
&\quad + \alpha_1 \left(r_{it-1} - rm_{t-1}\right) + \alpha_2 \left(r_{it-2} - rm_{t-2}\right) + \alpha_3 \left(r_{it+1} - rm_{t+1}\right) \\
&\quad + \alpha_4 IndustryGrowth_{t+1} + \alpha_5 \log\left(\widetilde{Assets_{it}}\right) + \epsilon_{it+1}
\end{aligned}
$$

In addition to the mutual fund flow variable, $Flow_{it+1}$, another key variable is the excess return of the mutual funds. Excess annual return is computed by differencing r_{it}, fund i's return in year t, and r_{mt}, the return of a value weighted market index in year t. Not only are the past performance in year $t-1$, $t-2$ and the current performance in year t included in the model, but also the excess fund return in year $t+1$. The market benchmark return in year $t+1$ is included to reflect the fund flows in response to the intra-year returns. Funds with high return in year $t+1$ have additional growth due to the internal growth of investments made before the end of the year $t+1$.

The remaining explanatory variables in the model are $log\left(\widetilde{Assets_{it}}\right)$ and the mutual fund industry growth. $log\left(\widetilde{Assets_{it}}\right)$ is the natural logarithm of the ratio of the total net asset under management of fund i at the end of year t to the geometric mean of the assets under management across all funds in the sample at the end of year t. The mutual fund industry growth is defined to be the growth of the total capitalization of all mutual funds at the end of the calender year. Finally, $f(.)$ is the nonparametric function that estimates the relationship between future mutual fund flows in year $t+1$ and the past performance in year t.

Since Chevalier and Ellison (1997) are concerned that funds of different age groups may have different growth rates, they allow separate intercepts and loading on the nonparametric function $f(.)$ for each age category $2, 3, 4, 5, 6-7, 8-10$ and 11 or greater, which are denoted by δ and γ respectively. $Agek_{it}$ is an indicator which takes the value of one when the age of fund i at the end of year t is within the age category $k = 2, 3, 4, 5, 6-7, 8-10$ and 11 or greater.

In this chapter, I modify the Chevalier and Ellison (1997) model slightly in the age dimension. Instead of forming the six age categories as in Chevalier and Ellison (1997), I divide the sample of mutual funds into three age groups and separately estimate the flow-performance model for each group (See equation 2.2 for the modified model). The three age groups are (1) young funds which are funds between 2 to 5 years old, (2) mid-age funds which are funds between 6 to 10 years old, and (3) old funds which are funds older than 11 years old. This model is referred as the flow-performance model using the market return as a benchmark.

$$
\begin{aligned}
(2.2) \qquad Flow_{it+1} &= f\left(r_{it} - rm_t\right) + \alpha_1\left(r_{it-1} - rm_{t-1}\right) \\
&\quad + \alpha_2\left(r_{it-2} - rm_{t-2}\right) + \alpha_3\left(r_{it+1} - rm_{t+1}\right) \\
&\quad + \alpha_4 IndustryGrowth_{t+1} + \alpha_5 \log\left(\widetilde{Assets_{it}}\right) + \epsilon_{it+1}
\end{aligned}
$$

The estimates from the above model are reported in section 2.3.1.

2.3. Empirical Findings

2.3.1. Overall Mutual Fund Flows

Although the semiparametric model does not apriori impose a functional form, large volume of data is needed for reliable estimates. In contrast to the dataset used in the analysis, the dataset used by Chevalier and Ellison (1997) is significantly shorter in duration and smaller in the sample size. In addition, the dataset in Chevalier and Ellison (1997)[5] contains problem of back-filling and survivorship-bias. Therefore, I study if a larger and cleaner data sample alters the results of the flow-performance analysis, by comparing the results of Chevalier and Ellison (1997) to the findings using the sample described in the previous section[6]. I also investigate if the mutual fund flow-performance relationship changes over time, by comparing the estimated flow-performance relationship for the period 1980 to 1995 to the estimated flow-performance relationship for the period 1995 to 2005.

Table 2.1: **Number of fund-years observations in the estimation of the flow-performance model:** (1) the entire sample period from 1980 to 2005, (2) the earlier sample period 1980 to 1995, and (3) the latter sample period 1995 to 2005.

	Young: Age 2-5	**Mid: Age 6-10**	**Old: Age 11 and up**
Entire Sample	6155	4111	4896
Earlier Sample	1292	727	2341
Latter Sample	4863	3384	2555

2.3.1.1. Analysis for the Period 1980 to 2005. I examine the estimation of the mutual fund flow-performance model using the market return as a benchmark, for the

[5]Chevalier and Ellison (1997) estimate their flow-performance model with a dataset consisting of 449 funds and 3,036 fund-years observations, from the period 1983 to 1993.

[6]Please see table 2.1 for the number of observations in the dataset.

entire sample which consists of all US domestic equity mutual funds over the years 1980 to 2005. I first discuss the findings on the sensitivity of the flow-performance relationship, the nonparametric component $f(.)$. The estimated loadings on the linear components are reported in table 2.4 and the estimated nonparametric function $f(.)$ is reported in figure 2.1. A 5% bootstrap confidence interval for the kernel smoothers is also reported in figure 2.1. The top panel in figure 2.1 contains the estimated nonparametric function of the young funds in the sample. The second panel contains the estimated nonparametric function of the mid-age funds in the sample. The bottom panel contains the estimated nonparametric function of the old mutual funds in the sample.

As seen in figure 2.1, in the full sample, the flow-performance relationship of young funds is very similar to the flow-performance relationship of mid-age funds, especially in the outflow region. The outflow region is the region where a fund expects an outflow of capital, i.e. when the fund performs poorly. In contrast to young funds and mid-age funds, the flow-performance relationship of old funds is fairly flat. For both young funds and mid-age funds, when the funds perform extremely well, for example 40% excess fund return relative to the market return, the expected mutual fund flow is around 36% for the following year. On the other hand, given the same performance, the expected mutual fund flow for old funds is around 14%.

The estimated flow-performance relationships of young funds and mid-age funds are significantly different than the estimated flow-performance relationship of old funds. Similar to the findings of Chevalier and Ellison (1997), the future fund flows of younger funds in year $t+1$ are more sensitive to the past fund performance in year t than older funds. The overall expected capital inflows and outflows are lower for old funds than young funds, given the same excess fund return. As shown in the bottom panel of figure 2.1, when an old mutual fund performs poorly, with excess return of -40%, the expected outflow is 18%. However, for the same fund performance relative to the market, a young mutual fund expects more than 30% capital outflow in the following year.

Moreover, as shown in table 2.4, the future fund flows of old funds in year $t + 1$ are less dependent on the industry growth, the size of the fund and the excess return in year t and year $t - 1$, but more dependent in the excess return in year $t - 2$ than young and mid-age funds. This is because more track records and information are available on old funds, thus the investment strategy and the capital flow of the investor are less dependent on the fund performance in the previous year. The overall results in the full sample are very similar to the ones reported in Chevalier and Ellison (1997).

2.3.1.2. Analysis for the Period 1980 to 1995 and the Period 1995 to 2005. In order to investigate if mutual fund flow-performance relationship changes over time, I separately estimate the mutual fund flow-performance model using data for the period before 1995 and the period after 1995. Please see figure 2.2 and table 2.5 for the results from the earlier sample, and see figure 2.3 and table 2.6 for the results from the latter half of the sample.

The importance of the sample size in the estimation of semiparametric models is reflected by the confidence intervals reported in figure 2.1 and figure 2.2. The estimated confidence intervals of the nonparametric function $f(.)$ are spread wider apart in the earlier sample, which contains 4360 observations, than the confidence intervals in the full sample, which contains 15162 observations. Moreover, in the estimation for the period before 1995, the nonparametric function does not fit well in the region of excess fund return over 20% and the region of excess fund return below -20%. Therefore, I focus the analysis of the flow-performance relationship in the range of -20% to 20% excess fund return for the earlier sample period.

The trend of decreasing sensitivity of the flow-performance relationship with the age of the fund is observed in the earlier subsample, which is consistent with the findings of Chevalier and Ellison (1997). The changes in the sensitivity of the flow-performance relationship with respect to the age of the fund for both the full sample and the latter sample are not as dramatic as the changes observed in the earlier sample (See figure 2.2). For young mutual funds, the estimated flow-performance relationship using the full sample and the estimated flow-performance relationship using the earlier sample are similar. However, for old mutual funds, the sensitivity of the flow-performance relationship is higher in the full sample than the earlier sample. When an old mutual fund underperforms by 20%, relative to the market return, the expected mutual fund outflow is below 5% in the earlier sample. For the same underperformance, an old mutual fund in the full sample expects an outflow of 18%.

Since a large number of observations are available in the period 1995 to 2005 (See table 2.1, the estimates are quite accurate and the confidence intervals are tight (See figure 2.3 and table 2.6 for details). Similar to the flow-performance relationship of the full sample and the earlier sample, the sensitivity of the flow-performance relationship decreases with the age of the fund. Among the estimations using the full sample, the earlier sample and the latter sample, the strongest decrease in the sensitivity is observed in the earlier sample.

The estimated flow-performance relationships for young funds and mid-age funds are essentially the same in the earlier and latter sample period. Investors of old mutual funds in the latter period react strongly to past underperformance relative to the market return. Mutual fund managers of old funds expect a higher level of outflows if the performance is poor. However, in comparison to the flow-performance relationship in the earlier period, the reaction of the investors is much weaker in the inflow region for old mutual funds. In the period 1995 to 2005, when an old fund underperforms by 20% with respect to the market return in year t, the expected mutual fund flow in year $t+1$ is -20%. And when an old fund overperforms by 20% with respect to the market return in year t, the expected mutual fund flow in year $t+1$ is 10%. In comparison, the estimated expect mutual fund flow of an old fund for the earlier sample is -5% and 18% respectively.

In summary, the changes in the flow-performance relationship for young funds and mid-age funds seem to be insignificant among the different time periods. However, the sensitivity of the flow-performance relationship for old funds is higher in the latter period compared to the earlier period.

2.3.2. Fund Flows and the Fee Structure

In Chapter 1, the model predicts that mutual fund fee structure affects the sensitivity of the mutual fund flow-performance relationship. The inflow region of a no load fund should be similar to the inflow region of a fund with positive load fees. However, the outflow region in the flow-performance diagram of a no load fund should be steeper compared to the flow-performance diagram of a fund with positive load fees. Moreover, the flat/inactive region should be smaller in the mutual funds with no initial sales charge. The model

Table 2.2: **Number of fund-years observations in the estimation of the flow-performance model:** For (1) funds with zero average front load fees and high average rear load fees, (2) funds with zero average front load fees and low average rear load fees, (3) funds with zero average rear load fees and high average front load fees, (4) funds with zero average rear load fees and low average front load fees, and (5) funds with non-zero average front load fees and non-zero average rear load fees.

	Young: Age 2-5	**Mid: Age 6-10**	**Old: Age 11 and up**
Zero Front - High Rear	1608	1040	177
Zero Front - Low Rear	834	539	280
High Front - Zero Rear	804	412	747
Low Front - Zero Rear	1385	872	1762
Non-zero Front and Rear	1524	1248	1930

suggests that the future mutual fund flow of a no load fund is more sensitive to past poor performance, since more investors withdraw their capital when the fund underperforms.

To test the hypotheses, I separate the mutual fund data sample into five subsets, according to the fee structure of the mutual fund. The five groups[7] are created using the level of average front load fees and the level of average rear load fees of the funds,

- Funds with zero average front load fees and high average rear load fees above 1%
- Funds with zero average front load fees and low average rear load fees below 1%
- Funds with zero average rear load fees and high average front load fees above 1.5%
- Funds with zero average rear load fees and low average front load fees below 1.5%
- Funds with non-zero average front load fees and non-zero average rear load fees

Empirically, I find that the flow-performance relationship in case 1 and case 2 are very similar for young funds (See figure 2.4, figure 2.5, table 2.7 and table 2.8 for details). The evidence suggests that if the level of the front load fees is zero, the level of the rear load fees does not influence the estimated flow-performance relationship of young

[7]The different subsets are known as case 1, case 2, case 3, case 4 and case 5 respectively.

mutual funds. For mid-age funds in case 1 and case 2, the lower rear load fees increase the sensitivity of the flow-performance relationship in the inflow region and decrease the sensitivity of the flow-performance relationship in the outflow region. Moreover, given two funds with no front load fees, the flow-performance relationship of the fund with lower rear load fees is more sensitive to past performance. This observation is consistent with the predictions from Chapter 1, which explain the change in the sensitivity by the decrease in the discouragement in entering and exiting the mutual funds.

For funds with zero rear load fees (case 3 and case 4), there is a sizable decrease in the sensitivity of the flow-performance relationship with respect to the fund age groups. The findings for case 3 and case 4 are very similar, especially in the inflow region, as shown in figure 2.6 and figure 2.7. The evidence suggests that if the level of rear load fees is zero, the level of the front load fees does not influence the estimated flow-performance relationship, especially in the inflow region. For the loadings on the linear components of the flow-performance model in case 3 and case 4, please see table 2.9 and table 2.10 respectively. In comparison to funds with no front load fees (case 1 and case 2), funds with no rear load fees are less sensitive to the past fund performance in the previous year, in the outflow region.

Comparing between case 1 and case 3, the flow-performance relationship of young funds with high average rear load fees and zero front load fees (case 1) are steeper than the flow-performance relationship of young funds with high front load fees and zero rear load fees (case 3), especially in the inflow region. Since the defined level of high rear load fees is greater than the defined level of high front load fees, i.e. above 1% versus above 1.5%, the average load fees in case 3 is higher than the average load fees in case 1. The observed differences in the sensitivity of the flow-performance relationship with respect to the level of load fees is consistent with the predictions from Chapter 1 for young funds. The findings are alike for mid-age funds and old funds in case 1 and case 3. Both of the flow-performance relationships for old funds are very flat, thus, managers of old funds in case 1 and case 3 do not expect a large change in the future fund size with respect to the past fund performance.

In general, the flow-performance relationship does differ with the fee structure of the fund, as seen in the difference in the results among figure 2.4 to figure 2.8 and among table 2.7 to table 2.11. In particular, the loading on the linear components for the funds with zero average rear load fees and high average front load fees (case 3) is significantly different than the loading for funds with other fee structures.

Unfortunately, since the empirical flow-performance relationship does not have an identifiable inactive region, the Chapter 1 prediction on the size of the inactive region is not testable. However, the changes in the sensitivity of the flow-performance relationship are consistent with the predictions from the model in Chapter 1.

2.3.3. Fund Flows and Investment Styles

Although Chevalier and Ellison (1997) impose no restrictions on the parametric form between the relationship of the excess return in year t and the fund flow in year $t + 1$, the model does not take into account the investment styles of the mutual funds. As shown in Sirri and Tufano (1998), mutual fund investment styles affect the flow of funds. Therefore, in this section, I separate the data samples into four investment style groups. The investment style groups are constructed following the methodology of Pástor and

Stambaugh (2002). The groups are (1) aggressive growth, (2) growth, (3) income, and (4) growth and income. By separately estimating the model for each investment style group, funds with different investment styles are no longer constrained to have the same curvature and sensitivity in the flow-performance relationship.

Table 2.3: **Number of fund-years observations used in the estimation of the flow-performance model:** For (1) aggressive growth funds, (2) growth funds, (3) income funds and (4) growth and income funds. The various investment styles are constructed following the methodology in Pástor and Stambaugh (2002).

	Young: Age 2-5	**Mid: Age 6-10**	**Old: Age 11 and up**
Agg. Growth	1535	1037	447
Growth	2697	1795	2030
Income	407	276	245
Growth & Income	1355	931	1221

Table 2.3 reports the total number of fund-year observations in the dataset used for the kernel estimation with fund investment styles. Overall, most of the observations are in the growth and growth and income investment style groups. The growth investment style group alone contains 47% of the observations used in the estimation. Unfortunately, there are not many observations on income funds for the fitting of the flow-performance relationship, merely 6.6% of the observations are in the income investment style group. In particular, there are only 245 fund-year observations for old income funds, as compared to 2030 observations for old growth funds. An interesting pattern is found in the number of observations for aggressive growth funds across the different age groups. Notice that the number of observations in the old age group is very small relative to the number of observations in the young and mid-age group for aggressive growth funds. This suggests

that either most of the aggressive growth funds started in the recent years or that aggressive growth funds do not have longevity, and thus do not survive to be included in the old age group.

The overall estimated loading $\{\alpha_1, \alpha_2, \alpha_3, \alpha_4, \alpha_5\}$ on the past excess returns and industry growth are significantly different among the different styles as shown in table 2.12 to table 2.15. With the exception of aggressive growth funds, young funds have the highest sensitivity to the one year lagged excess return compared to mid-age funds and old funds. As the fund ages, future fund flows become more sensitive to the two year lagged excess return and less dependent on the one year lagged excess return. In addition, there are differential loadings on the lagged excess returns among the different fund investment styles. Although the loading on the one year lagged return drops as the fund ages, the change is the most significant for income funds, from 0.8401 for young income funds to 0.2598 for old income funds (see table 2.14 for details). The overall dependence of the mutual fund flows on the one year lagged return is the lowest for aggressive growth funds, with a loading of 0.2172 compared to 0.8401 for income funds (See table 2.12 and table 2.14).

Although there are differences in the nonparametric component $f(.)$ of the flow-performance model across each age group, the differences are minor across the different investment styles. Please see figure 2.9 to figure 2.12 for the estimated flow-performance relationship of the four investment styles.

2.3.4. Market Benchmark versus Style Benchmark

The incorporation of the fund investment styles raises an interesting question about the validity of using the overall market return as the benchmark for all funds. It is plausible that investors compare the fund return not to the overall market return but to the overall return within each investment style group. Therefore, another relevant benchmark is the overall value weighted fund return constructed from all of the funds within the same investment style group.

In addition to analyzing the flow-performance relationship using Chevalier and Ellison (1997)'s model, with excess return relative to the value weighted market return and overall mutual fund industry growth, I examine the flow-performance relationship using a fund investment style specific flow-performance model, with excess return relative to the value weighted style specific average fund return and investment style specific growth rate.

$$
\begin{aligned}
(2.3) \qquad Flow_{it+1} &= f\left(\tilde{r}_{it}\right) + \alpha_1\left(\tilde{r}_{it-1}\right) + \alpha_2\left(\tilde{r}_{it-2}\right) + \alpha_3\left(\tilde{r}_{it+1}\right) \\
&\quad + \alpha_4 StyleIndustryGrowth_{t+1} + \alpha_5 \log\left(\widetilde{Assets}_{it}\right) + \epsilon_{it+1}
\end{aligned}
$$

For the investment style specific model, $\tilde{r}_{it}$ is the difference between the return of fund i in year t and the value weighted average return of the investment style group of fund i in year t. The $IndustryGrowth$ variable from Chevalier and Ellison (1997)'s model is replaced by the overall growth in the total capital within the investment style group of fund i in year t, $StyleIndustryGrowth_t$.

The modified model is estimated for each of the three age groups *(Young, Mid-age, Old)* and each investment strategy *(Aggressive Growth, Growth, Income, Growth & Income)*, with 12 overall combinations. For each age-investment style variation, the set of estimates include a nonparametric function $f(.)$, which takes the current annual year-end excess return as an input, and the linear loading $\{\alpha_1, \alpha_2, \alpha_3, \alpha_4, \alpha_5\}$ on the past year-end excess returns, the investment style specific mutual fund industry growth and the fund size ratio.

One important finding using the style specific flow-performance model is that the estimated flow-performance relationship is less nonlinear and less asymmetrical than the estimated flow-performance relationship using market benchmark model, equation (2.2). The decrease in the nonlinearity and asymmetry are found in all of the variations using the investment style specific flow-performance model. These include the results from the full sample, the earlier subsample, the latter subsample, and the four investment style group samples, please see figure 2.13 to 2.19 for details. The finding is interesting since researchers have difficulty using a rational model to explain the magnitude of the nonlinearity and the asymmetry in the observed flow-performance relationship.

The concept of an investment style specific benchmark is not new. Many existing mutual funds report their performance relative to an investment style specific benchmark or a geographic specific benchmark. Although the nonlinearity and asymmetry persist in all of the estimations and variations of the flow-performance model, using a more relevant benchmark in the evaluation of the mutual fund performance, I find that the curvature is not as strong as documented in the literature.

Finally, for most of the fund investment styles and age groups, with the exception of young income funds, the loading on the one year lagged excess return in the investment style specific model is lower than the loading on the one year lagged excess return in the market benchmark model. Similarly, the loading on the industry growth variable is lower in the style specific flow-performance model, with the exception of old income funds.

2.4. Conclusion

In this chapter, I study the interaction between mutual fund characteristics and the flow-performance relationship, using an extension of the semiparametric model developed by Chevalier and Ellison (1997). The advantage of the model is that it does not impose a functional form on the relationship between past fund performance and future fund flows. To my knowledge, this is the first attempt to incorporate individual fund characteristics and different mutual fund investment styles into a semiparametric analysis of the flow-performance relationship.

I find that the flow-performance relationship of old mutual funds in the earlier half of the sample differs from the flow-performance relationship in the latter period. However, I do not observe any apparent difference for young funds and mid-age funds. Moreover, the mutual fund fee structure does affect the flow-performance relationship. The future mutual fund flows of funds with lower load fees are more sensitive to the past fund performance. This finding is consistent with the prediction of the model in Chapter 1.

Finally, I show that the mutual fund investment style is an important factor in the flow-performance relationship. Using an investment style specific flow-performance model, I show that the level of nonlinearity and asymmetry of the flow-performance relationship are overstated in the literature. The results presented in this chapter may help to resolve the longstanding debate on rationality of mutual fund investors.

CHAPTER 3

Anticipated Versus Unanticipated Flows: Do Mutual Funds Hedge Liquidity Risk?

3.1. Introduction

In this chapter, I study if mutual fund managers consider liquidity to be an important attribute and if they actively manage the level of liquidity of the fund. I use expected and unexpected flows to show how mutual fund managers change the portfolio liquidity level and the portfolio allocation of the mutual fund in response to flows. In particular, I consider a mutual fund manager that expects a capital outflow from his mutual fund. I try to answer the question if he hedges the flow liquidity risk by shifting his asset allocation to a more liquid portfolio or if he optimizes the fund performance and risks being forced to sell illiquid assets in short notice when the outflow occurs.

I use the investment style specific flow-performance relationship developed in Chapter 2, to decompose the realized mutual fund flows into an anticipated/expected part and an unanticipated/unexpected part. Having done this decomposition I can identify events of extreme expected and extreme unexpected fund flows. I show that mutual fund managers optimize the mutual fund portfolio liquidity level by examining the movement of the portfolio liquidity around periods with extreme flows. It is important to study liquidity in the mutual fund context, since liquidity is a key economics factors that affects the required return on assets. This has been shown in a theoretical model by Kyle (1985), who shows that the price impact from order flow affects asset prices. In empirical studies, Amihud and Mendelson (1986) and Pástor and Stambaugh (2003) among others show that both the level of liquidity and liquidity risk are priced. I extend these studies to the area of mutual funds and examine how mutual fund managers control the fund portfolio liquidity to further our understanding of the mutual fund industry.

Massa and Phalippou (2004) and Coval and Stafford (2005) also study liquidity in the context of mutual funds. Coval and Stafford (2005) examine asset fire sales and institutional price pressure, focusing on mutual funds that are undergoing significant flows. They find that investors who trade against the constrained mutual funds earn very significant returns for providing liquidity to these mutual funds, an indication that forced transactions create significant financial distress for mutual funds. Their findings are consistent with the results of this paper. The difference between Coval and Stafford (2005) and my paper is that Coval and Stafford (2005) use mutual funds to identify securities under price pressure whereas I investigate the portfolio liquidity level of the mutual funds during periods of extreme flows. Massa and Phalippou (2004) on the other hand explain the level of the fund liquidity and the liquidity risk loading. They find that five factors, portfolio size, fee structure, portfolio concentration, trading frequency and the investment style, drive the observed fund portfolio liquidity. Contrary to Massa and Phalippou (2004), I focus on the dynamic movement of the fund liquidity level, and examine the changes of the liquidity level around periods of significant expected and unexpected fund flows.

I find that large expected and unexpected capital movement significantly changes the portfolio liquidity level of the fund. If a mutual fund manager expects high capital outflows in the following quarter, he increases the portfolio liquidity level of the fund in anticipation of the future outflow. Similarly, if the mutual fund manager faces an unexpected outflow, he reduces the trading cost by selling liquid assets and thus shifting the portfolio allocation to be less liquid.

3.2. Data and Methodology

I use five databases to construct the mutual fund portfolio liquidity. In order to estimate the flow-performance relationship and for the construction of the fund investment styles, I use the Center for Research in Security Prices (CRSP) Survivor-Bias Free US Mutual Fund Database, developed by Carhart (1997), for the period from 1980 to 2005. To merge between the CRSP mutual fund database and the Thomson Financial database, which contains the quarterly mutual fund holdings, I use the MFLinks database. To construct the quarterly averages of the quoted spread, the effective spread, the proportional effective spread and the proportional quoted spread of the mutual fund equity holdings, I use the NYSE Trade and Quote (TAQ) database. TAQ contains the tick-by-tick trades and quotes of securities traded on the New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and NASDAQ National Market System. Finally, I calculate the quarterly Amihud (2002) illiquidity measure using the price and volume data from the CRSP daily stock file.

3.2.1. Liquidity Measures

I use two types of equity liquidity measures, price impact and spread measures. I start by computing the measures for each individual security, then aggregate them to calculate the mutual fund portfolio liquidity level.

3.2.1.1. Amihud (2002)'s Illiquidity Measure. As shown in Amihud (2002), Amihud's illiquidity measure reflects the relative price change per dollar traded. Amihud's measure has the advantage that it only requires daily data to be computed. It has also been shown to be highly positively correlated to other microstructure measures and Kyle

(1985)'s price impact coefficient λ. I construct Amihud's illiquidity measure for all ordinary common shares traded on NYSE, NASDAQ and AMEX, using the CRSP US stock database from the beginning of 1980 to the end of year 2005.

The daily measure is calculated and averaged by quarter to form the quarterly Amihud illiquidity measure, $A_{i,t}$. The quarterly Amihud's illiquidity measure for stock i in quarter t is defined as

$$A_{i,t} = \frac{1}{numdays_{i,t}} \sum_{k=1}^{d_t} \frac{|r_{i,k}|}{dvol_{i,k}}, \tag{3.1}$$

where $numdays_{i,t}$ is the number of active trading days for stock i in quarter t, $|r_{i,k}|$ is the absolute value of the daily return of stock i on day k, $dvol_{i,k}$ is the dollar trading volume of stock i on day k, and d_t is the total number of trading days in quarter t.

Given the overall growth in the trading activity of the US security market, Amihud's illiquidity measure drops exponentially in the recent years if no adjustment is made. Thus, the measure is scaled by an adjustment factor that proxies the overall market growth with respect to the level at the beginning of 1980. The unadjusted measure at quarter t is multiplied by the ratio of the market capitalization at the end of quarter t to the market capitalization at the end of the first quarter in 1980.

Since the Amihud's illiquidity measure of individual securities are aggregated into an illiquidity measure on the mutual fund portfolio level, the measure should be independent of the exchange the stocks are traded on. It is well documented that the trading volume in NASDAQ is overstated since it contains interdealer volume. Therefore the trading volume must be adjusted for the NASDAQ stocks before the construction of Amihud's illiquidity measure at the mutual fund portfolio level. The adjustment on NASDAQ stocks is essential since the liquidity measures are aggregated on the fund portfolio level together with NYSE and AMEX stocks, and many mutual funds have a significant portion of their holdings in stocks traded on NASDAQ. The adjustment factor is chosen based on the finding of Atkins and Dyl (1997) and Andersen and Dyl (2005). First, for NASDAQ stocks traded before 1997, the trading volume is halved. With the increase in the number of electronic trades, the adjustment factor is changed to 1/1.35 for the period after 1997.

Finally, I aggregate the quarterly Amihud illiquidity measure of the individual securities by taking the value weighted average by the fund portfolio holdings, to form the quarterly proxy of the mutual fund portfolio liquidity using Amihud's illiquidity measure.

3.2.1.2. Spread Measures. Four different spread measures are used to proxy for liquidity and trading cost. (1) *Quoted Spread*: the quoted bid-ask spread associated with the transaction, (2) *Proportional Quoted Spread*: the ratio of the quoted bid-ask spread to the mid-point of the quote (in percentage), (3) *Effective Spread*: the difference between the execution price and the mid-point of the prevailing bid-ask quote, and (4) *Proportional Effective Spread*: the ratio of the effective spread to the mid-point of the prevailing bid-ask quote (in percentage).

The spread measures are constructed using the NYSE Trade and Quote (TAQ) database. Since TAQ is only available from 1993 onwards, the analyses with the spread measures are performed for the subsample spanning from 1993 to 2005. The data cleaning and filtering of the trades and quotes are based on Chordia et al. (2001) and Chordia et al. (2002); details are available in the data appendix for chapter 3.

After the filtering, the four spread measures are computed for every valid observation in the TAQ database, which are averaged over each day to form the daily spread measures.

The daily stock liquidity measures are then averaged for each quarter to form the quarterly spread measures. Using the mutual fund portfolio holding, I estimate the liquidity level of the mutual fund by value weighting the individual spread measures. The resulting measures of mutual fund portfolio liquidity are used to capture the mutual fund trading cost at the end of each quarter.

3.2.2. Decomposition of Mutual Fund Flows

I use the semiparametric mutual fund flow-performance model presented in Chapter 2, to forecast fund flows for the next quarter. The realized fund flows are then decomposed into two components, an anticipated/expected component and an unanticipated/unexpected component. Among the various flow-performance models, I use the investment style specific flow-performance model to decompose fund flows since the fund style affects the decisions of investors and their capital allocation.

In order to use the semiparametric model to forecast the quarterly mutual fund flow, I assume the mutual fund managers form expectations of the future market conditions at the end of each quarter. The conditional version of the investment style specific flow-performance model is,

$$
\begin{aligned}
(3.2) \qquad E_t[Flow_{it+1}] \; = \; & f\left(\tilde{r}_{it}\right) + \alpha_1 \left(\tilde{r}_{it-1}\right) + \alpha_2 \left(\tilde{r}_{it-2}\right) \\
& + \alpha_4 E_t[StyleIndustryGrowth_{t+1}] + \alpha_5 \log\left(\widetilde{Assets}_{it}\right),
\end{aligned}
$$

where $Flow_{it+1}$ is the mutual fund flow of fund i in year $t+1$, $\tilde{r}_{it}$ is the difference between the return of fund i in year t and the value weighted average return of the investment style group of fund i in year t. $StyleIndustryGrowth_t$ is the overall capital growth within the investment style group of fund i in year t. $log\left(\widetilde{Assets}_{it}\right)$ is the natural logarithm of the ratio of the total net asset under management of fund i at the end of year t to the geometric mean of the assets under management across all funds in the sample at the end of year t. Finally, $f(.)$ is the nonparametric component of the partial linear model of flow-performance relationship[1].

The above flow-performance model yields the one year forecast of the annualized future fund flows. In order to the match the frequency of the analysis on mutual fund portfolio liquidity, I assume one fourth of the predicted annualized future flow occurs in each quarter. The forecast of the future fund flow is formed at the end of every quarter, using the total net asset value of the fund in the past 12 months, the excess fund return in the past 12 months and a forecast of the investment style specific industry growth for the next 12 months.

The investment style specific industry growth is forecasted using two methods. The first method assumes that the industry growth rate in the following quarter is the same as the current growth rate. The second method is estimated using an ARMA model on the investment style specific growth rate. I estimate various specifications of ARMA models and the resulting optimal ARMA model is a first order autoregressive model for all the investment styles. The estimated coefficients and t-statistics of the optimal model are reported in 3.1.

3.2.2.1. Semiparametric Model Versus Linear Model. Since the decomposition of the mutual fund flows is an integral part of the analysis, it is crucial to have the most reliable estimates on future mutual fund flows. Therefore, I compare the predictive power

[1]I assume that excess returns are unpredictable, i.e. $E_t[\tilde{r}_{it+1}]$ in the investment style specific flow-performance model is zero. See equation (2.3).

Table 3.1: **Optimal ARMA model for the fund investment style specific industry growth.** The various investment styles are constructed as in Pástor and Stambaugh (2002). The fund investment style growth rate is the growth rate of the aggregated TNA of funds in the same investment style category. A series of ARMA models are estimated for each investment style, and the resulting optimal models are reported below.

	Model	**Parameter**	**Estimate**	**t-stats**
Agg. Growth	AR(1)	μ	0.41853	3.31
			0.82465	13.62
Growth	AR(1)	μ	0.14843	2.35
			0.85947	14.92
Income	AR(1)	μ	-0.04387	-0.42
			0.96401	32.92
Growth & Income	AR(1)	μ	0.10166	1.39
			0.92586	21.95

of the most referenced flow-performance models, which are the semiparametric model used in Chevalier and Ellison (1997) and the linear model used in Coval and Stafford (2005).

For the details on Chevalier and Ellison (1997)'s model, please refer to Chapter 2 of the dissertation. The advantage of the semiparametric flow-performance model is that it does not impose a functional form on the relationship. However, the estimation requires a large amount of data and is more involved than the estimation of a simple linear regression.

To compare the two models, I estimate the linear regression model in Coval and Stafford (2005). They regress four periods of lagged quarterly fund flows and eight periods of lagged quarterly return on the current quarterly flow, using the Fama and MacBeth (1973) approach. The estimated result of the linear model is reported in table 3.2. The reported coefficients are the time series average of the periodic cross sectional regression coefficient in each quarter. The t-statistics reported are calculated by using the time series standard error of the mean.

Table 3.2: **Linear regression on quarterly mutual fund flows.** The estimated model is a linear model with $Flow_{i,t}$, the mutual fund flow of fund i in quarter t, as the left hand side variable. The right hand side variables include four periods lagged quarterly fund flow and eight periods lagged quarterly fund return. The adjusted R^2 for the model is 0.1334.

	Coefficients	**t-stats**
Intercept	-0.0156	-3.0024
Flow$_{t-1}$	0.0828	3.8567
Flow$_{t-2}$	0.0526	3.7032
Flow$_{t-3}$	0.0787	5.8877
Flow$_{t-4}$	0.0329	3.2432
Return$_{t-1}$	0.3280	5.8003
Return$_{t-2}$	0.3749	6.9666
Return$_{t-3}$	0.3055	6.6718
Return$_{t-4}$	0.1501	3.2050
Return$_{t-5}$	0.0570	1.1152
Return$_{t-6}$	-0.0088	-0.2014
Return$_{t-7}$	0.0602	1.4497
Return$_{t-8}$	0.1254	2.2308

The adjusted R-squared of the investment style specific flow-performance model is higher than the adjusted R-squared of the linear regression model, which are 0.1597 and 0.1334 respectively. More importantly, the mean squared error from the prediction in the next quarter fund flow is much lower using the semiparametric model.

The average mean squared error of the fund style specific flow-performance model with the two forecast methods are both 0.007385. In contrast, the mean square error of the linear model without differentiating the fund investment styles is 0.9837. When the linear model is estimated for each investment style and age group, the means squared error drops to 0.4139. The improvement supports the view that flow-performance relationship is sensitive to the investment style of the fund. However, the mean squared error of the linear model remains significantly higher than that of the semiparametric investment style specific flow-performance model[2].

Notice that the two industry growth forecasts do not affect the prediction power of the semiparametric flow-performance model. This is due to the fact that the optimal ARMA model chosen is an AR(1) model with a fairly high coefficient on the one period lagged industry growth. The predicted industry growth using the optimal ARMA model is fairly close to the predicted industry growth using the simple assumption, resulting in minor differences in the flow prediction.

In conclusion, although the semiparametric model is more time consuming to estimate, it performs significantly better in forecasting future fund flows than the linear model commonly used in the literature.

[2]In comparison to other flow-performance models described in Chapter 2, the mean squared error of all estimated semiparametric models are significantly lower than the mean squared error of the linear model.

3.2.3. Mutual Fund Holdings and Mutual Fund Portfolio Liquidity

I obtain the mutual fund portfolio holdings from the Thomson Financial mutual fund database for the period 1980 to 2005. Then, I use the MFLinks database to connect the CRSP mutual fund database and the Thomson Financial mutual fund database. MFLinks is a database created by the Wharton Research Data Services (WRDS) that merges the two databases following the methodology suggested in Wermers (2000). The resulting dataset contains quarterly holdings for 3037 funds and 108,974 fund-quarter observations for the period from 1980 to 2005. For the details on the merge between the databases and the filters imposed on the mutual fund holding data, please refer to the appendix of Chapter 3.

3.3. Results and Findings

3.3.1. Expected Extreme Mutual Fund Outflows

In this section, I study whether mutual fund managers optimize the liquidity level of the fund. In particular, I investigate if there is any abnormal movement in the liquidity level of the fund around an event of extreme expected fund flows.

Future mutual fund flows are forecasted using the semiparametric model discussed in the previous section. In general, I define a flow event as the event when a mutual fund experiences a quarterly flow greater than 5%, either in terms of expected fund flow or unexpected fund flow. Hence, an event of extreme expected fund flow is defined as the event when the quarterly expected fund flow is greater than 5%.

In order to ensure that the observed movement in the fund portfolio liquidity level is caused by to the extreme expected flows, I impose the restriction that no other flow event occurs in the 6 months prior to and after the expected extreme flow. In total, there are around 900 observations of isolated expected extreme outflow events, depending on the flow prediction model used.

For clarity, let quarter t be the period when the mutual fund manager forecasts a high level of outflow. I normalize the fund portfolio liquidity reported in table 3.3 to table 3.7 for the ease of comparison. The fund portfolio liquidity is normalized to one for the quarter prior to the extreme flow event for all of the funds anticipating significant outflows, then the normalized liquidity level is averaged over all of the funds within the same investment group. As reported in table 3.3 to table 3.7[3], the normalized fund liquidity is compared among 3 periods: the period before the extreme expected outflow event, quarter $t-1$, the period at which the manager forms expectation of high outflow for the following quarter, quarter t, and the period after the expected outflow event, $t+1$.

I find evidence that mutual fund managers increase the fund portfolio liquidity in anticipation of high fund flow in the following quarter. However, without further information, one cannot differentiate between the possible reasons why the fund portfolio liquidity increases. The increase may be due to the managers selling off the most illiquid assets, thus increasing the average portfolio liquidity, or it may be due to the fund managers holding more liquid securities in the entire portfolio, thus shifting the average liquidity level upwards. I repeat the analysis on the fund portfolio liquidity movement in the top and bottom liquidity quintile of the fund holdings. The top liquidity quintile contains the 20% most liquid stocks of the fund holdings, and the bottom liquidity quintile contains the 20% least liquid stocks of the fund holdings.

[3] If the decrease in the fund portfolio liquidity is greater than 1%, the table cell is shaded; and if the decrease is greater than 5%, the content is bolded.

3.3.1.1. Summary of Results. I observe a sizable increase in the fund portfolio liquidity level at the event time when the expectation of extreme outflow is formed, with all of the five liquidity measures. The fund manager increases the liquidity of the fund in anticipation of a high expected outflow. If the fund is under pressure to sell quickly, it incurs high transaction costs and suffers from high price impact for the more illiquid assets. The evidence shows that the fund manager sacrifices the optimal allocation and increases the fund portfolio liquidity, to avoid selling the assets in short notice. By preemptively adjusting the fund portfolio liquidity level higher, the fund does not suffer as heavily in the liquidation cost of the assets when the extreme fund outflow realizes.

3.3.1.2. Detail Analysis Using Amihud's Illiquidity Measure. For the Amihud illiquidity measure[4], with the exception of income funds, the magnitude of the decrease in quarter t is large. As shown in table 3.3, for many of the investment styles, the decrease is higher than 10%. The pattern is found consistently for the different flow prediction settings. A possible reason why the pattern is not observed for the income investment group is the small sample size of income funds experiencing an extreme expected outflow event.

The decrease in the Amihud illiquidity measure is also observed in the top liquidity quintile and the bottom liquidity quintile of the fund holdings. The top quintile contains the 20% most liquid stocks of the fund holdings, and the bottom quintile contains the 20% least liquid stocks of the fund holdings, measured using Amihud's illiquidity measure. The changes in the average liquidity for the 20% most liquid securities and the 20% least liquid securities suggests that the fund manager reallocates the overall portfolio holdings

[4]Since Amihud's illiquidity measure is an illiquidity measure, the lower the value of the measure, the more liquid is the fund portfolio.

to adjust the fund liquidity level when he anticipates an extreme outflow. However, the decrease in Amihud's illiquidity measure is not uniform across all of the fund holdings. For growth funds, the decrease in the measure is significantly stronger in the bottom liquidity quintile of the fund holdings, at 12% compared to 5.5% in the top liquidity quintile of the fund holdings. On the contrary, for aggressive growth funds, the decrease is stronger in the top liquidity quintile of the fund holdings compared to the bottom liquidity quintile, with 5% and 2.4% change in the top and bottom liquidity quintile respectively. In contrast, for growth and income funds, the magnitude of the decrease in the Amihud's illiquidity measure is the same for the top and bottom liquidity quintile. Interestingly, the Amihud's illiquidity measure continues to drop in the quarter after the expected outflow event for the top liquidity quintile of the fund holdings. The fund manager maintains a high level of liquidity in the top liquidity quintile even after the realization of the extreme flow.

3.3.1.3. Detail Analysis Using Spread Measures. Four different spread measures are used. They are the quoted spread measure, the effective spread measure, the proportional effective spread measure and the proportional quoted spread measure. However, the sample size of the analysis using the spread measures is lower than the sample size of the analysis using Amihud's illiquidity measure. This is due to the availability of the TAQ database and the event of tick size changes.

Although the spread measures are good proxies of the trading cost of the mutual funds, there are abnormal movements in the fund portfolio liquidity during periods when the tick size is changed. In the month of June 1997, both NASDAQ and NYSE dropped the minimum tick size from $\frac{1}{8}$ to $\frac{1}{16}$. The tick size is reduced to $\frac{1}{100}$ in January 2001 for most of the NYSE stocks and in April 2001 for most NASDAQ stocks. As shown in Goldstein and Kavajecz (2000) and Jones and Lipson (2001), the change of the tick size from one eighth to one sixteenth has reduced both the quoted spread and effective spread. Moreover, Bessembinder (2003) shows that the change to decimal pricing has substantially changed the trade execution costs. The quoted spread declined significantly, with the largest impact observed in heavily traded stocks.

In order to avoid contaminating the results of the mutual fund liquidity analysis, the observations four quarters before and after any tick size change are not used. I repeat the extreme expected flow analysis on the reduced dataset using the four spread liquidity measures[5].

For the proportional effective spread (see table 3.4), the lack of observations for income funds does not seem to impact the findings. The proportional effective spread decreases at the event time and the period after the flow event, for all of the investment styles. A systematic difference is observed between the changes in the liquidity level of the top liquidity quintile and the bottom liquidity quintile of the fund holdings, measured by the proportional effective spread. The reduction of the proportional effective spread measure at the flow event time is higher in the top quintile of the fund portfolio holdings than the bottom quintile. This shows a non-uniform adjustment in the liquidity of the overall holdings. The adjustment of the proportional effective spread measure is the strongest among the most liquid assets in the fund.

For the proportional quoted spread (see table 3.5), the trend of the decreasing fund liquidity measure is also observed. However, there is only weak evidence of a further decrease in the proportional quoted spread in quarter $t + 1$, especially in the bottom

[5] Since the spread measures approximate the trading cost of the securities, the lower the spread measures, the more liquid is the fund portfolio.

liquidity quintile. Although the result in the post event quarter $t + 1$ is mixed, the decrease at the event time is observed for the overall fund portfolio liquidity measure, and the liquidity measure of the top liquidity quintile and the bottom liquidity quintile of the fund holdings. The initial decrease in the top liquidity quintile of the analysis using the proportional quoted spread is much stronger than the decrease in the top liquidity quintile of the analysis using Amihud's illiquidity measure. Using the investment style specific flow-performance model with AR(1) industry growth forecast, the proportional quoted spread measure of growth and income funds drops 19% from the pre-event level.

On the other hand, in the analysis with the effective spread liquidity measure, I find a decrease in the measure not only in period when the expectation is formed, but also in the following period. The decrease in the effective spread measure is found in both of the analysis in the top liquidity quintile and the bottom liquidity quintile of the fund holdings.

Although similar trends are observed using the quoted spread measure, in comparison to the effective spread measure, the initial change of the liquidity using the quoted spread measure is higher in the top liquidity quintile and the bottom liquidity quintile of the fund holdings (see table 3.6 and table 3.7).

In conclusion, in anticipation of high fund outflows, fund managers increase the fund portfolio liquidity level by a large magnitude in the period when the expectation of extreme flow is formed. With little exceptions, the trend of decreasing spread measures is observed in the mutual funds, although, the evidence is weakest for the income funds. In the analysis with all the different spread measures, the liquidity measure of the top liquidity quintile not only drops for the event time but continues to drop for the period after.

The continuing decrease in the liquidity measure implies that the fund managers do not immediately shift the fund holdings back to the pre-event composition. The mutual funds maintain a high fund portfolio liquidity in preparation of any additional redemption.

3.3.2. Unexpected Extreme Mutual fund Outflows

Given the conditional flow-performance model, unexpected flow is computed by differencing the realized quarterly fund flow and the expected quarterly flow. I define an event of extreme unexpected outflow as the event when the realized fund flow of a mutual fund is at least 5% lower than anticipated[6]. Four different extreme outflow scenarios are studied. They are (1) an isolated event of unexpected outflow, (2) two continuous quarters of unexpected outflow, (3) three continuous quarters of unexpected outflow, and (4) four continuous quarters of unexpected outflow.

The mutual fund portfolio liquidity is analyzed for a two year window and the liquidity level is tracked for four quarters after the last flow event at time t. Restrictions are imposed that no other flow related event occurs during the 8 quarters event window. In the analysis on extreme unexpected outflows, I focus on the results that use the industry growth forecasted by the optimal ARMA model[7]. For liquidity measures, I focus on the Amihud illiquidity measure and the proportional effective spread measure, since they are the most economically interesting measures among the five measures computed. Amihud's illiquidity measure has been shown in the liquidity literature to be a good proxy of the

[6]Note that an event of extreme unexpected outflow does not necessarily imply 5% or more outflow occurred in the period. The results from the analysis do not change when I impose an additional requirement that the realized outflow is greater than 5%.

[7]As shown in the analysis for the extreme expected outflow, the results using the simple growth assumption and the fitted ARMA growth prediction are similar. Therefore, I report only the results using the industry growth forecasted by the optimal ARMA model.

price impact of trades. The proportional effective spread measure is selected among the four spread measures because the measure takes into account the trading price of the security and it is proportional to the value of the security.

3.3.2.1. Summary of Results. As shown in table 3.8 to table 3.13, when a mutual fund experiences an extremely high unexpected outflow, the initial reaction from the fund manager is to sell the liquid assets, decreasing the overall fund liquidity level by up to 15%. The impact of the unexpected outflow on the fund portfolio liquidity is stronger in terms of price impact, measured by Amihud's illiquidity measure, than the transaction cost, measured by the proportional effective spread measure. However, when a fund faces continuous high level of unexpected outflow for several quarters, the fund manager eventually starts rebalancing, selling the illiquid assets in the fund portfolio. This increases the overall fund portfolio liquidity in the latter periods, after the initial drop in the portfolio liquidity. A reversion of the fund liquidity level is observed by the third quarter of the series in extreme unexpected outflow events.

I investigate the dynamics of the fund portfolio liquidity for the overall fund, the top quintile of the fund holdings and the bottom quintile of the fund holdings, around an extreme unexpected flow event. In contrast to the extreme expected outflow analysis, the observed change in the fund portfolio liquidity is larger in the bottom quintile of the fund holdings compared to the top quintile of the fund holdings in the extreme unexpected outflow analysis. The liquidity measures reported in the following analysis are not normalized.

3.3.2.2. Results Using Amihud's Illiquidity Measure. There is strong evidence of a sudden increase in the average Amihud's illiquidity measure of the fund at the initial period with a high unexpected outflow as shown in table 3.8[8]. For example, an isolated event of unexpected outflow increases the Amihud illiquidity measure in aggressive growth funds by more than 15%. Although the changes in the fund portfolio liquidity for the other investment styles are not as dramatic as the change in aggressive growth funds, the pattern is observed across all fund styles at the first period of the event. The decrease in the fund portfolio liquidity is consistent with the conjecture that fund managers liquidate more liquid assets when surprised by unexpected outflows, in order to reduce trading cost and possible price impact on the trades.

An interesting movement in the mutual fund portfolio liquidity is observed when funds experience multiple quarters of extreme unexpected outflows. In this scenario, the fund portfolio liquidity measure rises dramatically initially, similar to the movement of the fund portfolio liquidity when a fund faces an isolated event of high unexpected outflow. However, the Amihud illiquidity measure does not continue to increase after the first period of high unexpected outflow event. Contrary to the isolated flow event scenario, the illiquidity of the fund remains high for only one additional quarter, then the fund portfolio liquidity reverts toward the pre-event level. The increased liquidity measure reverses after two quarters even if the fund continues to face a high level of unexpected outflow. This suggests that fund managers initially sell off liquid assets when surprised by a lower than expected amount of capital for investment. However, when the capital continues to be lower than anticipated, the managers rebalance the overall portfolio holdings and sell the illiquid component of the fund. The reversion reflects the trade off between keeping the optimal portfolio for investment and minimizing liquidation cost.

[8]Cells in the tables are shaded if the change in the liquidity measure is more than 5%, relative to the average fund portfolio liquidity level of the past four quarters before the first extreme outflow event.

So how does the trading described above affect the distribution of the liquidity in the fund holdings? Similar to the extreme expected flow analysis, I sort the fund holdings by the liquidity level and study the dynamics of the liquidity level in the top liquidity quintile and the bottom liquidity quintile. Interestingly, there is only weak evidence of a sudden increase in the average illiquidity measure in the top quintile of the fund holdings. Although the overall fund average illiquidity measure increases, the liquidity of the most liquid assets in the portfolio do not change significantly. Contrary to the movement of the fund portfolio liquidity in the top liquidity quintile of the fund holdings, the average liquidity measure of the bottom quintile of the fund holdings rises dramatically in the first quarter of the extreme unexpected outflow event. The sudden increase in the Amihud illiquidity measure at the initial event time is accompanied by the reversion of the liquidity measure after 2 quarters. The pattern of the movement in the liquidity measure is similar between the liquidity of the overall fund and the liquidity of the least liquid assets in the fund. The impact of the high unexpected outflow is much stronger on the overall fund portfolio and the bottom quintile of the fund holdings than the top quintile of the fund holdings.

3.3.2.3. Results Using Spread Measures. In order to avoid capturing any changes in the trading cost due to the lowering of tick size, the spread measures are not used from the second quarter of 1996 to the second quarter of 1998 and from the first quarter of 2001 to the second quarter of 2002[9].

Using the analysis with the proportional effective spread measure, there are some evidences of a sudden decrease in the spread measure at the initial event time. The change

[9]Please see the discussion in subsection 3.3.1.3 for details

in the proportional effective spread measure is the strongest for aggressive growth funds and income funds (See table 3.11). Similar to the findings with the Amihud illiquidity measure, the pattern of change in the proportional effective spread measure is the strongest in the bottom quintile of the fund holdings, as shown in table 3.13. However, one should note that the magnitude of the change is smaller in the analysis using the proportional effective spread measure compared to the analysis using the Amihud illiquidity measure. This may be due to the smaller sample size used in the analysis with spread measures.

In conclusion, the results suggest that fund managers do take into account fund portfolio liquidity in the allocation of assets. In order to reduce the transaction cost and the price impact of the trade, liquid assets are first liquidated when funds experience lower than expected fund flow. However, the managers do rebalance the overall portfolio holding and reduce the overall weight in highly illiquid assets when the funds continue to experience lower than expected fund flow. Similar patterns are observed in the analyses using the other spread measures, however, the impact of the high unexpected outflow is the strongest in the analysis using the Amihud illiquidity measure, which proxies for price impact.

3.4. Conclusion

In this paper, I propose to use a semiparametric model to predict fund flows for economic analysis. By comparing the semiparametric model with the commonly used linear specification, the updated Chevalier and Ellison (1997) model forms better predictions of the following quarter fund flows. I decompose realized fund flows into two components, anticipated flow and unanticipated flow, for the identification of extreme fund flow events.

I then examine the abnormal changes in the fund portfolio liquidity level around events of high expected outflow and high unexpected outflow. I show that liquidity is an important choice variable that fund managers control. When fund managers expect a high level of outflow in the following period, they increase the fund portfolio liquidity in preparation of the potentially large capital withdrawal and thus hedge liquidity risk. Furthermore, when the fund experiences an extreme unexpected outflow, the fund manager restrains from selling the illiquid assets initially, by selling the more liquid securities. This behavior reflects the desire to avoid the high trading cost and potential high price impact on trades of illiquid assets. However, the managers are forced to liquidate the illiquid assets after continuous periods of unexpected high outflows.

In this chapter, I attempt to establish the importance of liquidity in the optimization problem of the mutual fund managers. My findings support the view that fund managers actively control the level of liquidity in portfolio allocation. Since illiquid assets are compensated by a higher level of expected return as shown in Amihud and Mendelson (1986), the changing fund portfolio liquidity under the extreme flows is likely to affect the mutual fund performance. Therefore, a complete analysis on fund performance should incorporate the mutual fund flows and the fund portfolio liquidity.

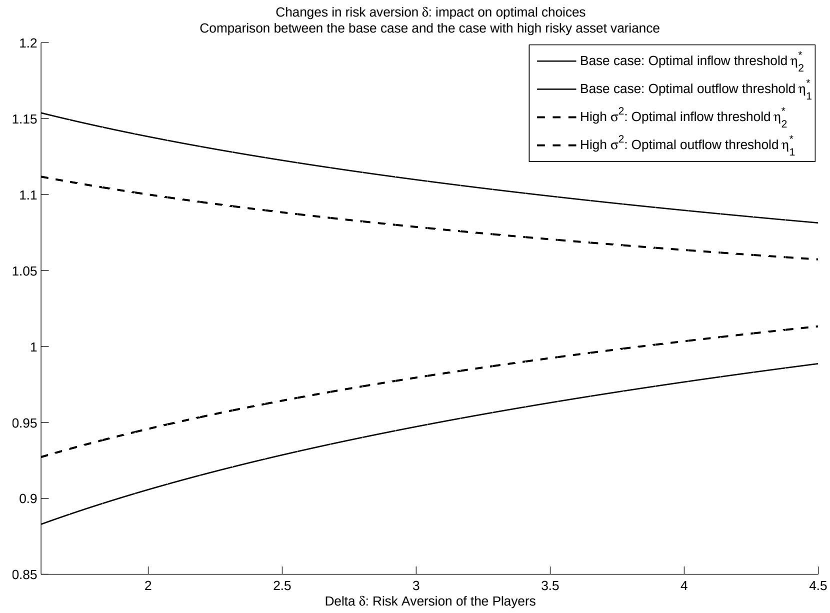


Figure 1.12: Investor optimal threats η_1^* and η_2^* in the high risky asset variance case, contrasted to the base case.

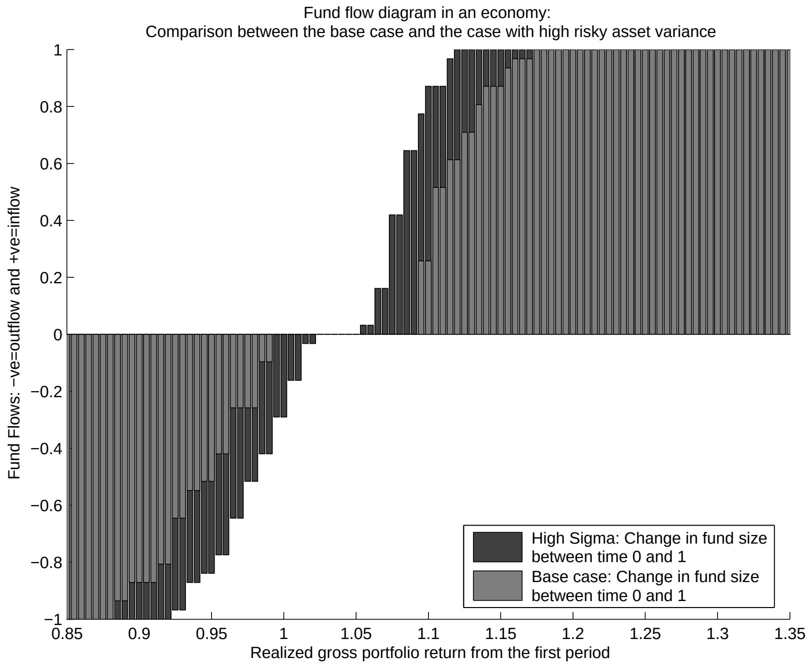


Figure 1.13: The predicted fund flows in an economy with high variance in the risky asset, contrasted to the base case.

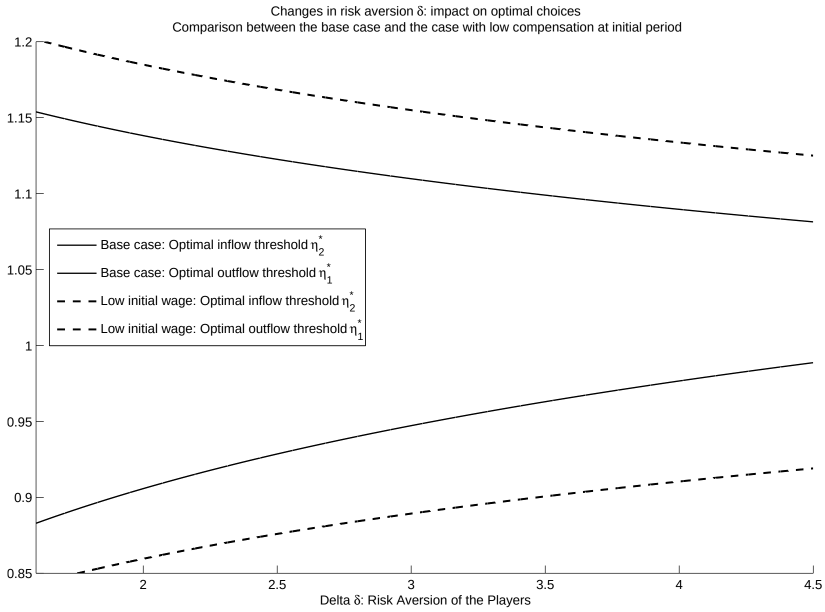


Figure 1.14: Investor optimal threats η_1^* and η_2^* in the case with different compensations in time 0 and time 1, contrasted to the base case. In the initial period, the investor has half the income as in the base case. In the next period, the income of the investor is the same in both cases.

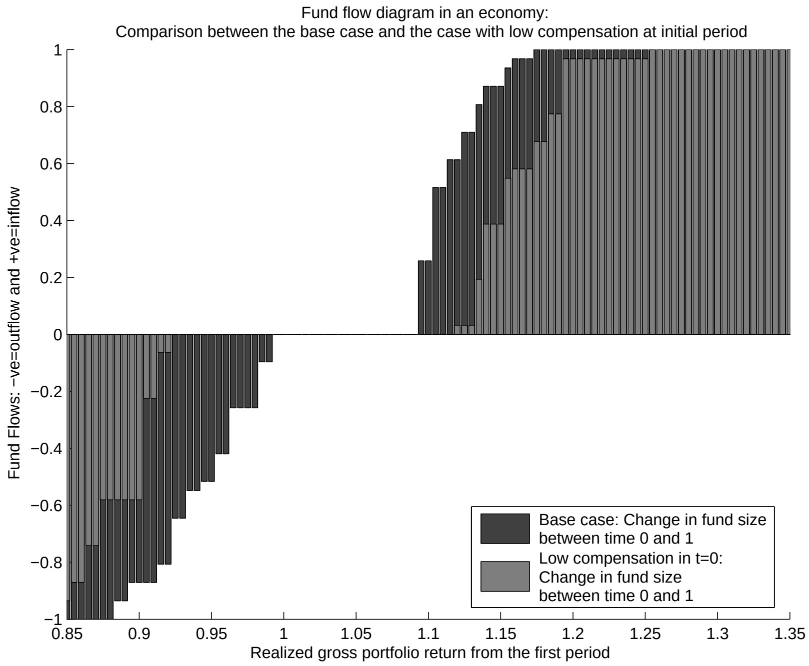


Figure 1.15: The predicted fund flows in an economy with different compensations in time 0 and time 1, contrasted to the base case.

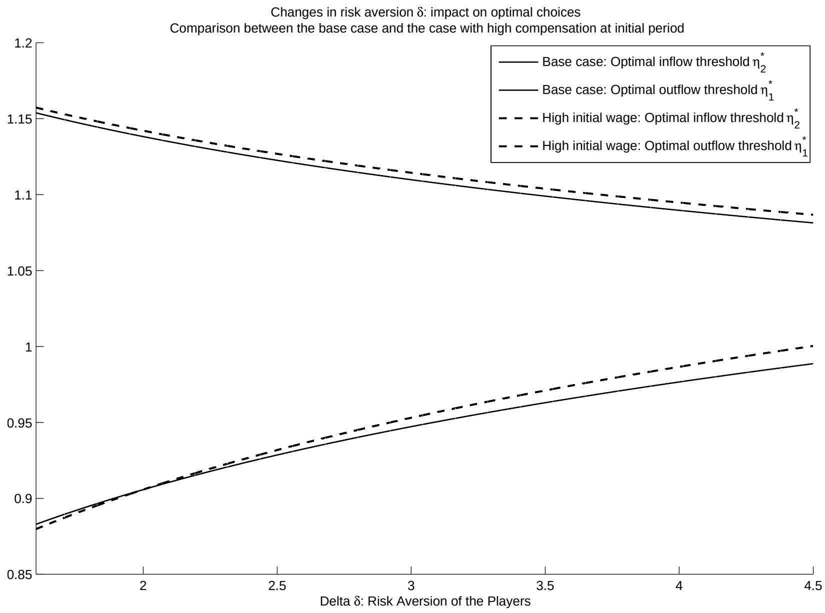


Figure 1.16: Investor optimal threats η_1^* and η_2^* in the case with different compensations in time 0 and time 1, contrasted to the base case. In the initial period, the investor has the same income as in the base case. In the next period, the income of the investor is halved compared to the base case.

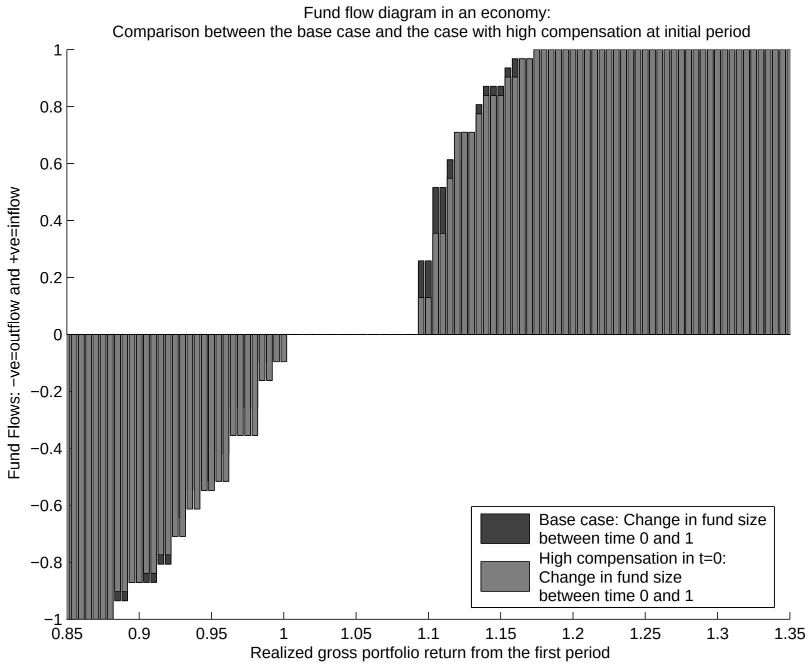


Figure 1.17: The predicted fund flows in an economy with different compensations in time 0 and time 1, contrasted to the base case.

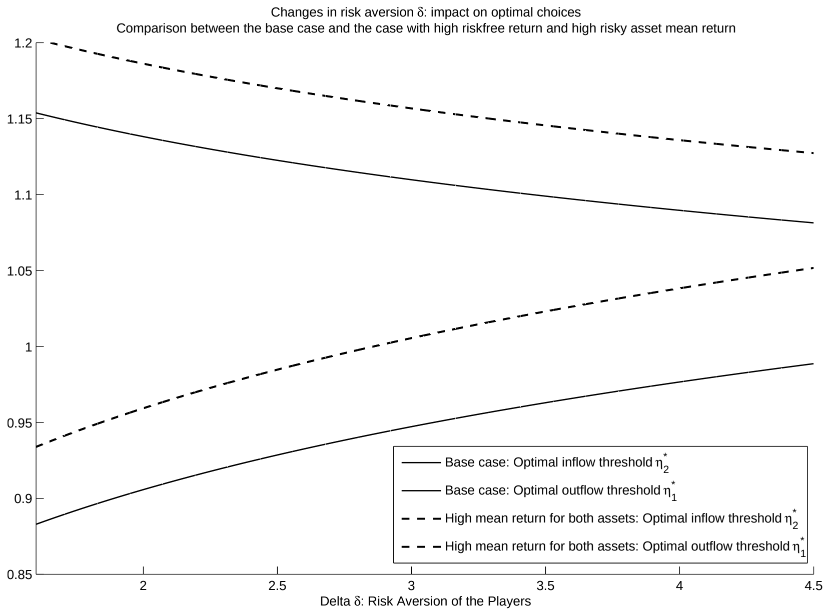


Figure 1.18: Investor optimal threats η_1^* and η_2^* in the case with high return in the riskfree asset and high risky asset mean return, contrast to the base case.

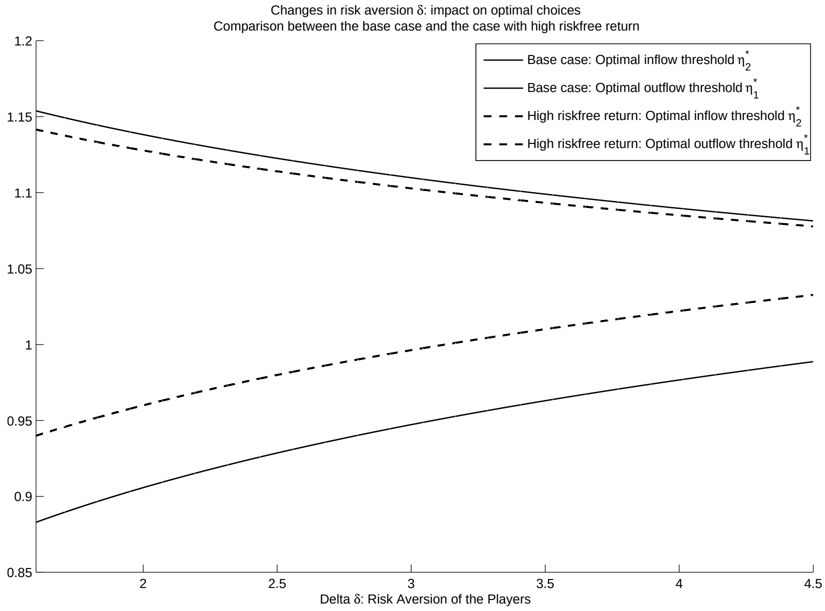


Figure 1.19: Investor optimal threats η_1^* and η_2^* in the case with high return in the riskfree asset, contrasted to the base case.

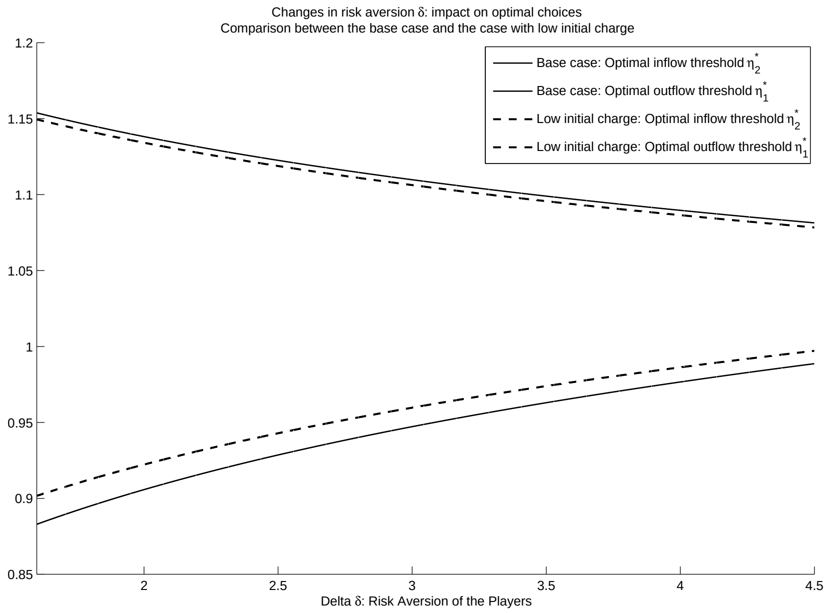


Figure 1.20: Investor optimal threats η_1^* and η_2^* in the case with low initial sales charge, contrasted to the base case. The region above the series of η_2^* is the region of fund inflow. The region below the series of η_1^* is the region of fund outflow. The remaining region is the no-flow region.

Figure 2.1: **The estimated nonparametric function $f(.)$ in the flow-performance model using the market benchmark model**: For young, mid-age and old mutual funds in the period from 1980 to 2005 respectively. A 5% bootstrap confidence interval for the kernel smoothers is also reported in the figure.

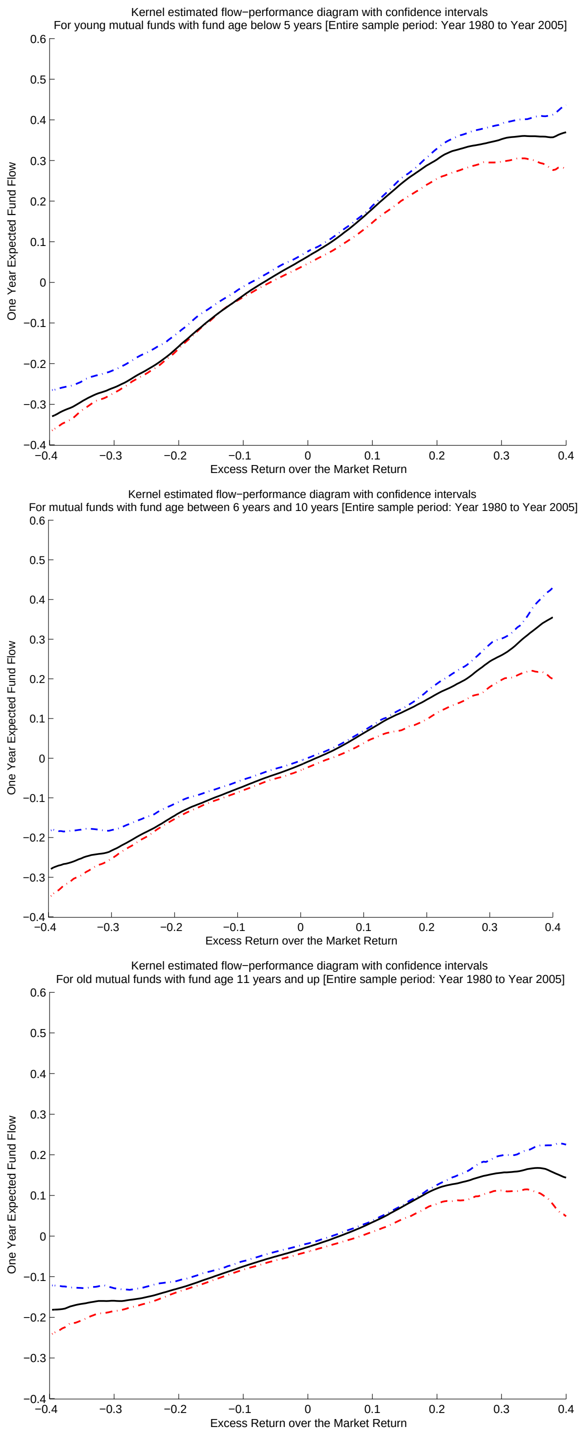


Figure 2.2: **The estimated nonparametric function $f(.)$ in the flow-performance model using the market benchmark model**: For young, mid-age and old mutual funds in the period from 1980 to 1995 respectively. A 5% bootstrap confidence interval for the kernel smoothers is also reported in the figure.

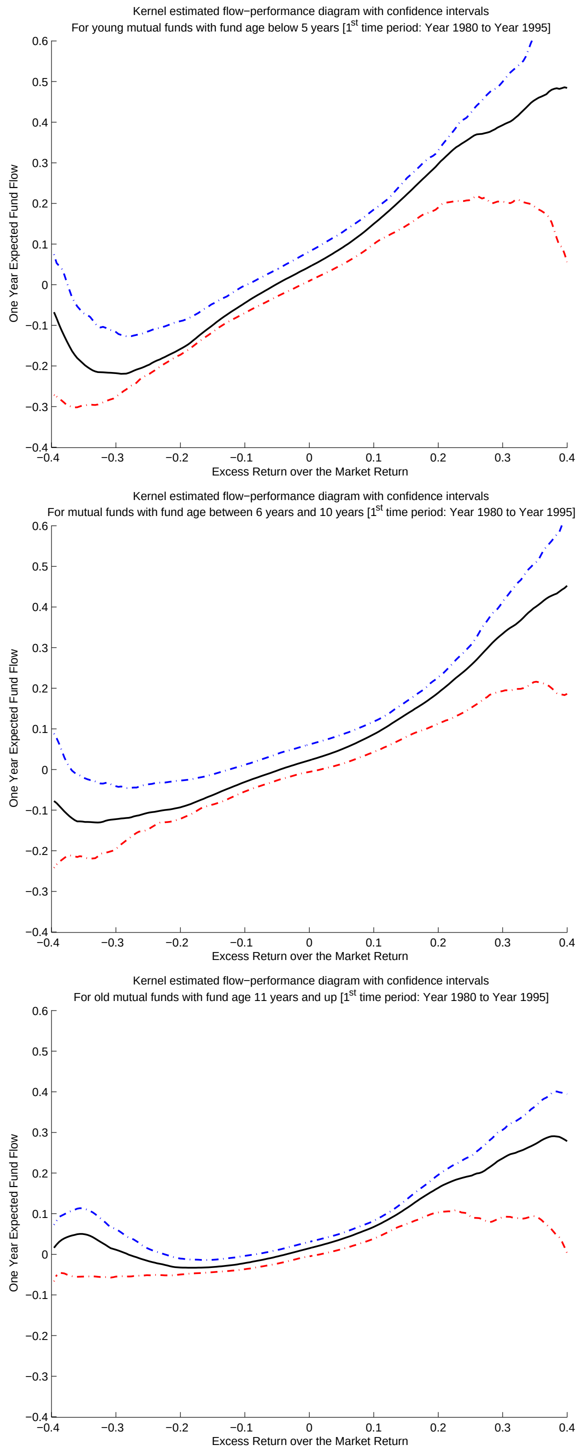


Figure 2.3: **The estimated nonparametric function $f(.)$ in the flow-performance model using the market benchmark model**: For young, mid-age and old mutual funds in the period from 1995 to 2005 respectively. A 5% bootstrap confidence interval for the kernel smoothers is also reported in the figure.

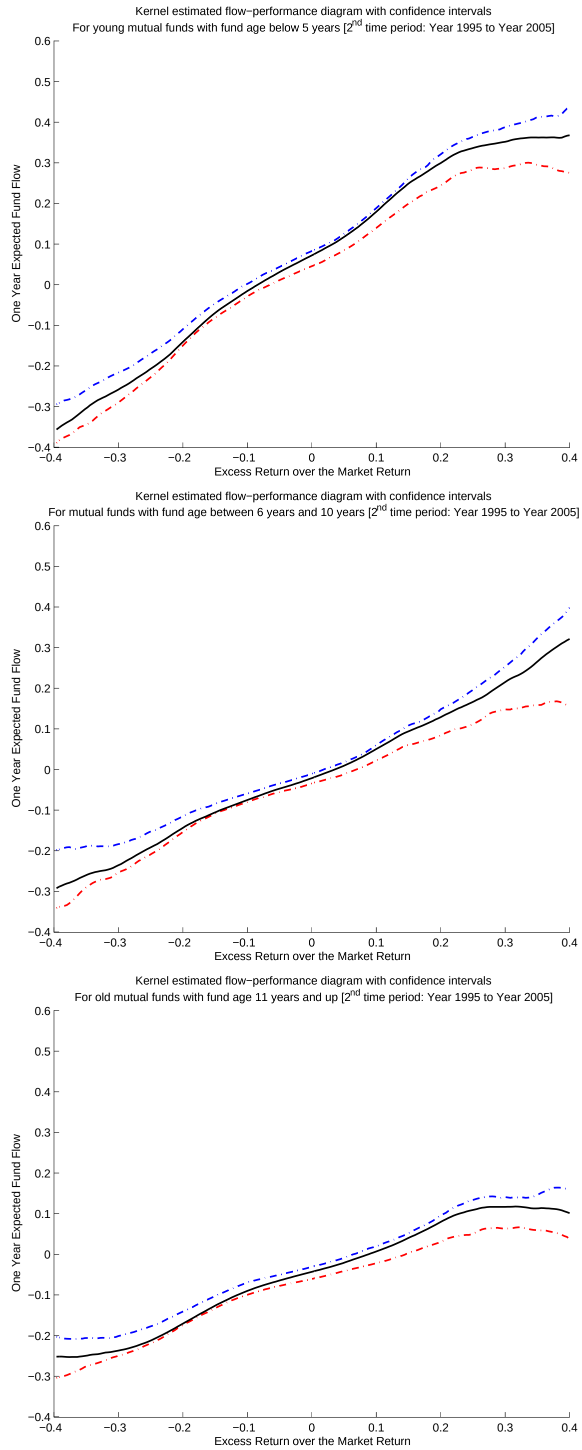


Figure 2.4: **The estimated nonparametric function $f(.)$ in the flow-performance model using the market benchmark model**: For young, mid-age and old mutual funds with zero average front load fees and high average rear load fees respectively. A 5% bootstrap confidence interval for the kernel smoothers is also reported in the figure.

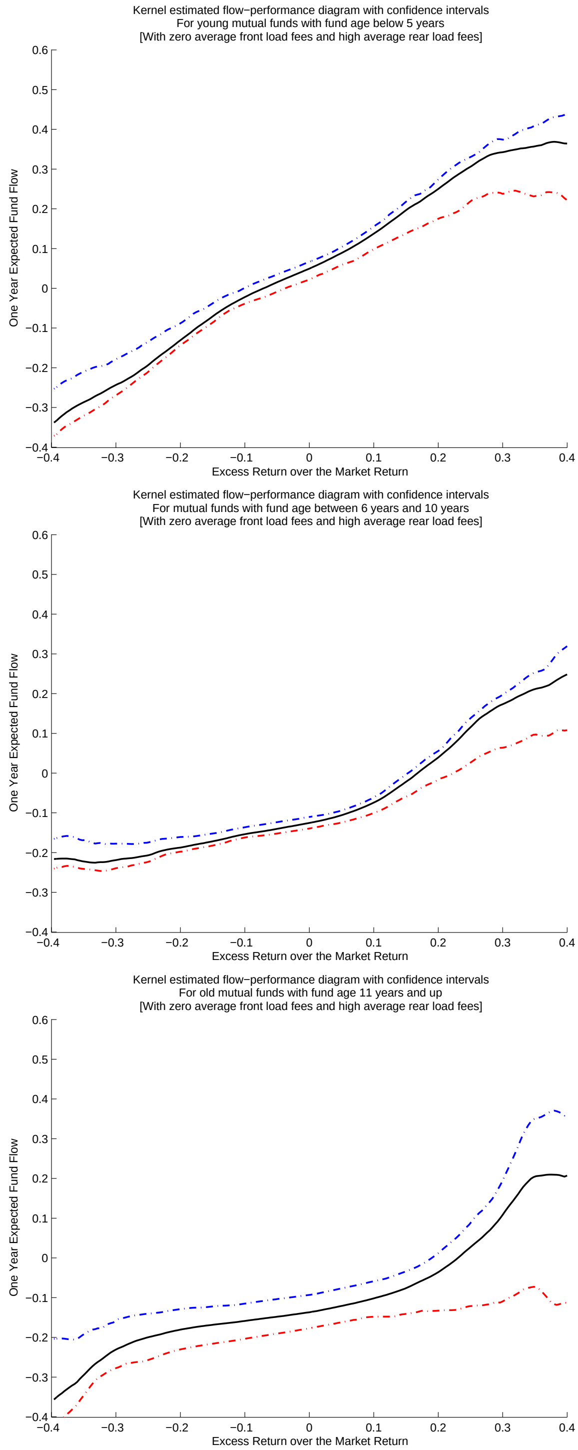


Figure 2.5: **The estimated nonparametric function $f(.)$ in the flow-performance model using the market benchmark model**: For young, mid-age and old mutual funds with zero average front load fees and low average rear load fees respectively. A 5% bootstrap confidence interval for the kernel smoothers is also reported in the figure.

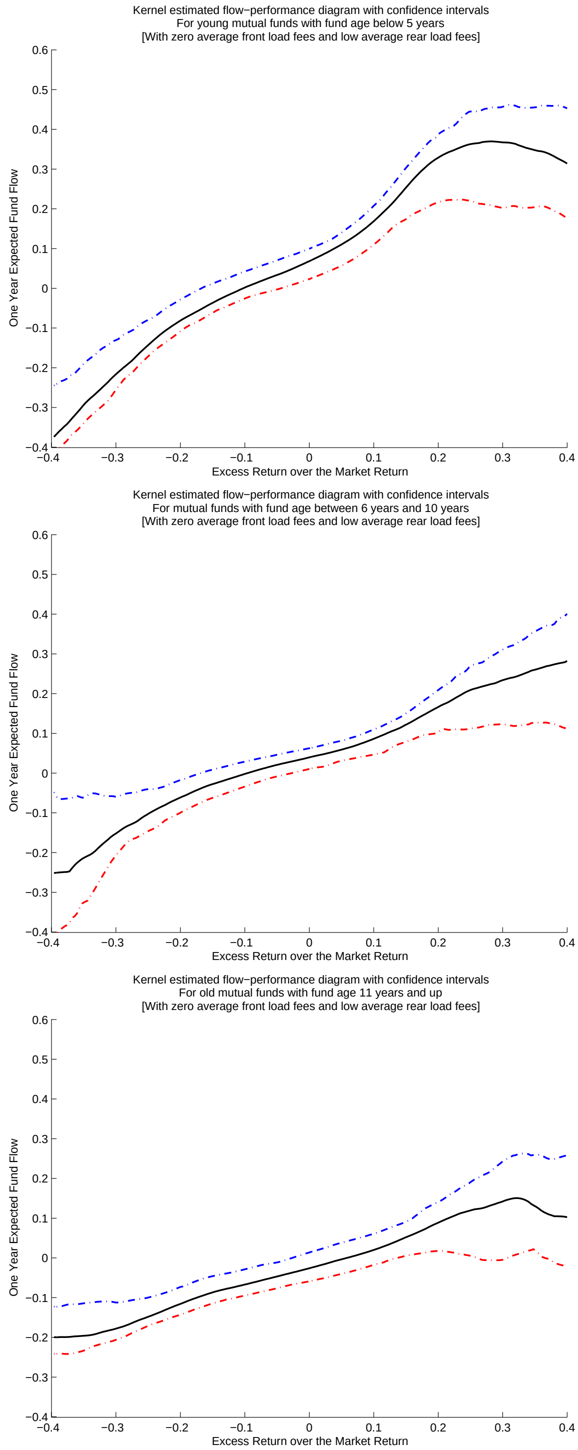


Figure 2.6: **The estimated nonparametric function $f(.)$ in the flow-performance model using the market benchmark model**: For young, mid-age and old mutual funds with zero average rear load fees and high average front load fees respectively. A 5% bootstrap confidence interval for the kernel smoothers is also reported in the figure.

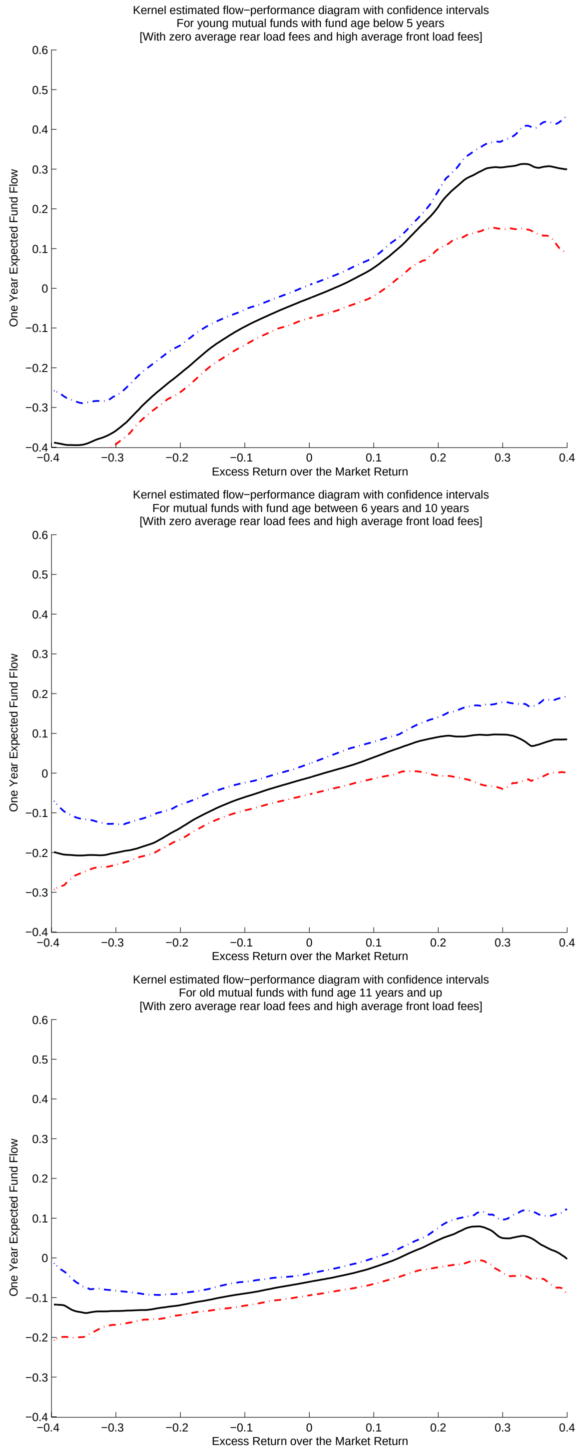


Figure 2.7: **The estimated nonparametric function $f(.)$ in the flow-performance model using the market benchmark model**: For young, mid-age and old mutual funds with zero average rear load fees and low average front load fees respectively. A 5% bootstrap confidence interval for the kernel smoothers is also reported in the figure.

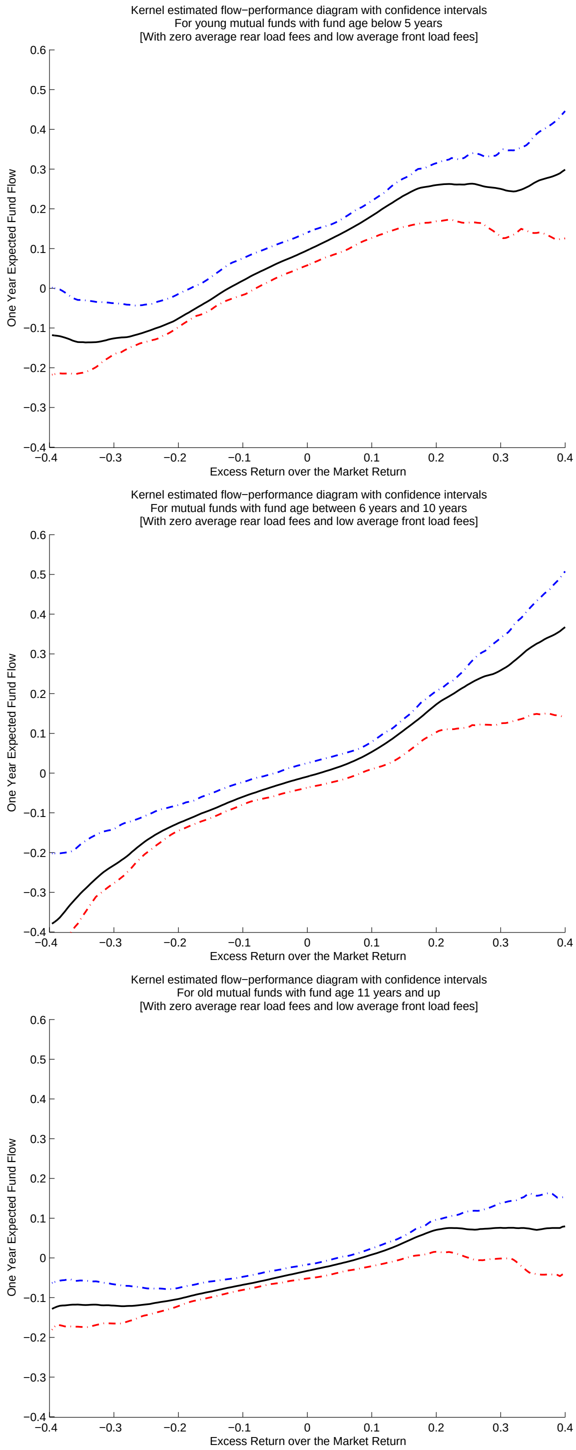


Figure 2.8: **The estimated nonparametric function $f(.)$ in the flow-performance model using the market benchmark model**: For young, mid-age and old mutual funds with non-zero average front and rear load fees respectively. A 5% bootstrap confidence interval for the kernel smoothers is also reported in the figure.

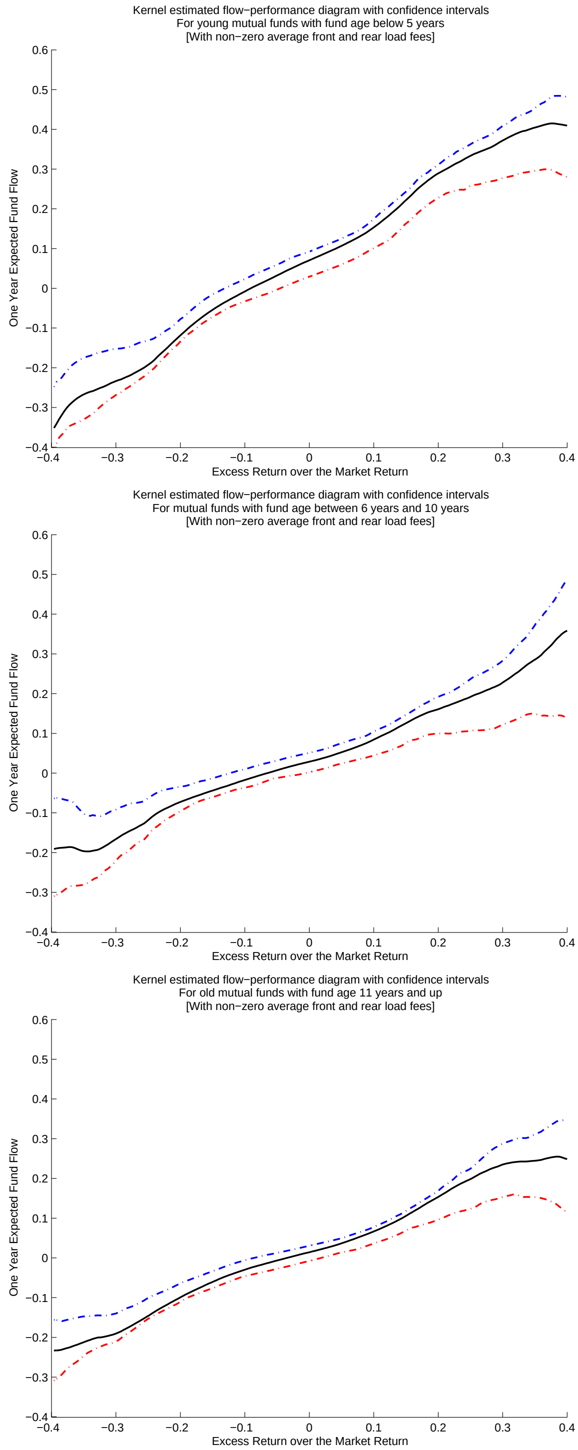


Figure 2.9: **The estimated nonparametric function $f(.)$ in the flow-performance model using the market benchmark model**: For young, mid-age and old aggressive growth mutual funds respectively. A 5% bootstrap confidence interval for the kernel smoothers is also reported in the figure.

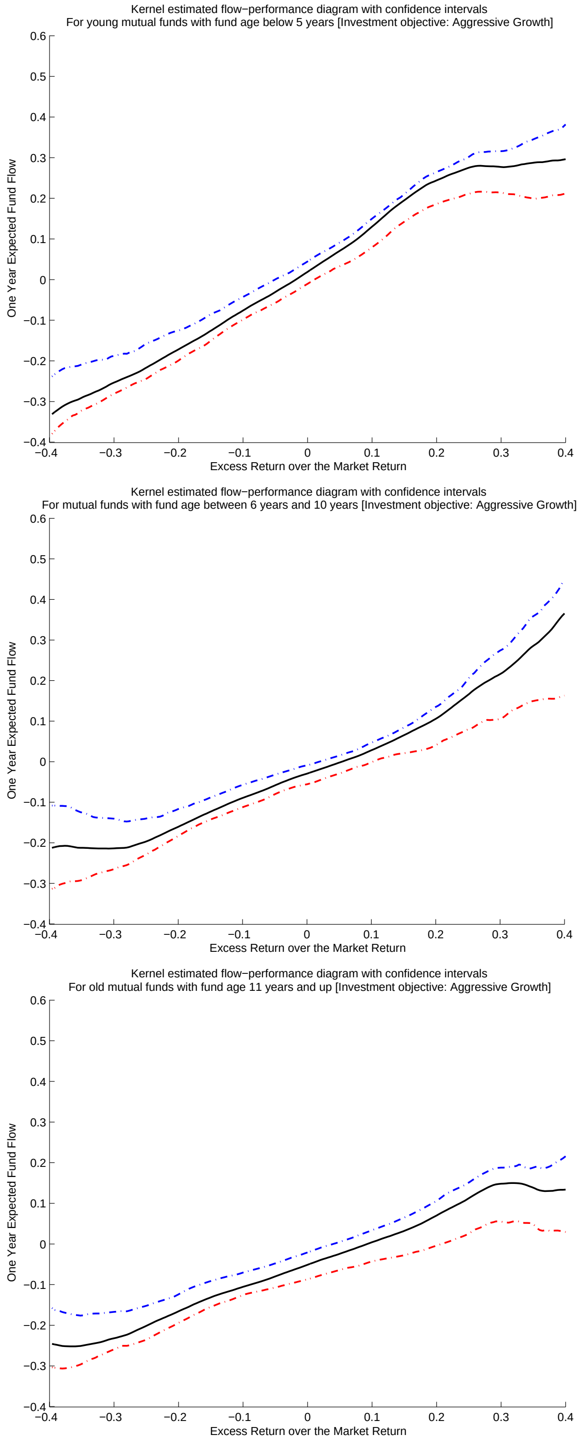


Figure 2.10: **The estimated nonparametric function $f(.)$ in the flow-performance model using the market benchmark model**: For young, mid-age and old growth mutual funds respectively. A 5% bootstrap confidence interval for the kernel smoothers is also reported in the figure.

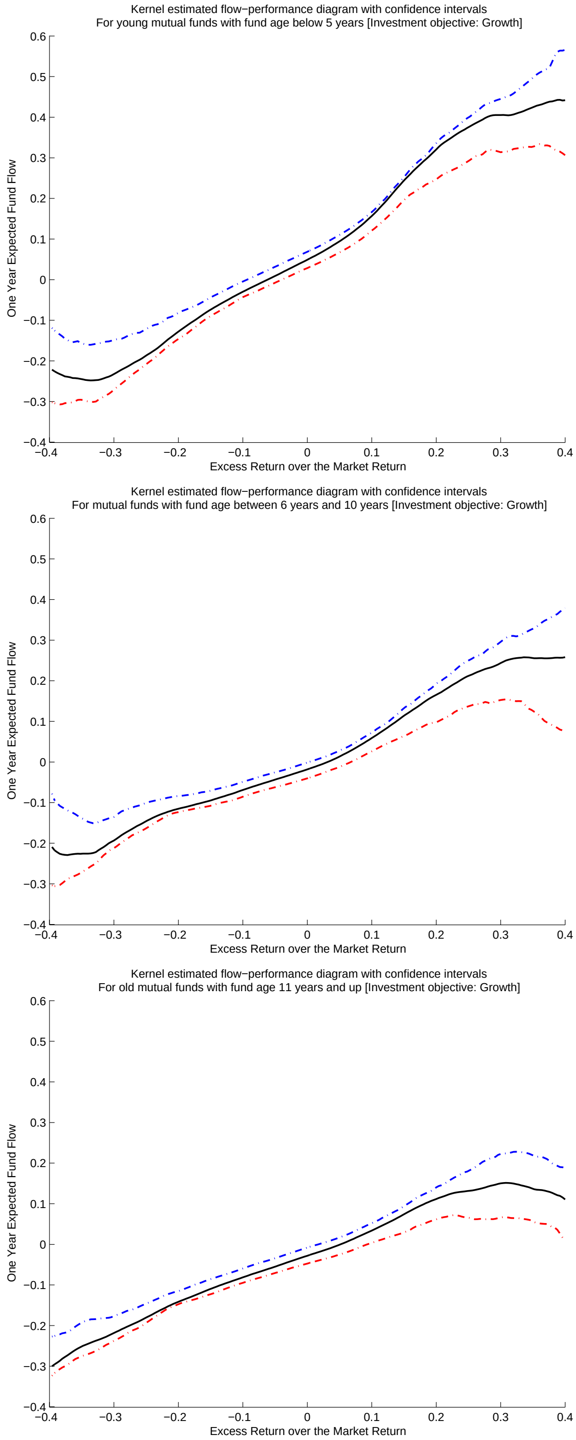


Figure 2.11: **The estimated nonparametric function $f(.)$ in the flow-performance model using the market benchmark model**: For young, mid-age and old income mutual funds respectively. A 5% bootstrap confidence interval for the kernel smoothers is also reported in the figure.

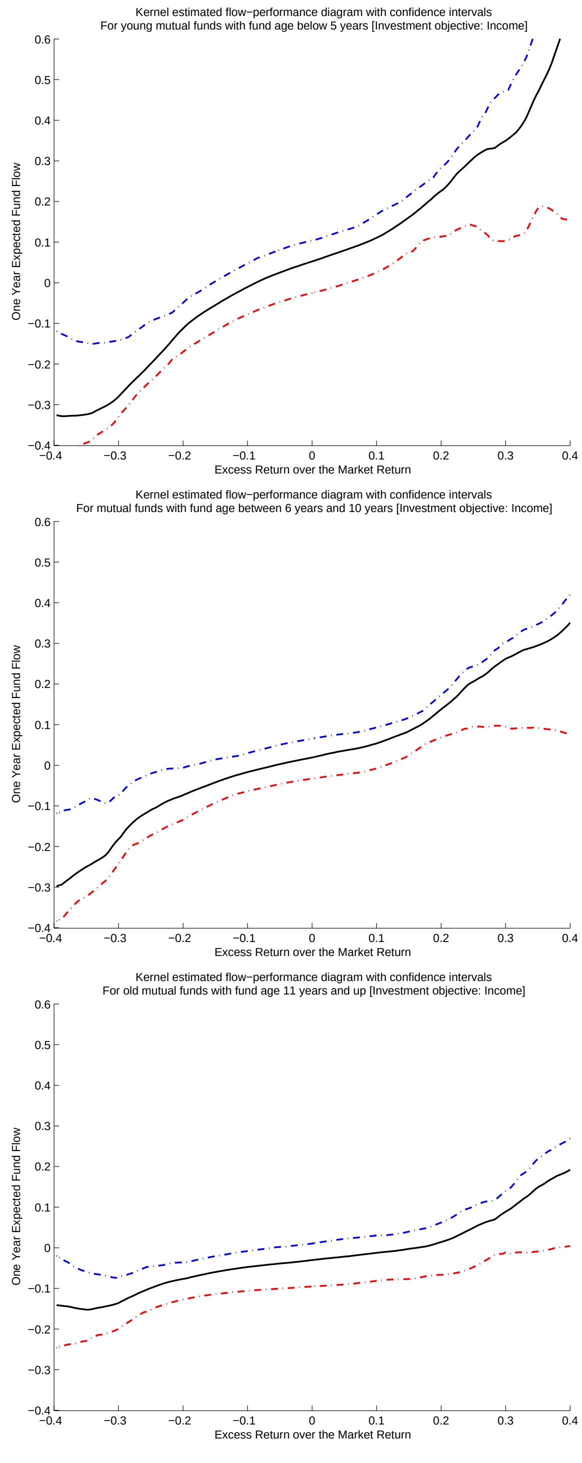


Figure 2.12: **The estimated nonparametric function $f(.)$ in the flow-performance model using the market benchmark model**: For young, mid-age and old growth and income mutual funds respectively. A 5% bootstrap confidence interval for the kernel smoothers is also reported in the figure.

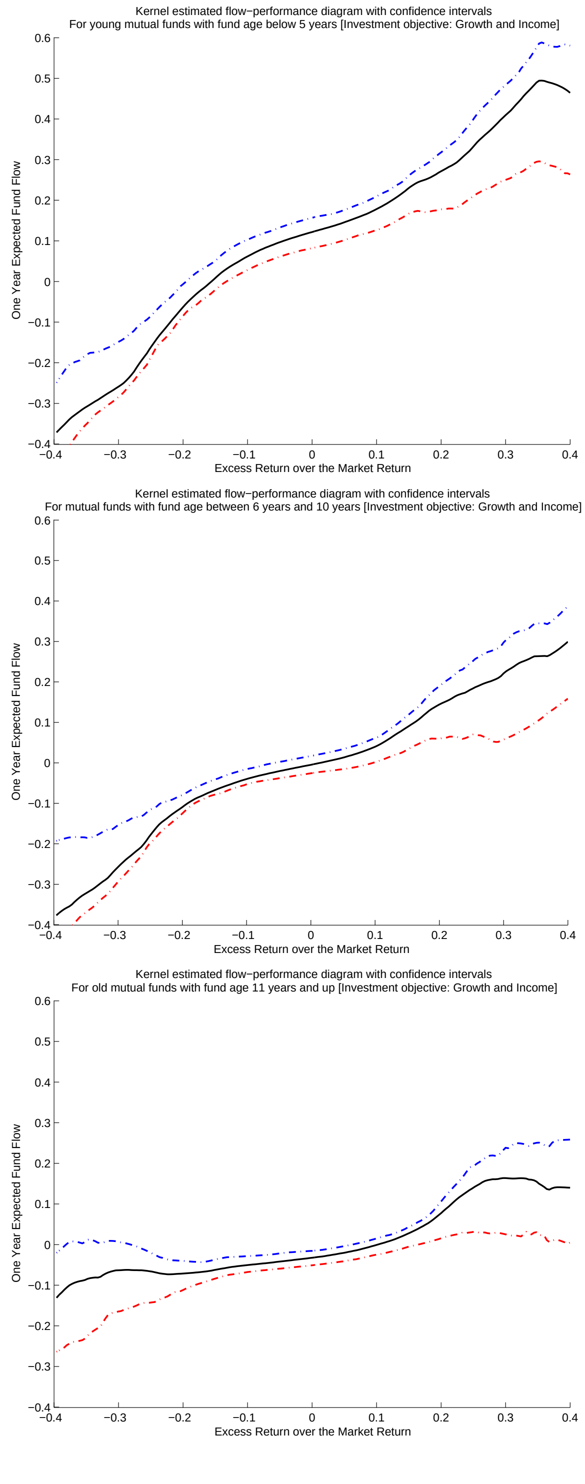


Figure 2.13: **The estimated nonparametric function $f(.)$ in the flow-performance model using the style specific benchmark model**: For young, mid-age and old mutual funds in the period from 1980 to 2005 respectively. The top figure is the flow-performance diagram using the style specific benchmark. The bottom figure is the flow-performance diagram using the market benchmark.

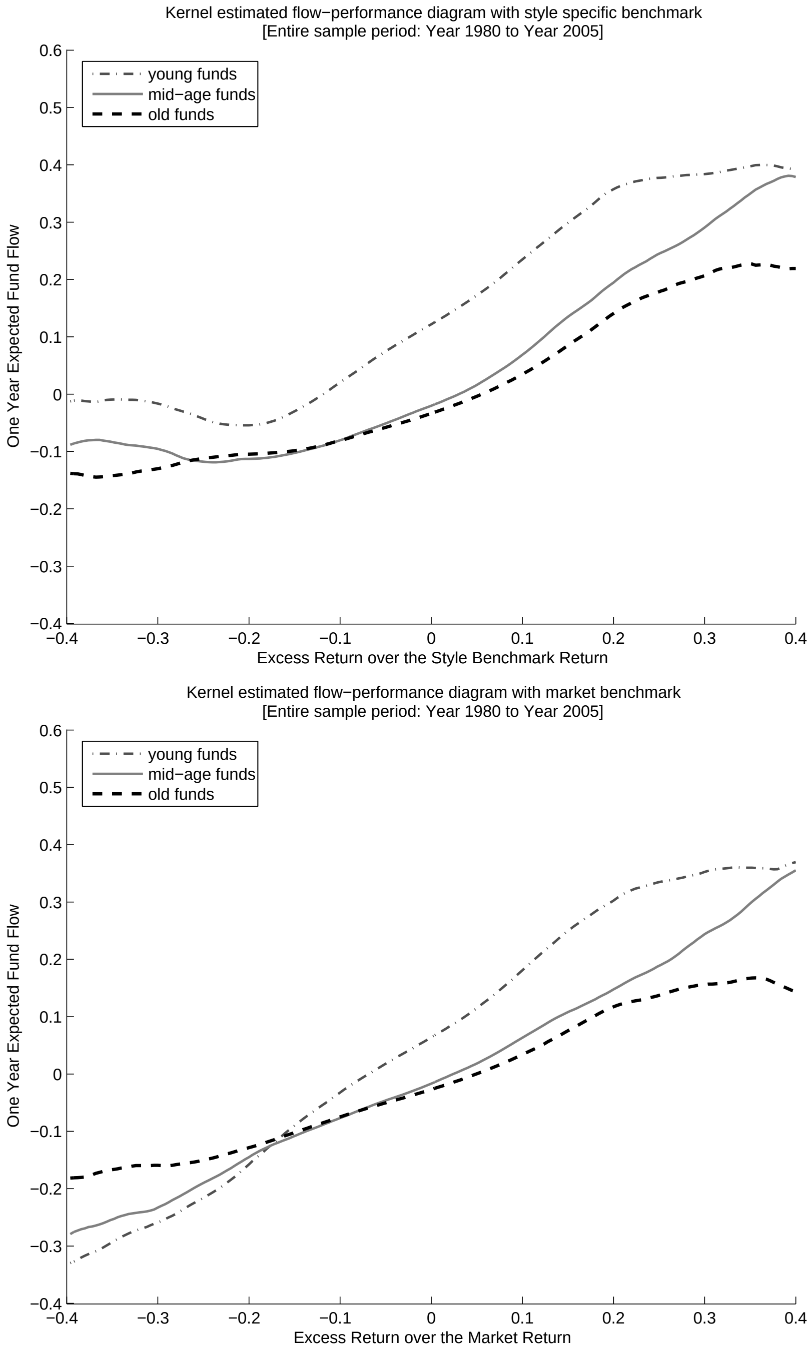


Figure 2.14: **The estimated nonparametric function $f(.)$ in the flow-performance model using the style specific benchmark model**: For young, mid-age and old mutual funds in the period from 1980 to 1995 respectively. The top figure is the flow-performance diagram using the style specific benchmark. The bottom figure is the flow-performance diagram using the market benchmark.

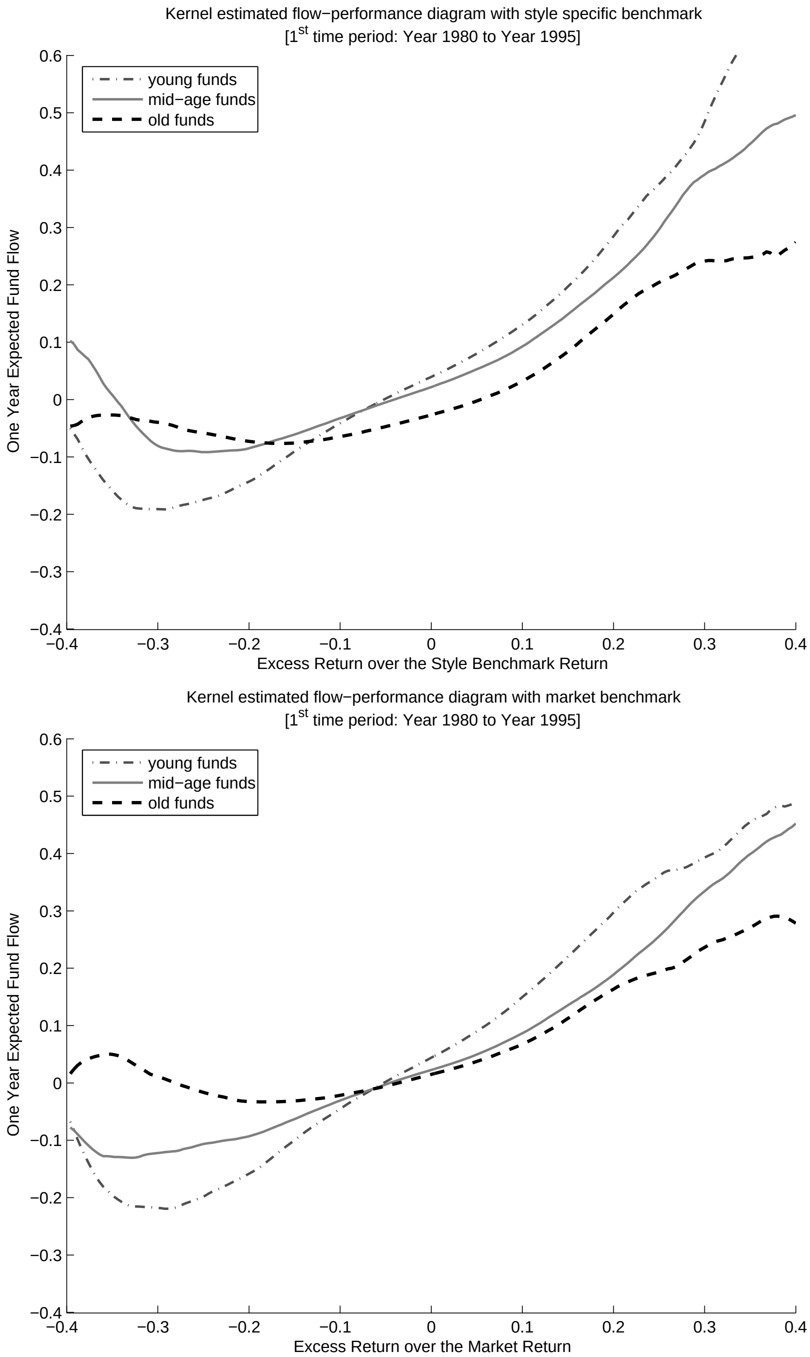


Figure 2.15: **The estimated nonparametric function $f(.)$ in the flow-performance model using the style specific benchmark model**: For young, mid-age and old mutual funds in the period from 1995 to 2005 respectively. The top figure is the flow-performance diagram using the style specific benchmark. The bottom figure is the flow-performance diagram using the market benchmark.

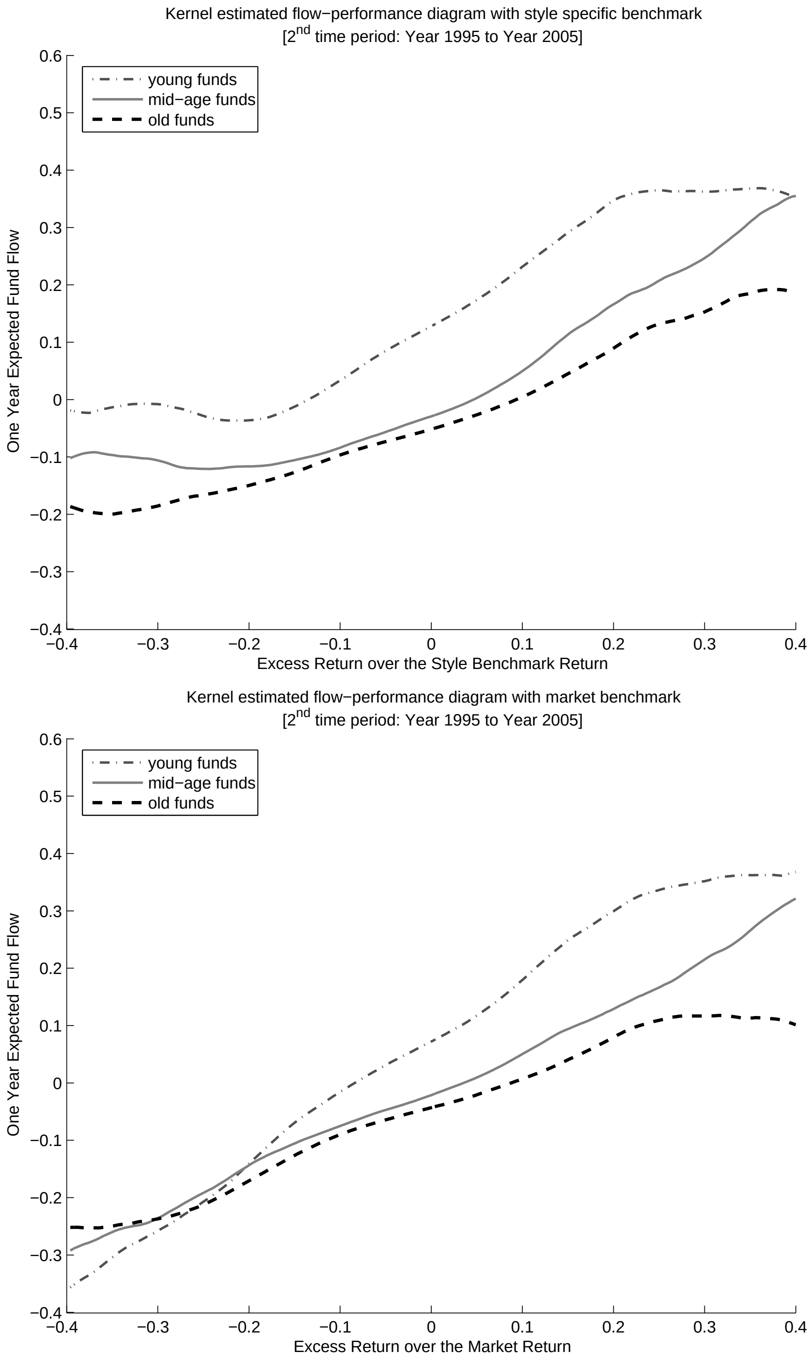


Figure 2.16: **The estimated nonparametric function $f(.)$ in the flow-performance model using the style specific benchmark model**: For young, mid-age and old aggressive growth mutual funds respectively. The top figure is the flow-performance diagram using the style specific benchmark. The bottom figure is the flow-performance diagram using the market benchmark.

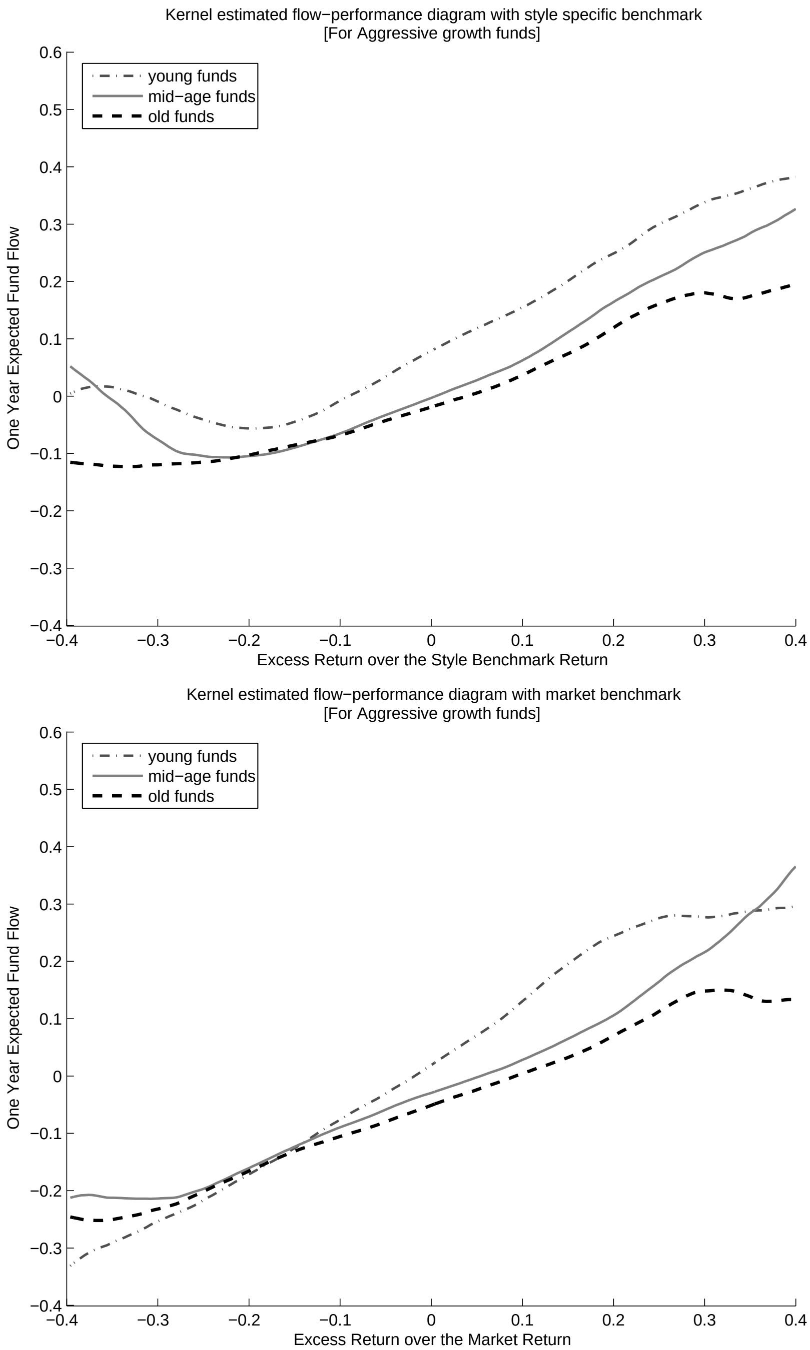


Figure 2.17: **The estimated nonparametric function $f(.)$ in the flow-performance model using the style specific benchmark model**: For young, mid-age and old growth mutual funds respectively. The top figure is the flow-performance diagram using the style specific benchmark. The bottom figure is the flow-performance diagram using the market benchmark.

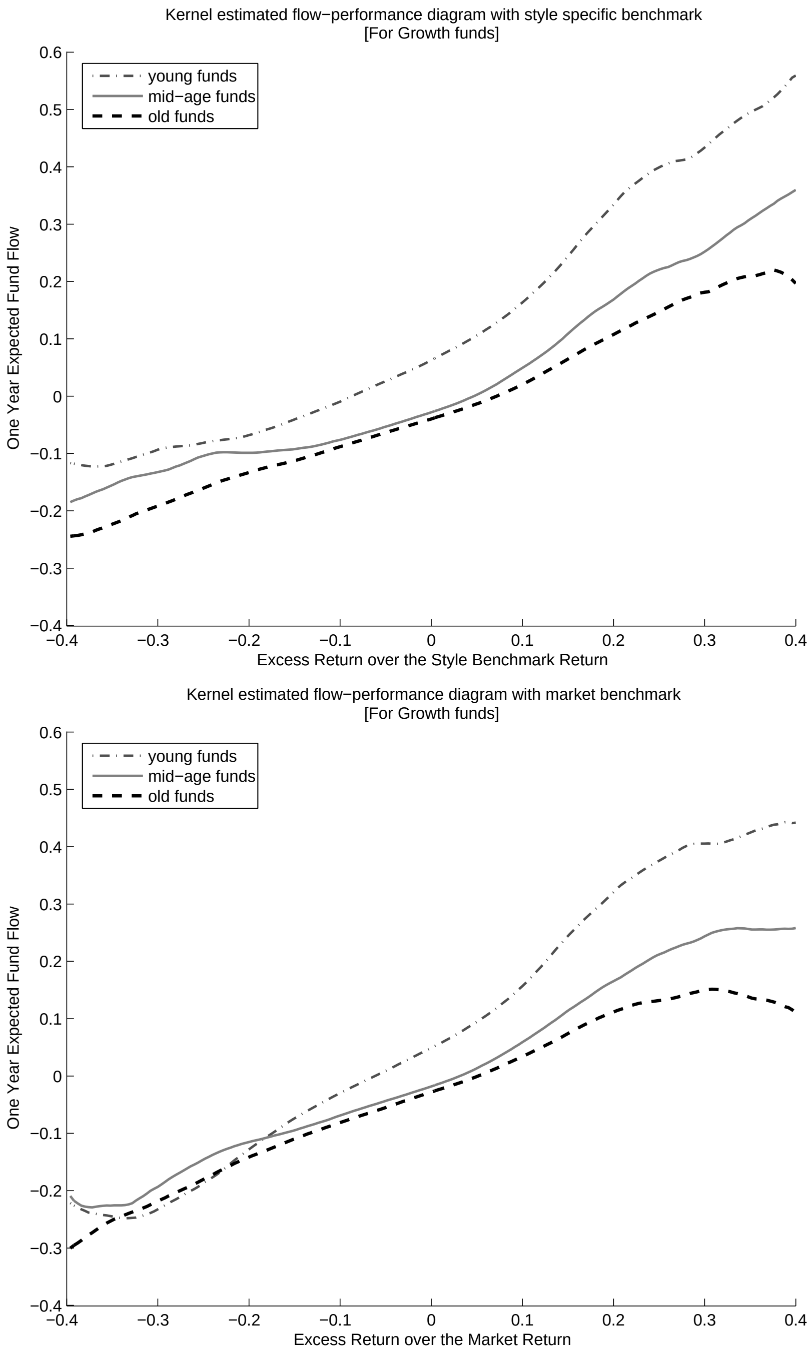


Figure 2.18: **The estimated nonparametric function $f(.)$ in the flow-performance model using the style specific benchmark model**: For young, mid-age and old income mutual funds respectively. The top figure is the flow-performance diagram using the style specific benchmark. The bottom figure is the flow-performance diagram using the market benchmark.

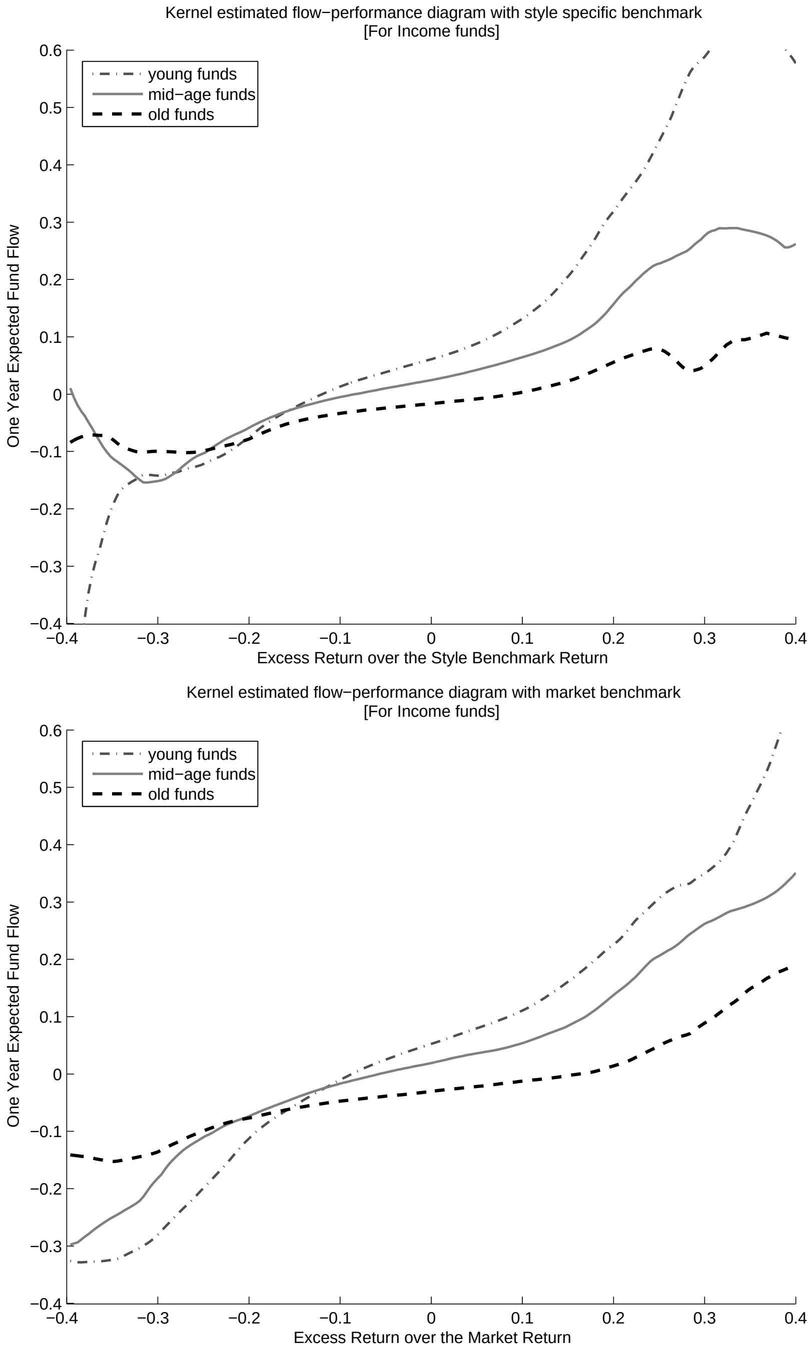


Figure 2.19: **The estimated nonparametric function $f(.)$ in the flow-performance model using the style specific benchmark model**: For young, mid-age and old growth and income mutual funds respectively. The top figure is the flow-performance diagram using the style specific benchmark. The bottom figure is the flow-performance diagram using the market benchmark.

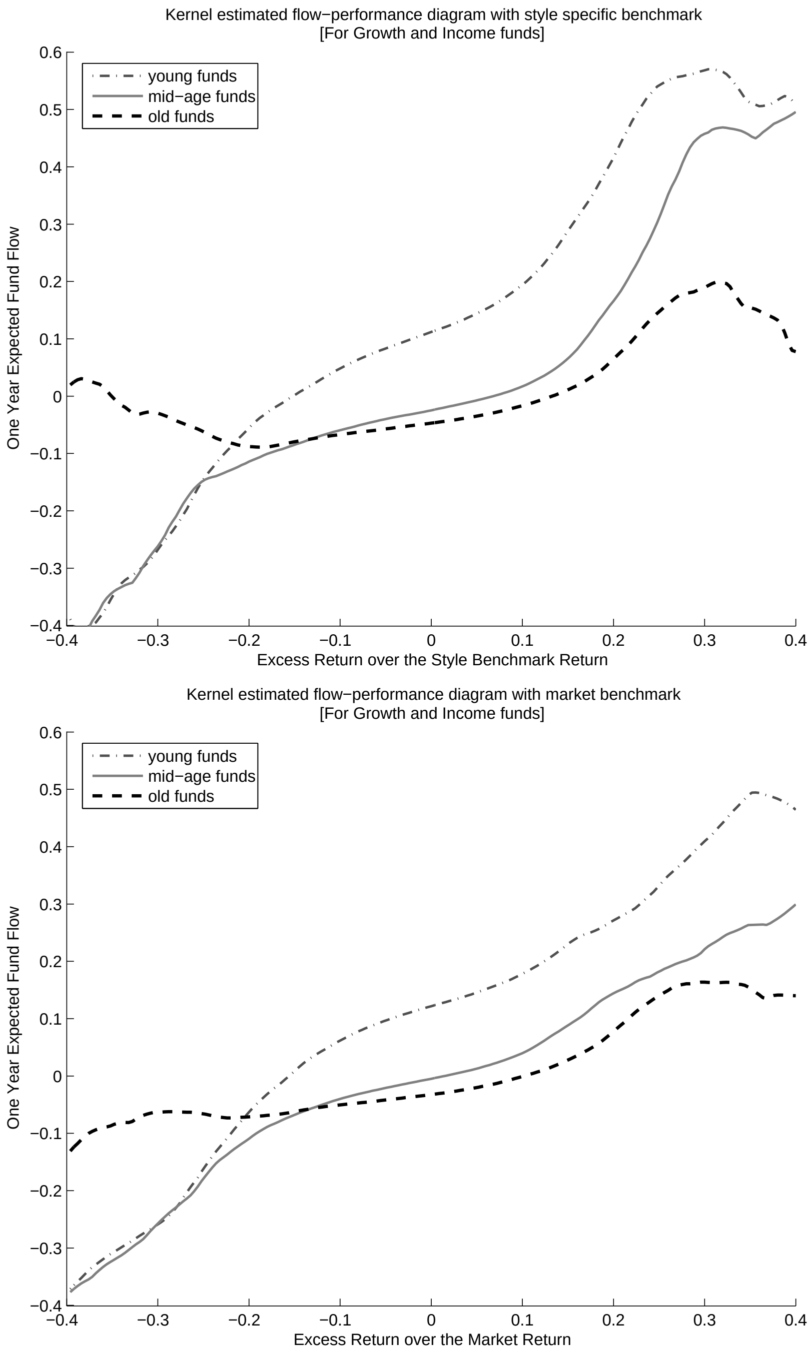


Table 2.4: **Kernel estimates for the full sample of mutual funds using the market return as a benchmark, for the period 1980 to 2005.** The model is $Flow_{it+1} = f(\tilde{r}_{it}) + \alpha_1(\tilde{r}_{it-1}) + \alpha_2(\tilde{r}_{it-2}) + \alpha_3(\tilde{r}_{it+1}) + \alpha_4 IndustryGrowth_{t+1} + \alpha_5 \log\left(\widetilde{Assets}_{it}\right) + \epsilon_{it+1}$, where $\tilde{r}_{it}$ is the difference between the fund return in year t and the value weighted market return in year t. (t-statistics are reported in parentheses)

	Young: Age 2-5	**Mid: Age 6-10**	**Old: Age 11 and up**
Excess return$_{t-1}$	0.3434	0.3478	0.2548
	(9.0512)	(9.7960)	(8.6925)
Excess return$_{t-2}$	0.0530	0.2915	0.2836
	(1.3986)	(8.7525)	(9.0539)
Excess return$_{t+1}$	0.5898	0.6001	0.2440
	(10.9258)	(9.6312)	(6.0162)
Industry Growth$_{t+1}$	0.5472	0.2677	0.1115
	(11.5767)	(8.0657)	(5.1058)
Log($\widetilde{Assets}_t$**)**	-0.0299	-0.0052	-0.0043
	(-8.7858)	(-1.7082)	(-1.9635)

Table 2.5: **Kernel estimates for the full sample of mutual funds using the market return as a benchmark, for the period 1980 to 1995.** The model is $Flow_{it+1} = f(\tilde{r}_{it}) + \alpha_1(\tilde{r}_{it-1}) + \alpha_2(\tilde{r}_{it-2}) + \alpha_3(\tilde{r}_{it+1}) + \alpha_4 IndustryGrowth_{t+1} + \alpha_5 \log\left(\widetilde{Assets}_{it}\right) + \epsilon_{it+1}$, where $\tilde{r}_{it}$ is the difference between the fund return in year t and the value weighted market return in year t. (t-statistics are reported in parentheses)

	Young: Age 2-5	**Mid: Age 6-10**	**Old: Age 11 and up**
Excess return$_{t-1}$	0.5739	0.4131	0.3346
	(4.7591)	(3.6030)	(6.2631)
Excess return$_{t-2}$	0.0032	0.2992	0.3105
	(0.0364)	(2.9250)	(5.6645)
Excess return$_{t+1}$	1.1510	0.6858	0.3388
	(8.3088)	(5.4043)	(4.2167)
Industry Growth$_{t+1}$	0.3437	0.1616	-0.0680
	(3.4728)	(1.7033)	(-2.1370)
Log($\widetilde{Assets}_t$**)**	-0.0442	-0.0121	-0.0089
	(-5.5128)	(-1.3133)	(-2.2737)

Table 2.6: **Kernel estimates for the full sample of mutual funds using the market return as a benchmark, for the period 1995 to 2005.** The model is $Flow_{it+1} = f(\tilde{r}_{it}) + \alpha_1(\tilde{r}_{it-1}) + \alpha_2(\tilde{r}_{it-2}) + \alpha_3(\tilde{r}_{it+1}) + \alpha_4 IndustryGrowth_{t+1} + \alpha_5 \log\left(\widetilde{Assets_{it}}\right) + \epsilon_{it+1}$, where $\tilde{r}_{it}$ is the difference between the fund return in year t and the value weighted market return in year t. (t-statistics are reported in parentheses)

	Young: Age 2-5	**Mid: Age 6-10**	**Old: Age 11 and up**
Excess return$_{t-1}$	0.3042	0.3429	0.2211
	(7.5776)	(9.2836)	(7.0910)
Excess return$_{t-2}$	0.0383	0.2894	0.2695
	(0.9030)	(8.3172)	(7.5494)
Excess return$_{t+1}$	0.5316	0.5921	0.2438
	(8.7307)	(8.3619)	(5.2008)
Industry Growth$_{t+1}$	0.6127	0.2526	0.2300
	(11.0751)	(6.5378)	(7.1226)
Log($\widetilde{Assets_t}$**)**	-0.0270	-0.0035	0.0004
	(-7.1588)	(-1.0807)	(0.1559)

Table 2.7: **Kernel estimates using the market return as a benchmark for funds with zero average front load fees and high average rear load fees.** The model is $Flow_{it+1} = f(\tilde{r}_{it}) + \alpha_1(\tilde{r}_{it-1}) + \alpha_2(\tilde{r}_{it-2}) + \alpha_3(\tilde{r}_{it+1}) + \alpha_4 IndustryGrowth_{t+1} + \alpha_5 \log\left(\widetilde{Assets_{it}}\right) + \epsilon_{it+1}$, where $\tilde{r}_{it}$ is the difference between the fund return in year t and the value weighted market return in year t. (t-statistics are reported in parentheses)

	Young: Age 2-5	**Mid: Age 6-10**	**Old: Age 11 and up**
Excess return$_{t-1}$	0.3313	0.3059	0.1268
	(5.0965)	(5.4558)	(1.4021)
Excess return$_{t-2}$	-0.0768	0.1782	0.1824
	(-1.1900)	(3.9001)	(1.8960)
Excess return$_{t+1}$	0.4256	0.3107	0.1130
	(4.4683)	(3.2808)	(0.6958)
Industry Growth$_{t+1}$	0.9027	0.1876	0.3862
	(12.5568)	(3.9545)	(3.2248)
Log($\widetilde{Assets_t}$**)**	-0.0429	-0.0061	-0.0106
	(-7.3072)	(-1.4291)	(-1.0119)

Table 2.8: **Kernel estimates using the market return as a benchmark for funds with zero average front load fees and low average rear load fees.** The model is $Flow_{it+1} = f(\tilde{r}_{it}) + \alpha_1(\tilde{r}_{it-1}) + \alpha_2(\tilde{r}_{it-2}) + \alpha_3(\tilde{r}_{it+1}) + \alpha_4 IndustryGrowth_{t+1} + \alpha_5 \log\left(\widetilde{Assets_{it}}\right) + \epsilon_{it+1}$, where $\tilde{r}_{it}$ is the difference between the fund return in year t and the value weighted market return in year t. (t-statistics are reported in parentheses)

	Young: Age 2-5	**Mid: Age 6-10**	**Old: Age 11 and up**
Excess return$_{t-1}$	0.3886	0.2894	0.2492
	(4.1663)	(3.1663)	(2.3586)
Excess return$_{t-2}$	-0.0568	0.2868	0.1773
	(-0.5744)	(3.8806)	(1.3549)
Excess return$_{t+1}$	0.8547	0.8844	0.2595
	(5.8592)	(5.2860)	(2.1503)
Industry Growth$_{t+1}$	0.6648	0.2035	0.0730
	(7.3968)	(2.3883)	(1.0679)
Log($\widetilde{Assets_t}$**)**	-0.0236	-0.0065	0.0013
	(-2.6140)	(-0.8520)	(0.2034)

Table 2.9: **Kernel estimates using the market return as a benchmark for funds with zero average rear load fees and high average front load fees.** The model is $Flow_{it+1} = f(\tilde{r}_{it}) + \alpha_1(\tilde{r}_{it-1}) + \alpha_2(\tilde{r}_{it-2}) + \alpha_3(\tilde{r}_{it+1}) + \alpha_4 IndustryGrowth_{t+1} + \alpha_5 \log\left(\widetilde{Assets_{it}}\right) + \epsilon_{it+1}$, where $\tilde{r}_{it}$ is the difference between the fund return in year t and the value weighted market return in year t. (t-statistics are reported in parentheses)

	Young: Age 2-5	**Mid: Age 6-10**	**Old: Age 11 and up**
Excess return$_{t-1}$	0.6343	0.4583	0.2117
	(5.4215)	(4.1941)	(2.7817)
Excess return$_{t-2}$	0.3055	0.3985	0.3148
	(2.8268)	(2.7527)	(4.1670)
Excess return$_{t+1}$	0.3581	0.4786	0.2060
	(2.8742)	(4.0747)	(2.0328)
Industry Growth$_{t+1}$	0.3950	0.3407	0.1589
	(3.2300)	(4.0026)	(2.8063)
Log($\widetilde{Assets_t}$**)**	-0.0590	-0.0096	0.0048
	(-6.2244)	(-0.8881)	(0.9396)

Table 2.10: **Kernel estimates using the market return as a benchmark for funds with zero average rear load fees and low average front load fees.** The model is $Flow_{it+1} = f(\tilde{r}_{it}) + \alpha_1(\tilde{r}_{it-1}) + \alpha_2(\tilde{r}_{it-2}) + \alpha_3(\tilde{r}_{it+1}) + \alpha_4 IndustryGrowth_{t+1} + \alpha_5 \log\left(\widetilde{Assets_{it}}\right) + \epsilon_{it+1}$, where $\tilde{r}_{it}$ is the difference between the fund return in year t and the value weighted market return in year t. (t-statistics are reported in parentheses)

	Young: Age 2-5	**Mid: Age 6-10**	**Old: Age 11 and up**
Excess return$_{t-1}$	0.2883	0.2827	0.1900
	(4.9267)	(3.3293)	(4.2527)
Excess return$_{t-2}$	0.0932	0.3229	0.2020
	(1.2982)	(4.1877)	(3.8753)
Excess return$_{t+1}$	0.6757	0.6535	0.2763
	(6.2483)	(5.4584)	(4.2518)
Industry Growth$_{t+1}$	0.1331	0.2107	0.1129
	(1.0965)	(2.8641)	(3.4640)
Log($\widetilde{Assets_t}$**)**	-0.0107	0.0067	-0.0044
	(-1.6272)	(1.1538)	(-1.4017)

Table 2.11: **Kernel estimates using the market return as a benchmark for funds with non-zero average front load fees and non-zero average rear load fees.** The model is $Flow_{it+1} = f(\tilde{r}_{it}) + \alpha_1(\tilde{r}_{it-1}) + \alpha_2(\tilde{r}_{it-2}) + \alpha_3(\tilde{r}_{it+1}) + \alpha_4 IndustryGrowth_{t+1} + \alpha_5 \log\left(\widetilde{Assets_{it}}\right) + \epsilon_{it+1}$, where $\tilde{r}_{it}$ is the difference between the fund return in year t and the value weighted market return in year t. (t-statistics are reported in parentheses)

	Young: Age 2-5	**Mid: Age 6-10**	**Old: Age 11 and up**
Excess return$_{t-1}$	0.3548	0.4109	0.3510
	(4.4332)	(6.4435)	(7.0253)
Excess return$_{t-2}$	0.0557	0.3085	0.3760
	(0.7034)	(5.1142)	(9.2349)
Excess return$_{t+1}$	0.6042	0.6277	0.2627
	(6.1210)	(5.1672)	(3.6477)
Industry Growth$_{t+1}$	0.7350	0.2621	0.0301
	(7.7174)	(4.2030)	(0.9755)
Log($\widetilde{Assets_t}$**)**	-0.0345	-0.0044	-0.0108
	(-4.7435)	(-0.7434)	(-2.7487)

Table 2.12: **Kernel estimates using the market return as a benchmark for aggressive growth funds.** The model is $Flow_{it+1} = f(\tilde{r}_{it}) + \alpha_1(\tilde{r}_{it-1}) + \alpha_2(\tilde{r}_{it-2}) + \alpha_3(\tilde{r}_{it+1}) + \alpha_4 IndustryGrowth_{t+1} + \alpha_5 \log\left(\widetilde{Assets_{it}}\right) + \epsilon_{it+1}$, where $\tilde{r}_{it}$ is the difference between the fund return in year t and the value weighted market return in year t. The various investment styles are constructed as in Pástor and Stambaugh (2002). (t-statistics are reported in parentheses)

Investment Style: Aggressive Growth

	Young: Age 2-5	**Mid: Age 6-10**	**Old: Age 11 and up**
Excess return$_{t-1}$	0.2172	0.3001	0.1823
	(4.3599)	(5.5124)	(3.7552)
Excess return$_{t-2}$	-0.0003	0.2060	0.2830
	(-0.0046)	(4.5069)	(4.3090)
Excess return$_{t+1}$	0.3819	0.6375	0.1887
	(4.2382)	(6.2330)	(2.5608)
Industry Growth$_{t+1}$	0.7957	0.2803	0.3352
	(8.7792)	(4.3890)	(3.8949)
Log($\widetilde{Assets_t}$**)**	-0.0383	0.0082	-0.0034
	(-5.1104)	(1.1817)	(-0.4720)

Table 2.13: **Kernel estimates using the market return as a benchmark for growth funds.** The model is $Flow_{it+1} = f(\tilde{r}_{it}) + \alpha_1(\tilde{r}_{it-1}) + \alpha_2(\tilde{r}_{it-2}) + \alpha_3(\tilde{r}_{it+1}) + \alpha_4 IndustryGrowth_{t+1} + \alpha_5 \log\left(\widetilde{Assets}_{it}\right) + \epsilon_{it+1}$, where $\tilde{r}_{it}$ is the difference between the fund return in year t and the value weighted market return in year t. The various investment styles are constructed as in Pástor and Stambaugh (2002). (t-statistics are reported in parentheses)

Investment Style: Growth

	Young: Age 2-5	**Mid: Age 6-10**	**Old: Age 11 and up**
Excess return$_{t-1}$	0.5033	0.4385	0.2545
	(7.7190)	(7.1353)	(5.3787)
Excess return$_{t-2}$	0.1147	0.3712	0.3575
	(2.0832)	(6.5349)	(6.9329)
Excess return$_{t+1}$	0.8072	0.5747	0.2846
	(9.6803)	(5.9141)	(4.1676)
Industry Growth$_{t+1}$	0.5035	0.2065	0.0940
	(8.8799)	(4.0661)	(2.7196)
Log($\widetilde{Assets}_t$)	-0.0304	-0.0093	-0.0019
	(-6.3506)	(-2.0662)	(-0.5850)

Table 2.14: **Kernel estimates using the market return as a benchmark for income funds.** The model is $Flow_{it+1} = f(\tilde{r}_{it}) + \alpha_1(\tilde{r}_{it-1}) + \alpha_2(\tilde{r}_{it-2}) + \alpha_3(\tilde{r}_{it+1}) + \alpha_4 IndustryGrowth_{t+1} + \alpha_5 \log\left(\widetilde{Assets}_{it}\right) + \epsilon_{it+1}$, where $\tilde{r}_{it}$ is the difference between the fund return in year t and the value weighted market return in year t. The various investment styles are constructed as in Pástor and Stambaugh (2002). (t-statistics are reported in parentheses)

Investment Style: Income

	Young: Age 2-5	**Mid: Age 6-10**	**Old: Age 11 and up**
Excess return$_{t-1}$	0.8401	0.4235	0.2598
	(4.0706)	(4.3234)	(2.0125)
Excess return$_{t-2}$	-0.2718	0.6195	0.2679
	(-1.2404)	(3.6882)	(1.9908)
Excess return$_{t+1}$	0.8167	0.8737	0.1033
	(3.8319)	(2.4200)	(0.5703)
Industry Growth$_{t+1}$	0.7667	0.2837	0.2199
	(3.9261)	(1.8527)	(1.5159)
Log($\widetilde{Assets}_t$)	-0.0198	-0.0217	-0.0105
	(-1.5383)	(-1.9875)	(-1.5348)

Table 2.15: **Kernel estimates using the market return as a benchmark for growth and income funds.** The model is $Flow_{it+1} = f(\tilde{r}_{it}) + \alpha_1(\tilde{r}_{it-1}) + \alpha_2(\tilde{r}_{it-2}) + \alpha_3(\tilde{r}_{it+1}) + \alpha_4 IndustryGrowth_{t+1} + \alpha_5 \log\left(\widetilde{Assets_{it}}\right) + \epsilon_{it+1}$, where $\tilde{r}_{it}$ is the difference between the fund return in year t and the value weighted market return in year t. The various investment styles are constructed as in Pástor and Stambaugh (2002). (t-statistics are reported in parentheses)

Investment Style: Growth & Income

	Young: Age 2-5	**Mid: Age 6-10**	**Old: Age 11 and up**
Excess return$_{t-1}$	0.4775	0.3822	0.3261
	(3.2248)	(3.3608)	(3.6819)
Excess return$_{t-2}$	0.0655	0.4604	0.2135
	(0.5020)	(4.1133)	(2.3580)
Excess return$_{t+1}$	0.7845	0.8184	0.2247
	(6.0444)	(4.9305)	(2.5615)
Industry Growth$_{t+1}$	0.5159	0.3776	0.1175
	(3.9815)	(6.2331)	(3.7509)
Log$(\widetilde{Assets_t})$	-0.0378	-0.0109	-0.0062
	(-5.1464)	(-1.9623)	(-1.2131)

Table 2.16: **Kernel estimates for the full sample of mutual funds using the style-specific fund return as a benchmark, for the period 1980 to 2005.** The model is $Flow_{it+1} = f(\tilde{r}_{it}) + \alpha_1(\tilde{r}_{it-1}) + \alpha_2(\tilde{r}_{it-2}) + \alpha_3(\tilde{r}_{it+1}) + \alpha_4 StyleIndustryGrowth_{t+1} + \alpha_5 \log\left(\widetilde{Assets_{it}}\right) + \epsilon_{it+1}$, where $\tilde{r}_{it}$ is the difference between the fund return at the end of year t and the value weighed average return of the corresponding investment style at the end of year t. (t-statistics are reported in parentheses)

	Young: Age 2-5	**Mid: Age 6-10**	**Old: Age 11 and up**
Excess return$_{t-1}$	0.3426	0.3481	0.2615
	(8.3845)	(8.5808)	(7.7269)
Excess return$_{t-2}$	0.0977	0.2456	0.2689
	(2.2582)	(6.5502)	(8.2841)
Excess return$_{t+1}$	0.5812	0.6019	0.3388
	(10.8589)	(10.1752)	(7.9875)
Industry Growth$_{t+1}$	-0.0006	0.1490	0.1252
	(-1.0810)	(7.1479)	(7.6338)
Log$(\widetilde{Assets_t})$	-0.0235	-0.0016	-0.0042
	(-6.5874)	(-0.5642)	(-2.1636)

Table 2.17: **Kernel estimates for the full sample of mutual funds using the style-specific fund return as a benchmark, for the period 1980 to 1995.** The model is $Flow_{it+1} = f(\tilde{r}_{it}) + \alpha_1(\tilde{r}_{it-1}) + \alpha_2(\tilde{r}_{it-2}) + \alpha_3(\tilde{r}_{it+1}) + \alpha_4 StyleIndustryGrowth_{t+1} + \alpha_5 \log\left(\widetilde{Assets_{it}}\right) + \epsilon_{it+1}$, where $\tilde{r}_{it}$ is the difference between the fund return at the end of year t and the value weighed average return of the corresponding investment style at the end of year t. (t-statistics are reported in parentheses)

	Young: Age 2-5	**Mid: Age 6-10**	**Old: Age 11 and up**
Excess return$_{t-1}$	0.5905	0.6224	0.3582
	(4.5851)	(5.5384)	(5.5237)
Excess return$_{t-2}$	-0.0226	0.3903	0.3276
	(-0.2313)	(3.3973)	(5.4737)
Excess return$_{t+1}$	1.0384	0.8416	0.3738
	(7.9779)	(5.6662)	(4.7221)
Industry Growth$_{t+1}$	0.2191	0.1976	0.1495
	(4.3227)	(3.7138)	(5.1734)
Log($\widetilde{Assets_t}$**)**	-0.0400	-0.0142	-0.0088
	(-4.8688)	(-1.7089)	(-2.3811)

Table 2.18: **Kernel estimates for the full sample of mutual funds using the style-specific fund return as a benchmark, for the period 1995 to 2005.** The model is $Flow_{it+1} = f(\tilde{r}_{it}) + \alpha_1(\tilde{r}_{it-1}) + \alpha_2(\tilde{r}_{it-2}) + \alpha_3(\tilde{r}_{it+1}) + \alpha_4 StyleIndustryGrowth_{t+1} + \alpha_5 \log\left(\widetilde{Assets_{it}}\right) + \epsilon_{it+1}$, where $\tilde{r}_{it}$ is the difference between the fund return at the end of year t and the value weighed average return of the corresponding investment style at the end of year t. (t-statistics are reported in parentheses)

	Young: Age 2-5	**Mid: Age 6-10**	**Old: Age 11 and up**
Excess return$_{t-1}$	0.2984	0.3202	0.2038
	(6.9889)	(7.5338)	(5.7626)
Excess return$_{t-2}$	0.0849	0.2359	0.2334
	(1.7761)	(6.0763)	(6.3201)
Excess return$_{t+1}$	0.5236	0.5630	0.2972
	(8.9228)	(8.7212)	(5.9988)
Industry Growth$_{t+1}$	-0.0007	0.1031	0.1014
	(-1.1698)	(4.2961)	(5.1706)
Log($\widetilde{Assets_t}$**)**	-0.0206	0.0014	0.0036
	(-5.2725)	(0.4422)	(1.5816)

Table 2.19: **Kernel estimates using the style-specific fund return as a benchmark for aggressive growth funds.** The model is $Flow_{it+1} = f(\tilde{r}_{it}) + \alpha_1(\tilde{r}_{it-1}) + \alpha_2(\tilde{r}_{it-2}) + \alpha_3(\tilde{r}_{it+1}) + \alpha_4 StyleIndustryGrowth_{t+1} + \alpha_5 \log\left(\widetilde{Assets}_{it}\right) + \epsilon_{it+1}$, where $\tilde{r}_{it}$ is the difference between the fund return at the end of year t and the value weighed average return of the corresponding investment style at the end of year t. (t-statistics are reported in parentheses)

Investment Style: Aggressive Growth

	Young: Age 2-5	**Mid: Age 6-10**	**Old: Age 11 and up**
Excess return$_{t-1}$	0.2341	0.3211	0.1711
	(4.4861)	(5.1521)	(2.8988)
Excess return$_{t-2}$	0.0345	0.1329	0.2227
	(0.4968)	(2.5447)	(3.4836)
Excess return$_{t+1}$	0.6449	0.7049	0.3986
	(7.0715)	(6.8246)	(4.7228)
Style Growth$_{t+1}$	0.2534	0.1511	0.0667
	(6.4828)	(4.6118)	(1.8335)
Log($\widetilde{Assets}_t$**)**	-0.0365	0.0119	-0.0031
	(-4.5271)	(1.7012)	(-0.4470)

Table 2.20: **Kernel estimates using the style-specific fund return as a benchmark for growth funds.** The model is $Flow_{it+1} = f(\tilde{r}_{it}) + \alpha_1(\tilde{r}_{it-1}) + \alpha_2(\tilde{r}_{it-2}) + \alpha_3(\tilde{r}_{it+1}) + \alpha_4 StyleIndustryGrowth_{t+1} + \alpha_5 \log\left(\widetilde{Assets}_{it}\right) + \epsilon_{it+1}$, where $\tilde{r}_{it}$ is the difference between the fund return at the end of year t and the value weighed average return of the corresponding investment style at the end of year t. (t-statistics are reported in parentheses)

Investment Style: Growth

	Young: Age 2-5	**Mid: Age 6-10**	**Old: Age 11 and up**
Excess return$_{t-1}$	0.4809	0.3782	0.2749
	(7.2729)	(5.7831)	(5.2194)
Excess return$_{t-2}$	0.0712	0.3553	0.3510
	(1.2072)	(5.5215)	(6.2710)
Excess return$_{t+1}$	0.7846	0.5396	0.3354
	(9.5428)	(6.0970)	(4.6039)
Style Growth$_{t+1}$	0.2599	0.0982	0.0997
	(8.0740)	(3.2057)	(3.6241)
Log($\widetilde{Assets}_t$**)**	-0.0247	-0.0061	-0.0010
	(-4.9893)	(-1.5136)	(-0.3568)

Table 2.21: **Kernel estimates using the style-specific fund return as a benchmark for income funds.** The model is $Flow_{it+1} = f(\tilde{r}_{it}) + \alpha_1(\tilde{r}_{it-1}) + \alpha_2(\tilde{r}_{it-2}) + \alpha_3(\tilde{r}_{it+1}) + \alpha_4 StyleIndustryGrowth_{t+1} + \alpha_5 \log\left(\widetilde{Assets_{it}}\right) + \epsilon_{it+1}$, where $\tilde{r}_{it}$ is the difference between the fund return at the end of year t and the value weighed average return of the corresponding investment style at the end of year t. (t-statistics are reported in parentheses)

Investment Style: Income

	Young: Age 2-5	**Mid: Age 6-10**	**Old: Age 11 and up**
Excess return$_{t-1}$	1.5232	0.3155	0.3932
	(4.9109)	(1.0280)	(1.2141)
Excess return$_{t-2}$	-0.4853	0.7039	0.1512
	(-1.7931)	(2.6061)	(0.7204)
Excess return$_{t+1}$	0.9284	1.0975	0.0472
	(3.2234)	(2.2252)	(0.2128)
Style Growth$_{t+1}$	0.4305	0.2501	0.0651
	(4.1391)	(1.8529)	(0.8179)
Log($\widetilde{Assets_t}$)	-0.0262	-0.0265	-0.0105
	(-2.1943)	(-2.2782)	(-1.2121)

Table 2.22: **Kernel estimates using the style-specific fund return as a benchmark for growth and income funds.** The model is $Flow_{it+1} = f(\tilde{r}_{it}) + \alpha_1(\tilde{r}_{it-1}) + \alpha_2(\tilde{r}_{it-2}) + \alpha_3(\tilde{r}_{it+1}) + \alpha_4 StyleIndustryGrowth_{t+1} + \alpha_5 \log\left(\widetilde{Assets_{it}}\right) + \epsilon_{it+1}$, where $\tilde{r}_{it}$ is the difference between the fund return at the end of year t and the value weighed average return of the corresponding investment style at the end of year t. (t-statistics are reported in parentheses)

Investment Style: Growth & Income

	Young: Age 2-5	**Mid: Age 6-10**	**Old: Age 11 and up**
Excess return$_{t-1}$	0.7052	0.5864	0.3457
	(4.3450)	(4.0739)	(3.5775)
Excess return$_{t-2}$	0.1368	0.4587	0.2336
	(0.9582)	(3.7421)	(2.4427)
Excess return$_{t+1}$	0.8018	0.7950	0.2608
	(4.6419)	(4.3831)	(2.6437)
Style Growth$_{t+1}$	0.3071	0.3203	0.1755
	(4.7751)	(7.1743)	(6.3523)
Log($\widetilde{Assets_t}$)	-0.0383	-0.0104	-0.0057
	(-5.2183)	(-2.2007)	(-1.3458)

Table 3.3: **Changes in the mutual fund portfolio liquidity with extreme expected outflows, using Amihud's illiquidity measure.** In this table, the portfolio liquidity levels have been normalized such that the portfolio liquidity level at time $t-1$ equals 1. The top quintile contains the 20% most liquid stocks of the fund holdings, and the bottom quintile contains the 20% least liquid stocks of the fund holdings, measured using Amihud's illiquidity measure. If the decrease in the fund portfolio liquidity measure is greater than 1%, the table cell is shaded; and if the decrease is greater than 5%, the content is bolded.

Fund style specific flow-performance model with simple growth prediction:

	Overall		Top Quintile		Bottom Quintile	
time	t	$t+1$	t	$t+1$	t	$t+1$
Aggressive Growth	0.9545	0.9409	**0.9124**	0.9573	0.9945	**0.9235**
Growth	**0.8993**	0.9294	**0.9436**	**0.8638**	**0.8780**	0.9460
Income	1.0854	1.3374	1.0043	0.8868	1.0429	1.4328
Growth & Income	**0.8724**	0.8647	**0.8970**	**0.7242**	**0.8845**	0.8608

Fund style specific flow-performance model with AR(1) growth prediction:

	Overall		Top Quintile		Bottom Quintile	
time	t	$t+1$	t	$t+1$	t	$t+1$
Aggressive Growth	0.9545	0.9749	**0.9462**	0.9727	0.9765	0.9920
Growth	**0.9040**	0.8608	0.9562	0.9206	**0.8810**	0.9116
Income	1.0066	1.2082	0.9627	**0.8807**	1.0276	1.4279
Growth & Income	**0.8727**	**0.8149**	**0.8991**	**0.7176**	**0.8959**	0.8528

Table 3.4: **Changes in the mutual fund portfolio liquidity with extreme expected outflows, using the proportional effective spread liquidity measure.** In this table, the portfolio liquidity levels have been normalized such that the portfolio liquidity level at time $t-1$ equals 1. The top quintile contains the 20% most liquid stocks of the fund holdings, and the bottom quintile contains the 20% least liquid stocks of the fund holdings, measured using the proportional effective spread measure. If the decrease in the fund portfolio liquidity measure is greater than 1%, the table cell is shaded; and if the decrease is greater than 5%, the content is bolded.

Fund style specific flow-performance model with simple growth prediction:

	Overall		Top Quintile		Bottom Quintile	
time	t	$t+1$	t	$t+1$	t	$t+1$
Aggressive Growth	0.9872	0.9716	**0.9180**	0.9006	1.0060	1.0097
Growth	0.9746	0.9293	**0.8986**	0.8953	1.0031	1.0283
Income	**0.9116**	**0.8251**	**0.9244**	**0.8272**	0.9958	**0.8844**
Growth & Income	1.0085	**0.7689**	**0.9309**	**0.8077**	**0.9366**	**0.7411**

Fund style specific flow-performance model with AR(1) growth prediction:

	Overall		Top Quintile		Bottom Quintile	
time	t	$t+1$	t	$t+1$	t	$t+1$
Aggressive Growth	0.9528	0.9782	**0.9157**	0.8855	0.9701	1.0162
Growth	0.9798	**0.9228**	**0.9191**	0.9114	1.0314	0.9895
Income	**0.8825**	**0.7945**	**0.8668**	**0.7724**	0.9519	**0.8408**
Growth & Income	0.9704	**0.8043**	**0.9236**	**0.7981**	**0.9125**	**0.7711**

Table 3.5: **Changes in the mutual fund portfolio liquidity with extreme expected outflows, using the proportional quoted spread liquidity measure.** In this table, the portfolio liquidity levels have been normalized such that the portfolio liquidity level at time $t-1$ equals 1. The top quintile contains the 20% most liquid stocks of the fund holdings, and the bottom quintile contains the 20% least liquid stocks of the fund holdings, measured using the proportional quoted spread measure. If the decrease in the fund portfolio liquidity measure is greater than 1%, the table cell is shaded; and if the decrease is greater than 5%, the content is bolded.

Fund style specific flow-performance model with simple growth prediction:

	Overall		Top Quintile		Bottom Quintile	
time	t	$t+1$	t	$t+1$	t	$t+1$
Aggressive Growth	0.9679	0.9623	**0.9426**	**0.8864**	1.0069	0.9986
Growth	0.9537	0.9848	**0.8495**	0.8360	**0.9333**	0.9668
Income	**0.9255**	0.9975	**0.9373**	**0.6910**	**0.9224**	**0.8480**
Growth & Income	**0.8845**	0.8436	**0.7809**	0.7395	**0.9256**	**0.7476**

Fund style specific flow-performance model with AR(1) growth prediction:

	Overall		Top Quintile		Bottom Quintile	
time	t	$t+1$	t	$t+1$	t	$t+1$
Aggressive Growth	0.9539	0.9696	**0.9323**	**0.8739**	0.9596	1.0069
Growth	**0.9408**	0.9737	**0.8546**	0.8965	**0.9443**	0.9645
Income	0.9764	1.0398	**0.9183**	**0.4642**	**0.8396**	0.8878
Growth & Income	**0.8797**	**0.8239**	**0.8164**	0.7875	**0.9029**	**0.7788**

Table 3.6: **Changes in the mutual fund portfolio liquidity with extreme expected outflows, using the effective spread liquidity measure.** In this table, the portfolio liquidity levels have been normalized such that the portfolio liquidity level at time $t-1$ equals 1. The top quintile contains the 20% most liquid stocks of the fund holdings, and the bottom quintile contains the 20% least liquid stocks of the fund holdings, measured using the effective spread measure. If the decrease in the fund portfolio liquidity measure is greater than 1%, the table cell is shaded; and if the decrease is greater than 5%, the content is bolded.

Fund style specific flow-performance model with simple growth prediction:

	Overall		Top Quintile		Bottom Quintile	
time	t	$t+1$	t	$t+1$	t	$t+1$
Aggressive Growth	0.9517	**0.8886**	**0.9163**	**0.8099**	0.9612	**0.8331**
Growth	0.9600	**0.8307**	0.9520	**0.8681**	1.0048	**0.8107**
Income	**0.8363**	**0.7144**	**0.8652**	**0.7285**	**0.8972**	**0.8056**
Growth & Income	0.9578	**0.7187**	1.0008	**0.8235**	**0.9176**	**0.7178**

Fund style specific flow-performance model with AR(1) growth prediction:

	Overall		Top Quintile		Bottom Quintile	
time	t	$t+1$	t	$t+1$	t	$t+1$
Aggressive Growth	**0.9480**	**0.8886**	**0.9218**	**0.8065**	**0.9484**	**0.8455**
Growth	1.0169	**0.8168**	**0.9481**	**0.8735**	1.0449	**0.7900**
Income	**0.8261**	**0.6296**	**0.8346**	**0.7829**	**0.8404**	**0.7453**
Growth & Income	0.9548	**0.7714**	0.9596	**0.8235**	**0.8815**	**0.7863**

Table 3.7: **Changes in the mutual fund portfolio liquidity with extreme expected outflows, using the quoted spread liquidity measure.** In this table, the portfolio liquidity levels have been normalized such that the portfolio liquidity level at time $t-1$ equals 1. The top quintile contains the 20% most liquid stocks of the fund holdings, and the bottom quintile contains the 20% least liquid stocks of the fund holdings, measured using the quoted spread measure. If the decrease in the fund portfolio liquidity measure is greater than 1%, the table cell is shaded; and if the decrease is greater than 5%, the content is bolded.

Fund style specific flow-performance model with simple growth prediction:

	Overall		Top Quintile		Bottom Quintile	
time	t	$t+1$	t	$t+1$	t	$t+1$
Aggressive Growth	**0.9444**	**0.8762**	**0.8953**	**0.8139**	**0.9210**	0.8904
Growth	**0.9359**	**0.8795**	**0.8679**	0.8550	**0.9080**	0.8794
Income	**0.8811**	0.8555	**0.7784**	0.7558	**0.8691**	**0.7929**
Growth & Income	**0.8387**	**0.7965**	**0.8134**	0.8030	**0.8177**	**0.7518**

Fund style specific flow-performance model with AR(1) growth prediction:

	Overall		Top Quintile		Bottom Quintile	
time	t	$t+1$	t	$t+1$	t	$t+1$
Aggressive Growth	**0.9445**	**0.8694**	**0.9219**	**0.7899**	**0.9186**	0.8977
Growth	**0.9415**	**0.8608**	**0.8977**	0.8675	**0.9184**	0.8794
Income	**0.8914**	0.9158	**0.7701**	**0.5602**	**0.8349**	0.8614
Growth & Income	**0.8338**	0.7965	**0.8216**	0.8030	**0.8280**	**0.7518**

Table 3.8: **Analysis on unexpected outflows: Amihud's Illiquidity Measure.** The table reports the changes in the fund portfolio liquidity using the style specific benchmark flow-performance model and fitted ARMA growth prediction. Fund portfolio liquidity is measured by Amihud's illiquidity measure. The table cell is shaded if the change in the fund portfolio liquidity is greater than 5%, relative to the average fund portfolio liquidity level of the past four quarters before the first extreme outflow event.
The table contains the average Amihud's illiquidity measure of the mutual funds that experience (1) one isolated event of unexpected extreme outflow (the event is centered at time t), (2) two consecutive quarters of unexpected extreme outflow (the event begins at time $t-1$ and ends at t), (3) three consecutive quarters of unexpected extreme outflow (the event begins at time $t-2$ and ends at time t), (4) four quarters of consecutive unexpected extreme outflow (the event time is between time $t-3$ to time t).

Overall Amihud's illiquidity measure of the fund

1 period	$t-3$	$t-2$	$t-1$	t	$t+1$	$t+2$	$t+3$	$t+4$
Aggressive Growth	0.6042	0.6170	0.6210	0.7002	0.6530	0.6362	0.6209	0.5804
Growth	0.0997	0.1027	0.0978	0.1050	0.0945	0.0966	0.0971	0.0981
Income	0.0872	0.0851	0.1010	0.1258	0.1196	0.0973	0.1123	0.1058
Growth & Income	0.0809	0.0836	0.0836	0.0889	0.0850	0.0816	0.0880	0.0860
2 cont. periods	$t-3$	$t-2$	$t-1$	t	$t+1$	$t+2$	$t+3$	$t+4$
Aggressive Growth	0.7153	0.7934	0.8308	0.6881	0.6920	0.6507	0.6281	0.6782
Growth	0.1167	0.1125	0.1273	0.1229	0.1151	0.1156	0.1105	0.1173
Income	0.0924	0.0984	0.1001	0.0991	0.0962	0.1063	0.1090	0.0969
Growth & Income	0.1096	0.1035	0.1075	0.1116	0.0968	0.1073	0.1014	0.0977
3 cont. periods	$t-3$	$t-2$	$t-1$	t	$t+1$	$t+2$	$t+3$	$t+4$
Aggressive Growth	0.6803	0.7828	0.6955	0.6519	0.6333	0.6113	0.6022	0.5494
Growth	0.1398	0.1532	0.1362	0.1249	0.1186	0.1092	0.1200	0.1108
Income	0.0931	0.1062	0.1021	0.0960	0.1022	0.0963	0.0840	0.0865
Growth & Income	0.1118	0.1098	0.1068	0.0969	0.1006	0.0915	0.0944	0.0909
4 cont. periods	$t-3$	$t-2$	$t-1$	t	$t+1$	$t+2$	$t+3$	$t+4$
Aggressive Growth	0.8379	0.7683	0.7234	0.6910	0.6337	0.6087	0.5979	0.6106
Growth	0.1250	0.1185	0.1105	0.1084	0.1059	0.1085	0.1135	0.1086
Income	0.0816	0.0826	0.0832	0.0774	0.0765	0.0727	0.0727	0.0727
Growth & Income	0.1386	0.1364	0.1311	0.1303	0.1219	0.1216	0.1155	0.1175

Table 3.9: **Analysis on unexpected outflows: Amihud's Illiquidity Measure.** The table reports the changes in the fund portfolio liquidity using the style specific benchmark flow-performance model and fitted ARMA growth prediction, in the top liquidity quintile of the fund holdings. The top quintile contains the 20% most liquid stocks of the fund holdings, measured by Amihud's illiquidity measure. The table cell is shaded if the change in the fund portfolio liquidity is greater than 5%, relative to the average fund portfolio liquidity level of the past four quarters before the first extreme outflow event.
The table contains the average Amihud's illiquidity measure of the mutual funds that experience (1) one isolated event of unexpected extreme outflow (the event is centered at time t), (2) two consecutive quarters of unexpected extreme outflow (the event begins at time $t-1$ and ends at t), (3) three consecutive quarters of unexpected extreme outflow (the event begins at time $t-2$ and ends at time t), (4) four quarters of consecutive unexpected extreme outflow (the event time is between time $t-3$ to time t).

Amihud's illiquidity measure in the top quintile of the fund holdings

1 period	$t-3$	$t-2$	$t-1$	t	$t+1$	$t+2$	$t+3$	$t+4$
Aggressive Growth	0.0500	0.0512	0.0522	0.0559	0.0556	0.0525	0.0547	0.0542
Growth	0.0072	0.0072	0.0070	0.0069	0.0068	0.0068	0.0069	0.0067
Income	0.0089	0.0079	0.0083	0.0088	0.0083	0.0079	0.0086	0.0085
Growth & Income	0.0067	0.0067	0.0067	0.0070	0.0065	0.0067	0.0069	0.0069
2 cont. periods	$t-3$	$t-2$	$t-1$	t	$t+1$	$t+2$	$t+3$	$t+4$
Aggressive Growth	0.0590	0.0587	0.0580	0.0601	0.0578	0.0555	0.0597	0.0572
Growth	0.0081	0.0080	0.0084	0.0079	0.0072	0.0074	0.0075	0.0074
Income	0.0083	0.0090	0.0091	0.0087	0.0087	0.0089	0.0093	0.0084
Growth & Income	0.0082	0.0078	0.0080	0.0077	0.0075	0.0078	0.0076	0.0074
3 cont. periods	$t-3$	$t-2$	$t-1$	t	$t+1$	$t+2$	$t+3$	$t+4$
Aggressive Growth	0.0612	0.0600	0.0618	0.0595	0.0604	0.0609	0.0612	0.0589
Growth	0.0090	0.0082	0.0079	0.0072	0.0072	0.0075	0.0076	0.0074
Income	0.0092	0.0094	0.0089	0.0087	0.0088	0.0089	0.0084	0.0081
Growth & Income	0.0075	0.0080	0.0077	0.0074	0.0079	0.0075	0.0075	0.0070
4 cont. periods	$t-3$	$t-2$	$t-1$	t	$t+1$	$t+2$	$t+3$	$t+4$
Aggressive Growth	0.0603	0.0594	0.0590	0.0598	0.0585	0.0563	0.0512	0.0497
Growth	0.0079	0.0077	0.0074	0.0074	0.0073	0.0075	0.0075	0.0075
Income	0.0085	0.0085	0.0085	0.0085	0.0084	0.0084	0.0083	0.0084
Growth & Income	0.0090	0.0087	0.0084	0.0083	0.0081	0.0078	0.0077	0.0076

Table 3.10: **Analysis on unexpected outflows: Amihud's Illiquidity Measure.** The table reports the changes in the fund portfolio liquidity using the style specific benchmark flow-performance model and fitted ARMA growth prediction, in the bottom liquidity quintile of the fund holdings. The bottom quintile contains the 20% least liquid stocks of the fund holdings, measured by Amihud's illiquidity measure. The table cell is shaded if the change in the fund portfolio liquidity is greater than 5%, relative to the average fund portfolio liquidity level of the past four quarters before the first extreme outflow event.
The table contains the average Amihud's illiquidity measure of the mutual funds that experience (1) one isolated event of unexpected extreme outflow (the event is centered at time t), (2) two consecutive quarters of unexpected extreme outflow (the event begins at time $t-1$ and ends at t), (3) three consecutive quarters of unexpected extreme outflow (the event begins at time $t-2$ and ends at time t), (4) four quarters of consecutive unexpected extreme outflow (the event time is between time $t-3$ to time t).

Amihud's illiquidity measure in the bottom quintile of the fund holdings

1 period	$t-3$	$t-2$	$t-1$	t	$t+1$	$t+2$	$t+3$	$t+4$
Aggressive Growth	2.6393	2.8337	2.7910	3.1854	2.9377	2.7769	2.9185	2.6930
Growth	0.4843	0.4658	0.4481	0.4594	0.4418	0.4277	0.4474	0.4361
Income	0.4165	0.3962	0.4272	0.5884	0.5091	0.4404	0.4241	0.3954
Growth & Income	0.3813	0.3532	0.3769	0.3911	0.3871	0.3505	0.3714	0.3895
2 cont. periods	$t-3$	$t-2$	$t-1$	t	$t+1$	$t+2$	$t+3$	$t+4$
Aggressive Growth	3.8264	3.7556	3.4453	3.1751	3.2859	2.9985	2.9445	3.3401
Growth	0.5856	0.5209	0.6388	0.6054	0.5049	0.5145	0.4937	0.5373
Income	0.3754	0.4268	0.4650	0.4016	0.3676	0.3650	0.4504	0.3841
Growth & Income	0.4845	0.4838	0.4697	0.5001	0.4398	0.4487	0.4192	0.4125
3 cont. periods	$t-3$	$t-2$	$t-1$	t	$t+1$	$t+2$	$t+3$	$t+4$
Aggressive Growth	3.6894	3.4633	3.1210	3.2859	2.6747	2.7991	2.7654	2.6698
Growth	0.6962	0.6944	0.6287	0.5783	0.5171	0.4731	0.4945	0.5047
Income	0.4268	0.4390	0.3984	0.3788	0.3797	0.3590	0.3205	0.3619
Growth & Income	0.5167	0.5062	0.5002	0.4261	0.4494	0.4262	0.4251	0.4064
4 cont. periods	$t-3$	$t-2$	$t-1$	t	$t+1$	$t+2$	$t+3$	$t+4$
Aggressive Growth	3.7591	3.4742	3.2428	2.9520	2.7992	2.7006	2.6592	2.6986
Growth	0.5597	0.5336	0.4753	0.4699	0.4500	0.4658	0.4758	0.4869
Income	0.3305	0.3242	0.3044	0.2952	0.2932	0.2841	0.2926	0.2745
Growth & Income	0.6024	0.5915	0.5522	0.5771	0.5360	0.5345	0.5173	0.5126

Table 3.11: **Analysis on unexpected outflows: Proportional Effective Spread Measure.** The table reports the changes in the fund portfolio liquidity using the style specific benchmark flow-performance model and fitted ARMA growth prediction. Fund portfolio liquidity is measured by the proportional effective spread measure. The table cell is shaded if the change in the fund portfolio liquidity is greater than 5%, relative to the average fund portfolio liquidity level of the past four quarters before the first extreme outflow event.

The table contains the average proportional effective spread measure of the mutual funds that experience (1) one isolated event of unexpected extreme outflow (the event is centered at time t), (2) two consecutive quarters of unexpected extreme outflow (the event begins at time $t-1$ and ends at t), (3) three consecutive quarters of unexpected extreme outflow (the event begins at time $t-2$ and ends at time t), (4) four quarters of consecutive unexpected extreme outflow (the event time is between time $t-3$ to time t).

Overall proportional effective spread measure of the fund

1 period	$t-3$	$t-2$	$t-1$	t	$t+1$	$t+2$	$t+3$	$t+4$
Aggressive Growth	0.4591	0.4529	0.4604	0.4812	0.4866	0.4686	0.4727	0.5084
Growth	0.2742	0.2721	0.2663	0.2753	0.2693	0.2702	0.2585	0.2491
Income	0.2796	0.2793	0.2930	0.2960	0.2992	0.2783	0.2807	0.2748
Growth & Income	0.2748	0.2593	0.2607	0.2600	0.2689	0.2585	0.2570	0.2514
2 cont. periods	$t-3$	$t-2$	$t-1$	t	$t+1$	$t+2$	$t+3$	$t+4$
Aggressive Growth	0.4811	0.4901	0.5128	0.4701	0.4708	0.4663	0.4811	0.5256
Growth	0.2916	0.2793	0.2936	0.2962	0.2841	0.2646	0.2510	0.2697
Income	0.2833	0.2554	0.2807	0.2837	0.2774	0.2831	0.3005	0.2823
Growth & Income	0.2725	0.2813	0.2849	0.2849	0.2578	0.2678	0.2674	0.2705
3 cont. periods	$t-3$	$t-2$	$t-1$	t	$t+1$	$t+2$	$t+3$	$t+4$
Aggressive Growth	0.4916	0.5128	0.4736	0.4520	0.4404	0.4442	0.4734	0.4946
Growth	0.2920	0.2964	0.3110	0.2902	0.2842	0.2521	0.2785	0.3096
Income	0.3175	0.2595	0.2602	0.2903	0.2822	0.2784	0.2694	0.3009
Growth & Income	0.2928	0.2849	0.2813	0.2585	0.2774	0.2623	0.2793	0.2743
4 cont. periods	$t-3$	$t-2$	$t-1$	t	$t+1$	$t+2$	$t+3$	$t+4$
Aggressive Growth	0.5175	0.4946	0.4825	0.4575	0.4479	0.4597	0.4819	0.4755
Growth	0.3008	0.2915	0.2780	0.2697	0.2533	0.2640	0.2792	0.2810
Income	0.3391	0.3315	0.3137	0.3135	0.3112	0.3087	0.3112	0.3124
Growth & Income	0.2891	0.2891	0.2925	0.2768	0.2634	0.2683	0.2871	0.2962

Table 3.12: **Analysis on unexpected outflows: Proportional Effective Spread Measure.** The table reports the changes in the fund portfolio liquidity using the style specific benchmark flow-performance model and fitted ARMA growth prediction, in the top liquidity quintile of the fund holdings. The top quintile contains the 20% most liquid stocks of the fund holdings, measured by the proportional effective spread measure. The table cell is shaded if the change in the fund portfolio liquidity is greater than 5%, relative to the average fund portfolio liquidity level of the past four quarters before the first extreme outflow event.
The table contains the average proportional effective spread measure of the mutual funds that experience (1) one isolated event of unexpected extreme outflow (the event is centered at time t), (2) two consecutive quarters of unexpected extreme outflow (the event begins at time $t-1$ and ends at t), (3) three consecutive quarters of unexpected extreme outflow (the event begins at time $t-2$ and ends at time t), (4) four quarters of consecutive unexpected extreme outflow (the event time is between time $t-3$ to time t).

Proportional effective measure in the top quintile of the fund holdings

1 period	$t-3$	$t-2$	$t-1$	t	$t+1$	$t+2$	$t+3$	$t+4$
Aggressive Growth	0.1533	0.1476	0.1491	0.1687	0.1701	0.1588	0.1640	0.1645
Growth	0.0973	0.0973	0.0926	0.0901	0.0878	0.0873	0.0867	0.0932
Income	0.1195	0.1137	0.1087	0.1120	0.1109	0.1107	0.1028	0.1029
Growth & Income	0.1040	0.1022	0.0975	0.0985	0.0958	0.0985	0.0920	0.1100
2 cont. periods	$t-3$	$t-2$	$t-1$	t	$t+1$	$t+2$	$t+3$	$t+4$
Aggressive Growth	0.1593	0.1617	0.1715	0.1658	0.1529	0.1534	0.1554	0.1551
Growth	0.1106	0.1005	0.0972	0.0977	0.0892	0.0847	0.0844	0.1080
Income	0.1244	0.1224	0.1238	0.1140	0.1196	0.1216	0.1256	0.1229
Growth & Income	0.1137	0.1148	0.1080	0.1062	0.0987	0.0992	0.1130	0.1221
3 cont. periods	$t-3$	$t-2$	$t-1$	t	$t+1$	$t+2$	$t+3$	$t+4$
Aggressive Growth	0.1654	0.1727	0.1610	0.1558	0.1526	0.1620	0.1599	0.1736
Growth	0.1120	0.1032	0.1044	0.0923	0.0877	0.0843	0.0866	0.1110
Income	0.1118	0.1163	0.1190	0.1114	0.1180	0.1186	0.1136	0.1212
Growth & Income	0.1081	0.1051	0.1045	0.0963	0.0922	0.1039	0.1151	0.1183
4 cont. periods	$t-3$	$t-2$	$t-1$	t	$t+1$	$t+2$	$t+3$	$t+4$
Aggressive Growth	0.1763	0.1724	0.1650	0.1573	0.1534	0.1574	0.1680	0.1747
Growth	0.1026	0.0997	0.0900	0.0865	0.0818	0.0868	0.1031	0.1147
Income	0.1364	0.1326	0.1225	0.1242	0.1212	0.1176	0.1225	0.1249
Growth & Income	0.0976	0.0976	0.0927	0.0920	0.0909	0.0958	0.1127	0.1206

Table 3.13: **Analysis on unexpected outflows: Proportional Effective Spread Measure.** The table reports the changes in the fund portfolio liquidity using the style specific benchmark flow-performance model and fitted ARMA growth prediction, in the bottom liquidity quintile of the fund holdings. The bottom quintile contains the 20% least liquid stocks of the fund holdings, measured by the proportional effective spread measure. The table cell is shaded if the change in the fund portfolio liquidity is greater than 5%, relative to the average fund portfolio liquidity level of the past four quarters before the first extreme outflow event.
The table contains the average proportional effective spread measure of the mutual funds that experience (1) one isolated event of unexpected extreme outflow (the event is centered at time t), (2) two consecutive quarters of unexpected extreme outflow (the event begins at time $t-1$ and ends at t), (3) three consecutive quarters of unexpected extreme outflow (the event begins at time $t-2$ and ends at time t), (4) four quarters of consecutive unexpected extreme outflow (the event time is between time $t-3$ to time t).

Proportional effective measure in the bottom quintile of the fund holdings

1 period	$t-3$	$t-2$	$t-1$	t	$t+1$	$t+2$	$t+3$	$t+4$
Aggressive Growth	1.0920	1.1088	1.1219	1.1253	1.1117	1.0589	1.0622	1.1013
Growth	0.5957	0.5854	0.5981	0.6079	0.6064	0.5807	0.5568	0.5174
Income	0.5667	0.5672	0.5999	0.6665	0.6272	0.6197	0.5578	0.5479
Growth & Income	0.5696	0.5399	0.5380	0.5692	0.5606	0.5201	0.5192	0.5241
2 cont. periods	$t-3$	$t-2$	$t-1$	t	$t+1$	$t+2$	$t+3$	$t+4$
Aggressive Growth	1.1642	1.1518	1.1432	1.1212	1.0433	1.0558	1.1356	1.1791
Growth	0.6146	0.5973	0.6429	0.6789	0.6404	0.5905	0.5386	0.5780
Income	0.5661	0.5665	0.5209	0.6099	0.5429	0.5581	0.5562	0.5485
Growth & Income	0.5972	0.6616	0.6237	0.6206	0.5328	0.5895	0.5546	0.5432
3 cont. periods	$t-3$	$t-2$	$t-1$	t	$t+1$	$t+2$	$t+3$	$t+4$
Aggressive Growth	1.1384	1.1837	1.0974	1.0128	0.9904	1.0109	1.0486	1.0202
Growth	0.6382	0.6547	0.6920	0.6436	0.5963	0.5620	0.6072	0.6917
Income	0.6125	0.5499	0.5074	0.6268	0.6351	0.5553	0.5485	0.6236
Growth & Income	0.6438	0.6224	0.6250	0.5404	0.6122	0.5512	0.5465	0.5817
4 cont. periods	$t-3$	$t-2$	$t-1$	t	$t+1$	$t+2$	$t+3$	$t+4$
Aggressive Growth	1.2553	1.1945	1.1228	1.0635	1.0176	1.0451	1.0815	1.0799
Growth	0.6497	0.6379	0.6120	0.5828	0.5609	0.5743	0.6162	0.6188
Income	0.7938	0.7522	0.6883	0.6803	0.6683	0.6565	0.6710	0.6785
Growth & Income	0.5991	0.6025	0.6227	0.6167	0.5413	0.5602	0.6262	0.6601

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APPENDIX A

Data Appendix for Chapter 3

A.1. NYSE Trade and Quote Database (TAQ)

For data cleaning of the TAQ database, I follow the methodology introduced by Chordia et al. (2001) and Chordia et al. (2002).

First, assets in the following categories are filtered out as their trading characteristics may differ from ordinary stocks: certificates, ADRs, shares of beneficial interests, unites, companies, company incorporated outsize of the US, Americus Trust components, closed-end funds, preferred stocks and REITs.

In order to avoid the influences of unduly high priced stocks and penny stocks, I will only consider securities priced between \$5 and \$1000. Moreover, only trades and quotes within the trading hours are considered. Trades with special settlement conditions and quotes with special conditions are removed. Any extremely large trade, with trade size larger than 10,000, are eliminated.

The following conditions must be satisfied for the quotes to be included in the database: the *quoted spread* is positive and less than \$5, the ratio between the *effective spread* and the *quoted spread* is less than 4, the ratio between the *proportional effective spread* and the *proportional quoted spread* is less than 4, and the ratio between the *quoted spread* and the transaction price is less than 4.

A.2. Thomson Financial and MFLinks

MFlinks is a data set that provides the link between two major mutual fund database: (1) CRSP mutual fund database which contains fund characteristics details such as fees and expense ratio, and (2) Thomson Financial mutual fund database which contains the equity holdings of the mutual funds. Created by the Wharton Research Data Services (WRDS) following the methodology suggested in Wermers (2000), MFLinks contains a new unique variable *wficn* (Wharton Financial Institution Center Number) that is linked to the identifier *icdi* from CRSP mutual fund database, and it is also linked to the identifier from Thomson Financials mutual fund database, *fundno*. MFlinks provides the link for approximately 92% of the US equity mutual fund universe.

A few additional adjustments are made to the data in MFLinks which are described below. First of all, the current version of MFlinks contains the link between the two databases only up to the end of 2004. Therefore, I have used the fund ticker, reported in both of the mutual fund databases in recent years, as an identifier to match the funds in 2005. The link extends the database for the funds that continue to exist in year 2005. The second issue concerns the specific date structure of the Thomson Financial database (TFN). There are two distinct date variables *fdate* and *rdate* in the TFN data. *fdate* is the date at which the mutual fund files the holding data and *rdate* is the date at which the mutual holding is valid.

Although in theory, the link between *wficn* and *fundno* should be unique at each point in time, this is not the case. Since the investigation in this chapter is concentrated at the end of each quarter, in the case that there are two valid *rdate* variables within the same quarter, only the latest one is kept. However, I find instances where two different *fundno*s are merged with the same *wficn* at the same point in time with *rdate* overlaps, resulting in two portfolio holdings at the same time for one fund. A close look at these merges reveals that there are two records of the same fund in the Thomson Financial database under two different *fundno*s. This could be due to the way Thomson Financial records startup, mergers and acquisition of funds over time. I compare the fund characteristics, such as the total net asset and the fund return, reported by TFN and CRSP mutual fund database. Preferences are given to the matched *fundno-icdi* pair with the closest total net asset value and return. In the case when both of the records seem the same, I choose the pair with the longer time series.

In the resulting database, one *fundno* is matched to one *wficn* at the end of each quarter. Moreover, the following filters are imposed to remove undesired observations from the sample:

- To filter any remaining data errors and mismatched funds, the difference between the total net asset value reported between Thompson and CRSP mutual fund database should not be too large: If the difference is greater than 35%, then the match is deleted from the entire data set. If there is a difference greater than 20% for more than 15% of the observations, the match is also deleted from the entire sample.
- If there is any activity of merger and acquisition or splits in a particular quarter, the observation is deleted.
- Without any requirements that *rdate* has to be equal to *fdate*, there could be stale data where the holding record is more than a year old. Therefore, if the

difference between *fdate* and *rdate* is more than 6 months, the observation is removed from the sample.

- Minimum requirement for fund inclusion: Fund must have at least 4 consecutive quarters of holdings, it must have at least 20 stock holdings and at least 10 million in total net assets at some point.
- The investment style assignment follows the algorithm by Pástor and Stambaugh (2002). Any funds with unknown objectives are filtered out of the sample.
- Although CRSP mutual fund database does not contain a detailed holdings file for earlier years, it does contain the percentage a fund holds in cash, bond, common stocks, convertible stocks, preferred stocks and warrants in an annual frequency. Since these variables are only reported at low frequency, it is not utilized in the analysis. However, they are used to further filter the funds to ensure a clean sample of equity funds. Funds that on average invest less than 80% in equities are filtered out of the entire sample.

The resulting dataset contains quarterly holdings for 3037 funds and 108,974 fund-quarter observations from 1980 to 2005.