TEODOR CHAVDAROV DYAKOV

Empirical Studies on Actively Managed Mutual Funds

New Insights into the Costs and Benefits of Portfolio Disclosure

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Chapter 1

Introduction

The growth of the mutual fund industry has been impressive. By the end of 2012, the amount of assets managed by mutual fund managers worldwide reached $26.8 trillion.[1] It is therefore not surprising that numerous studies have investigated the performance of fund managers and the implications stemming from their actions. This dissertation builds on this stream of research and includes three empirical studies that provide new insights into the mutual fund industry. Before I discuss these studies in greater detail, I provide a brief overview of the institutional context of mutual funds.

Mutual funds can broadly be defined as registered investment companies that pool capital from investors and collectively invest this capital in securities. Shares in mutual funds can be bought directly from the funds, via brokers, or in the open market. Mutual funds are usually classified by their investment objective, such as "growth stocks", "municipal bonds", "high-yield corporate bonds", etc. Funds can further be distinguished according to whether they try to mimic an index or actively try to beat an index, their fee structure, and other fund characteristics.

Interestingly, mutual funds have been around for a very long time. In fact, the first mutual fund was founded not very far from where most of the work involved for this dissertation was carried – Amsterdam. Following the financial crisis of 1772-1773, a Dutchman called Abraham van Ketwich offered subscriptions to a trust named "Eendracht Maakt Magt" ("Unity Creates Strength", the maxim of the Dutch Republic at that time). The idea behind the trust was to provide small investors the possibility to diversify their limited capital across stocks in various European countries and colonial plantations in the Americas (Rouwenhorst (2004)).

Central to this study is the portfolio disclosure regime under which mutual funds operate. The Securities and Exchange Commission in the US (SEC) requires mutual funds to disclose periodically the composition of their portfolios to existing and potential investors. As of 2004, mutual funds are required to report their holdings once every quarter. Prior to 2004, the SEC required mutual funds to disclose their holdings on a

[1] The number is obtained from the Investment Company Institute.

semi-annual basis, although many of the funds voluntarily reported on a quarterly basis. This rule intends to provide investors with more information for monitoring the actions of fund managers and to assist investors in deciding how to allocate capital across funds. Yet, concerns have been expressed that under a more frequent disclosure regime, predatory and free-riding practices would increase and harm funds' performance.

This dissertation bundles three empirical studies which provide new insights into the costs and benefits of portfolio disclosure. Chapter 2 demonstrates that the mandatory portfolio disclosure stipulated by the SEC exposes mutual funds in distress to predatory trading. To show this, we investigate the performance of a simple trading strategy which front-runs the anticipated forced sales by mutual funds in distress. Using the well-documented performance-flow relationship, we forecast the set of funds expected to experience extreme outflows. When future outflows arrive, funds have no other option but to sell assets in order to meet redemptions. Even though we do not observe the exact trading decisions of fund managers, we use portfolio holdings information to approximate the stocks most likely to experience selling pressure. Thus, we short-sale stocks that are commonly held by mutual funds expected to experience extreme outflows. To make this strategy work, however, we exclude the set of the largest stocks. The reason is that these stocks are so liquid that any fund driven selling pressure gets quickly offset by other market participants. The simple trading strategy produces 0.5% alpha per month. We further find a clear downward trend in the performance of the trading strategy, potentially due to improvements in market liquidity over time. We also show that the duration of the anticipated selling pressure has decreased from about a month in the 1990s to about two weeks in the most recent decade. The results in this chapter suggest that there are important potential negative effects stemming from mandatory holdings disclosure on mutual funds in distress.

Chapter 3 uses portfolio holdings data to study investor sophistication. Many recent papers argue that investors are naive and inexperienced in making their capital allocation decisions across the plenitude of funds available. This study, however, shows that information about managerial skill stemming from portfolio holdings is used by investors and enhances the performance of their investments. To do this, we construct a simple portfolio based measure of managerial skill – the "Return Gap" of Kacperczyk et al. (2008). This skill measure is easy to construct and interpret, is persistent, and can predict future performance over and above other indicators. We provide a number of empirical results, consistent with the hypothesis that investors use the return gap as an information variable for inferring managerial skill. We show that fund investors partially base their investment decisions on the return gap and that the effect is increasing in investor sophistication. Similarly to other performance measures, investors pay high attention to funds with higher return gaps and less attention to funds with lower return gaps. Our analysis further shows that in times when there is less information content in other performance measures, investors put a higher weight on the return gap. Last, we show that investors not only use the return gap as an information variable, but they also gain for utilizing this information. Overall, chapter 3 shows an important benefit from portfolio disclosure – investors use portfolio holdings in order to separate skilled from unskilled fund managers.

Chapter 4 looks at one of the most important questions about mutual funds – do funds possess an information advantage over other market participants? To study this question, we investigate the benchmark-adjusted performance of quarterly mutual fund trades. We find that prior to 2001 and consistent with the study of Chen et al. (2000), stocks purchased by actively managed mutual funds outperform stocks they sell. However, we find the opposite pattern after 2001 – stocks purchased by funds have lower returns than stocks sold. The drop in the performance of the aggregate mutual fund trades (buys minus sales) amounts to 1.45% per quarter. These findings suggest that mutual funds may have lost their information advantage over time. The effect is stronger for the largest funds, is present in both skilled and unskilled managers, is unlikely to be attributed to non-informational driven trades, and is concentrated among the most widely held stocks. We find that reduction in selective access to firm information, following the implementation of Regulation Fair Disclosure, is likely to contribute to the declining information advantage of mutual fund managers.

Chapter 2

Front-running of Mutual Fund Fire-sales

2.1 Introduction

Selling pressure among the common stocks of mutual funds in distress can create a transitory price pressure, moving prices away from fundamentals (Coval and Stafford (2007)). Since fund flows are to a certain extent predictable and information on fund holdings is publicly available (albeit with a delay), there may be an incentive among sophisticated investors to exploit the expected price pressure effects by short-selling stocks, anticipating trades of mutual funds in distress. This study investigates the performance of a hypothetical trading strategy based on public information which shorts anticipated fire-sales (i.e. the anticipated forced sales by mutual funds expected to experience extreme capital outflows).

We construct our trading strategy selecting the stocks most likely to be sold by those funds that are most likely to experience severe outflows. First, we forecast fund flows using the well-documented flow-performance relationship by, among others, Ippolito (1992), and Chevalier and Ellison (1997), and Sirri and Tufano (1998). Investors tend to put their money in funds with a recent successful track record and tend to pull money out of funds with a poor track record, which implies forecastability of fund flows. Next, we use this predictability to identify the subsets of funds that are expected to experience extreme outflows or inflows. To select the stocks most likely to experience downward selling pressure, we select the stocks most widely held by funds expected to experience extreme outflows, netting out possible buying pressure from funds expected to experience extreme inflows. To make sure our strategy uses publicly available information only, we assume a two month delay between the portfolio snapshot date and the time when the holdings

This chapter is based on Dyakov and Verbeek (2013) Front-running of Mutual Fund Fire-sales. Journal of Banking and Finance 37(12), 4931-4942. We would like to thank Hank Bessembinder, Mathijs van Dijk, Clemens Sialm, Hao Jiang, Stefan Ruenzi, and seminar participants at the Rotterdam School of Management, Erasmus University Rotterdam, the 15th Conference of the Swiss Society for Financial Market Research in Zurich, the European Financial Management 2012 Symposium on Asset Management in Hamburg, and the FMA European 2012 Meeting in Istanbul, for useful comments.

become available to the public. We rebalance our short portfolio of anticipated fire-sales every month, when new public information arrives.

Our results indicate that this strategy generates an alpha of 50 basis points per month during the 1990-2010 sample period, which stems from stocks that are below the NYSE mean size. The results are economically important and highly statistically significant. Generally, it is difficult to disentangle information from price pressures and hence determine the source of profitability of such a strategy. We apply an indirect approach and examine price reversals before and after the portfolio holding month. More specifically, we estimate five-factor alphas of our short portfolio around the holding month. We find strong evidence for reversals following outflow-induced price pressure and report high negative alphas before and during the holding period and high positive alphas immediately after the holding period. Furthermore, we show that the arrival of unexpected stock earnings or the realization of analysts' forecasting error cannot explain the success of the front-running strategy, thus ruling out alternative information-based explanations. Even though the stocks generating the success of the strategy are below the NYSE mean size, they are evenly distributed across the largest three size quintiles.[1]

Our analysis of the above NYSE mean size stocks reveals that they are also subject to outflow-driven selling by mutual funds, but the price pressure among those stocks is more transitory and is harder to exploit. We report a strong selling pressure among those stocks prior to the holding period measured by a five factor alpha. However, the alpha is highly positive during the holding period which indicates that reversals among those stocks start before the trading strategy can anticipate them. There are at least two reasons why price pressure could be weaker among the largest stocks. First, institutional ownership is generally higher among larger, more liquid stocks (e.g. Gompers and Metrick (2001)). This means that for large stocks, there are more sophisticated traders and hence there is more capital available to step in when prices diverge from fundamentals. Second, information on fundamentals is easier to obtain. Barth et al. (2001), among others, indicate that the number of analysts covering a stock is strongly positively related to firm size, even after controlling for other stock characteristics.

In addition to the aforementioned analysis, we examine time variation in the returns of the front-running strategy and report a decreasing pattern in risk-adjusted performance, captured by a 10-year rolling five-factor alpha. The reason behind this is that the duration of the anticipated price pressures has decreased and prices already start reverting during the portfolio holding month in the second half of our sample period. Our analysis of daily returns during the holding month indicates that before 2000, the front-running strategy detects price pressures a month before they start reverting. After 2000, the duration of the identifiable price pressures has decreased to two weeks. This implies that despite the decreasing trend, the front-running strategy offers attractive returns even in more recent times and will likely remain profitable, at least in the near future.

[1] Note that the size distribution is highly skewed and its mean value is located in the top quintile. Thus, there are very few, but very large companies located above the mean.

The results in this paper provide insight into an important channel through which the situation of funds already in distress could be aggravated. Funds experiencing substantial capital outflows face an easy to implement free-riding trading strategy that could negatively affect their performance. Front-running has the potential to create negative-feedback spirals through which the distress of funds experiencing outflows could be exacerbated via the front-running trades of other investors. Furthermore, there are broad market-wide implications of front-running such as price overshooting, reduced liquidity when it is most needed, movement of prices away from fundamentals, and increased volatility (see De Long et al. (1990) and Brunnermeier and Pedersen (2005)). The potential harm of front-running for funds in distress can be exacerbated due to payoff complementaries, or the incentive of fund managers to withdraw capital in expectation of the redemptions of other investors (Chen et al. (2010)). Shoven et al. (2000) show that tax externalities may cause mutual funds in distress to further sell some of their equity positions.

In general, extreme fund inflows may also result in an upward price pressure enabling other market participants to front-run. However, funds with high inflows have some discretion in what to do with the inflow of money – they can scale up, initiate new positions, or retain cash for a few days/weeks until undervalued stocks are identified. In contrast, funds with high outflows can only scale down their positions, which makes the link between flows and price pressure stronger on the short side. Furthermore, funds with extreme inflows may even benefit from front-running. A front-runner who anticipates a fund's flows would go long in that fund's stocks, but the fund manager may decide not to scale up her positions and hence buy other stocks. This will benefit the fund manager who can cash the price effects associated with the front-runner's buys. In contrast, funds with extreme outflows are more likely to suffer from front-running because they can only scale down positions in response to the outflows. This makes investigating front-running of outflow-driven sales more important as it has direct implications for funds that are already in distress.

Our paper is related to a recently developed literature on price pressure within equity markets. The common ground in this work is that it recognizes that short-term demand curves can be less than perfectly elastic due to non-informational demand shifts. For example, Mitchell et al. (2004) show that around mergers, uninformed shifts in demand among professional investors creates transitory price pressure. Related to mutual funds, Ben-Rephael et al. (2011) point to short-lived price distortions caused by aggregated daily flows to mutual funds in Israel, while Lou (2012) explains mutual fund persistence and stock momentum with the price pressure caused by the flow-induced trading of mutual funds. There is also evidence that firms' managers are aware of the exogenous price distortions caused by mutual fund flow trading – Khan et al. (2012) show that when a stock is overvalued due to high mutual fund inflows, the probability of an SEO and insider sales tends to increase.

The paper closest to ours is Coval and Stafford (2007). It identifies ex-post the price-pressure effects caused by funds in distress and focuses on their price impact. Coval and Stafford (2007) further show that there is price pressure predictability among stocks with expected high outflows. We deviate from their analysis by investigating whether investors who use publicly available information only can exploit this predictability.

First, since there is a delay of at most two months between the reporting date of mutual fund holdings and the date they become available, our front-running strategy uses the same portfolio snapshots two months later than the one by Coval and Stafford (2007). Second, we use fund flow forecasts based on publicly available fund information prior to the construction of the short portfolio, while Coval and Stafford (2007) use flow forecasts based on a flow-forecasting model which uses information from their whole time period.[2] We contribute to the literature by showing that the negative price pressure predictability can be exploited by investors who use public information only. However, we show that this predictability cannot be exploited among the largest stocks, because their prices revert before the real-time front-running strategy can identify the price pressures. Last but not least, we show that the returns of the front-running strategies are decreasing over time but they can still be substantial.

Our paper is also related to a body of literature showing the investment benefits of institutions' portfolio disclosure. Verbeek and Wang (2013) investigate the performance of mutual fund copycat funds – funds that duplicate the disclosed holdings of active mutual funds, and find that such funds can generate higher returns than their target funds. Brown and Schwartz (2013) look at hedge funds and find no evidence that investors can benefit from disclosed hedge fund holdings, attributing the difference from the Verbeek and Wang (2013) study to the much more frequent portfolio rebalancing of hedge funds in comparison to mutual funds. They do, however, provide some indirect evidence that hedge funds front-run their own positions, prior to disclosure, in expectation of copy-cat investors. Wermers et al. (2012) show that the relative stock overweighting/underweighting in the cross-section of fund managers contains information on future returns that could be exploited. More related to our study, Zhang (2009) shows that some mutual fund managers can consistently identify the flow-induced sales of mutual funds in distress and benefit from providing liquidity.

2.2 Data Construction and Sample Statistics

This study combines a number of commonly used databases - CRSP Mutual Fund Database, Thomson Financial CDA S12 equity holdings database, the CRSP monthly and daily stock files, Compustat, and I/B/E/S. The CRSP Mutual Fund Database provides monthly fund net investor returns, total net assets and annual data on expenses, fees, and other fund characteristics. The Thomson Financial/CDA database covers quarterly/semi-annual holdings of mutual funds, as reported to the SEC or voluntarily reported by the funds, which we link to the monthly and daily CRSP stock files in order to obtain information on holdings' prices and returns (adjusting for stock splits and other share adjustments). Both mutual fund databases are free of survivorship bias and linked via the MFLINKS tool provided by WRDS. Our study focuses on US domestic actively-manged equity mutual funds, for which the data is most complete and reliable. Thus, we exclude index, balanced, bond, money market, sector, and international funds, as well as funds who do not

[2] Note that the purpose of the front-running strategy of Coval and Stafford (2007) is to show that mutual fund flow-induced trading can establish predictability in prices, not whether this can be exploited by investors.

invest primarily in common stocks. Since most actively managed US equity funds offer different share classes to investors, we sum the net assets over different share classes and take asset-weighted share class averages of different attributes such as returns and expense ratios. More details on the merging process and sample selection is available in Appendix A. We also use accounting data from Compustat and analyst forecast data from I/B/E/S for constructing our public information variables discussed later.

The summary statistics of our sample are presented in Table 2.1. We provide both means and medians since there are a few exceptionally large funds which drive the sample means upwards. In total, our data sample includes 2639 US actively managed mutual funds during the 1990 - 2010 period, which is in line with previous studies. The number of funds has grown from 457 in 1990 to 1321 in 2010 and peaks around the dot com bubble. The median number of stocks in the portfolios of the funds is 73 which implies a reasonable degree of diversification. The median assets under management is $211 million and has steadily grown over time. While the mean assets under management are about 2.5 times larger than the median in 1990, they are 4 times higher in 2010 which implies that the gap in net assets between the larger and the median funds has grown over time. The returns of mutual funds vary over time and follow the business cycle, with a mean of 0.71% and a median of 1.11% per month. Turnover and expense ratios are stable over time with median yearly values of 63% and 1.17%, respectively. Larger funds appear to trade more often and charge higher fees, as evidenced by their higher mean turnover and expense ratio values.

Following standard procedures in the literature, we define flows for fund j during month t as the return-adjusted difference in total net assets between the start and end date of month t, scaled by the fund's total net assets at the start of the month:

$$flow_{j,t} = (TNA_{j,t} - TNA_{j,t-1} * (1 + R_{j,t}))/TNA_{j,t-1} \tag{1}$$

where $R_{j,t}$ is the net return for fund j in month t and $TNA_{j,t}$ refers to the total net assets of fund j in month t.[3]

We report summary statistics about the monthly fund flows in Table 2.2. The yearly flow patterns indicate that the extremes of the fund flow distribution are the same over time. Although the mean and median values of monthly flows vary over time, the monthly flow percentile numbers in the last two columns indicate that a substantial number of funds had very negative or positive extreme flows in any year. On average, fund flows are -3.27% per month in the lowest decile and there is no month where fund flows in the lower decile are above -2.5%. This is particularly important for our study since high negative monthly fund flows are the source of the stock price pressure patterns that our front-running strategy tries to exploit.

[3] Consistent with Coval and Stafford (2007), we exclude funds whose information is too different between CRSP and CDA ($1/1.3 < TNA_{j,t}^{CRSP}/TNA_{j,t,}^{CDA} < 1.3$) and funds with too extreme changes in TNA ($-0.5 < \Delta TNA_{j,t}/TNA_{j,t-1} < 2.0$).

Table 2.1. Sample Descriptive Statistics.

This table provides summary statistics for the mutual fund sample. Net Assets are measured in millions of US dollars and turnover and expense ratios are expressed in percentages per year. Note that CRSP does not provide turnover ratios for 1991.

Year	# of funds	# of stocks		Net Assets		Net Return		Turnover		Expenses	
		Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
1990	457	77	55	270	120	-0.42	-0.24	87	58	1.45	1.20
1991	545	82	54	307	120	2.63	2.70	.	.	1.35	1.18
1992	611	92	57	369	135	0.78	0.95	74	55	1.33	1.20
1993	785	102	61	426	164	1.17	1.26	78	61	1.29	1.19
1994	923	111	65	456	142	-0.06	0.24	81	56	1.30	1.17
1995	1012	117	66	539	155	2.31	2.44	88	63	1.30	1.20
1996	1100	112	70	669	205	1.57	1.85	91	64	1.30	1.21
1997	1269	110	72	783	195	1.86	2.29	90	68	1.28	1.20
1998	1345	110	71	903	214	1.39	2.79	91	70	1.29	1.23
1999	1446	106	68	1012	222	2.02	1.47	93	71	1.30	1.23
2000	1556	116	72	1172	257	-0.04	-0.78	99	74	1.30	1.23
2001	1639	124	74	987	231	-0.63	-0.14	104	77	1.34	1.25
2002	1719	124	76	840	184	-1.90	-2.05	105	70	1.39	1.29
2003	1791	131	77	819	176	2.51	2.04	94	66	1.41	1.31
2004	1815	134	81	985	208	1.02	1.36	87	62	1.35	1.28
2005	1809	136	77	1078	231	0.63	0.39	87	62	1.31	1.25
2006	1755	138	77	1191	267	1.03	1.25	86	63	1.30	1.23
2007	1774	137	77	1358	307	0.60	0.94	86	63	1.26	1.18
2008	1678	141	75	1194	249	-3.65	-2.41	96	70	1.23	1.18
2009	1555	148	76	1039	223	2.49	3.73	101	69	1.25	1.18
2010	1321	144	80	1283	315	1.60	2.95	90	63	1.22	1.17
1990 – 2010	2639	125	73	928	211	0.71	1.11	91	66	1.30	1.23

Table 2.2. Fund Flow Summary Statistics.

This table provides monthly fund flow summary statistics for our mutual fund sample. Monthly flows are calculated as the percentage change in fund total net assets across two consecutive months, adjusting for fund returns.

Year	Monthly Flows			
	Median	Mean	Perc10	Perc90
1990	-0.10	0.38	-6.58	6.91
1991	0.12	1.39	-2.99	6.72
1992	0.50	2.33	-2.55	7.45
1993	0.53	1.93	-2.66	7.70
1994	0.32	1.40	-2.74	6.10
1995	0.35	1.86	-2.74	6.57
1996	0.45	1.92	-2.86	6.65
1997	0.42	1.91	-3.10	7.06
1998	0.05	1.16	-3.74	5.71
1999	-0.32	0.57	-4.55	5.49
2000	-0.01	1.24	-3.96	6.36
2001	-0.05	1.02	-2.56	5.37
2002	-0.31	0.72	-3.17	5.18
2003	0.02	0.95	-2.52	4.70
2004	-0.17	0.82	-2.74	4.62
2005	-0.39	1.53	-3.07	4.74
2006	-0.45	0.63	-3.12	4.13
2007	-0.53	0.03	-3.33	3.25
2008	-0.73	-0.37	-3.97	2.94
2009	-0.53	0.20	-3.25	3.06
2010	-0.58	-0.09	-2.98	2.59
1990 – 2010	-0.17	0.90	-3.27	5.09

2.3 Constructing the Fire-sale Front-running Strategy

2.3.1 Forecasting Fund Flows

The front-running strategy that we investigate aims to profit from the likely price pressures caused by funds that are about to experience extreme outflows. Hence, for this strategy to work, we need to forecast fund-specific flows and identify the funds that are most likely to experience extreme flows. The summary statistics, reported in Table 2.2, indicate that extreme inflows are realized as frequently as extreme outflows. Coval and Stafford (2007) and Lou (2012) show that these extreme inflows can also cause buying price pressure. This implies that our front-running strategy has to net out any buying pressure from the selling pressure. Therefore, in order to identify both buying and selling pressure, we forecast extreme fund outflows *and* inflows.

To accomplish this, we rely on the well-documented persistence of fund flows and the predictability of investors chasing past returns. Ippolito (1992), Chevalier and Ellison (1997), and Sirri and Tufano (1998), among others, show that mutual fund investors have the tendency to invest in successful funds and withdraw money from losing funds. This indicates that fund flows are strongly related to past fund flows and returns. However, the relationship between flows and performance is non-linear – fund flows respond stronger to past successful performance than to past poor performance. This indicates that modeling separately extreme inflows and extreme outflows might produce better results than modeling all fund flows together.

Therefore, in our empirical analysis we specify two logistic regression models: one estimating the probability of a fund to experience extreme outflows, and another one estimating the probability of extreme inflows.

In the first model, the binary outcome variable is equal to 1 if a fund was in the lowest decile of the fund flow distribution and 0 otherwise. Similarly, in the second model, the binary outcome variable is equal to 1 if a fund was in the top decile of the fund flow distribution and 0 otherwise. We use the same set of fund-specific characteristics as explanatory variables in both models. More specifically, we assume:

$$P\{Extreme\_Flow_{j,t} = 1\} = \frac{1}{1 + e^{-z_{j,t}}} \tag{2}$$

$$z_{j,t} = \alpha_t + \sum_{\kappa=1}^{n} \beta_{\kappa,t} flow_{j,t-\kappa} + \sum_{\kappa=1}^{n} \gamma_{\kappa,t} R_{j,t-\kappa} + \delta_{1,t} ln(TNA)_{j,t-1} + \delta_{2,t} ln(TNA)^2_{j,t-1} \tag{3}$$

The number of lagged flows and returns to be included in (3) can be determined empirically. We follow a parsimonious approach and include flows and returns up to lag 3. We further include log and log squared of net assets in order to capture possible non-linear differences in flows relating to fund size.

Each month we estimate the two logistic regression models and report the time-series average of each estimated coefficient in Table 2.3. Standard errors are estimated using the time series of estimated coefficients (in a similar fashion to a Fama-Macbeth regression). The results are in line with those documented previously in the literature – lagged flows, returns, and net assets have a very strong explanatory power for current extreme flows, both in terms of statistical significance and economic magnitude. Similarly to the vast body of literature, we find that more recent information is more important for investors' asset allocation decisions, which is manifested in the decreasing magnitude of the estimated coefficients of lags 1 to 3.

We want to construct an implementable front-running strategy, so using the averaged coefficients in

Table 2.3. Logistic Regression Results.

This table provides the results from regressing extreme fund flows on lagged fund characteristics. At the end of each month t between 1990 and 2010 we perform logistic regressions where the dependent variable equals to 1 if the fund flow is in the lowest decile of fund flows at time t and 0 otherwise (Panel A) or the dependent variable equals to 1 if the fund flow is in the highest decile of fund flows at time t and 0 otherwise (Panel B). Explanatory variables are fund flows at time t-1, t-2, and t-3, fund net returns at time t-1, t-2, and t-3, and the log of net assets and log squared of net assets at time t-1. The estimated coefficients are averaged across time and standard errors are calculated using the standard error of the mean.

	Panel A: Extreme Outflows								
	Intercept	Flow			Fund Net Returns			Ln(TNA)	Ln^2(TNA)
		Lag1	Lag2	Lag3	Lag1	Lag2	Lag3	Lag1	Lag1
Est	-2.217	-10.144	-6.292	-4.484	-10.959	-3.027	-3.652	0.041	-0.018
StE	0.101	1.653	2.272	0.751	1.832	2.104	0.861	0.038	0.004
	Panel B: Extreme Inflows								
	Intercept	Flow			Fund Net Returns			Ln(TNA)	Ln^2(TNA)
		Lag1	Lag2	Lag3	Lag1	Lag2	Lag3	Lag1	Lag1
Est	-2.381	12.095	8.913	5.925	14.051	7.223	4.866	-0.104	-0.01
StE	0.135	1.28	1.23	0.65	1.362	1.332	0.936	0.043	0.004

Table 2.4. Characteristics of the Funds with Expected Extreme Flows.

This table provides characteristics of funds that are forecasted to experience extreme flows. At the end of each month t between 1990 and 2010 we perform logistic regressions where the dependent variable equals to 1 if the fund flow is in the lowest decile of fund flows at time t and 0 otherwise (Model 1) or the dependent variable equals to 1 if the fund flow is in the highest decile of fund flows at time t and 0 otherwise (Model 2). Explanatory variables are fund flows at time $t-1$, $t-2$, and $t-3$, fund net returns at time $t-1$, $t-2$, and $t-3$, and the log of net assets and log squared of net assets at time $t-1$. We use the estimated coefficients from Model 1 (Model 2) in time t and explanatory variables one period ahead in time to estimate the probability of a fund to experience extreme outflows (inflows) in time $t+1$. If a fund flow is in the lowest decile of the estimated probability distribution to experience extreme outflows, then we select that fund as an Expected Outflow Fund. If a fund flow is in the highest decile of the estimated probability distribution to experience extreme inflows, then we select that funds as an Expected Inflow Fund. Net Assets are reported in millions of US dollars. Actual flow refers to observed fund flows during month $t+1$, expressed as percentage of net assets.

	# of Funds		Net Assets		# of stocks		Actual Flow	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Exp Outflow Funds	123	134	588	196	91	89	-1.63	-2.16
Exp Inflow Funds	123	134	537	228	100	93	7.81	7.15

Table 2.3 would result in look-ahead bias. Instead, we use the most recent estimates in month t to forecast fund flows in month $t+1$. This means that we only use the most recent publicly available information to forecast next month's flows.[4] We expect a fund to experience extreme inflows if it is in the top decile of the forecasted probabilities of experiencing extreme inflows. Similarly, we expect a fund to experience extreme outflows if it is in the top decile of the forecasted probabilities of experiencing extreme outflows.

Table 2.4 reports descriptive statistics of the funds with expected high inflows and outflows. On average, we expect 123 funds to receive an extreme inflow/outflow in the next period. This is an artifact of the way we construct our strategy – the expected funds with high outflows (inflows) are the ones in the top decile of estimated probability of experiencing outflows (inflows). Generally, funds with expected extreme flows are not big in size. The small median numbers of assets under management – \$228 and \$196 million, are in line with this. The higher mean numbers indicate that sometimes the size of the funds with high probability of experiencing extreme flows can be substantial. In contrast to the average fund in our sample, funds with expected high inflows/outflows hold more stocks in their portfolios – the median is 100 for the funds with high expected inflows and 91 for the funds with high expected flows. Table 2.1 shows that the median for the whole sample is 73 stocks. The actual flow values in the last two columns are particularly important – they indicate that our forecasting model adequately captures funds with extreme flows. The median number is higher for the funds with high expected inflows – this reflects the fact that the flow-performance relationship is stronger for funds with high inflows than outflows. Hence, it is easier to forecast extreme inflows than extreme outflows.

We further evaluate the out-of-sample fit of our model using the realized flow distributions in the forecasted month. If a fund within the top decile of *estimated probabilities of experiencing* outflows in month

[4]We also tried to minimize the impact of estimation error by averaging the estimated coefficients over the last five months and then using those averages for forecasting the probability of funds to experience extreme flows. Results remain largely unchanged and we therefore proceed with the more simple specification where we use the most recent estimates.

t is in the bottom decile of *realized* flows in month t, then we consider that fund to be a correctly identified outflow fund. Similarly, if a fund within the top decile of *estimated probabilities of experiencing* inflows in month t is in the top decile of *realized* flows in month t, then we consider that fund to be a correctly identified inflow fund. We are able to correctly forecast 48% (30%) of the funds with extreme inflows (outflows), with a standard deviation of 10% (8%). In contrast, using the OLS approach of Coval and Stafford (2007) for forecasting the *actual* fund flows results in 42% (27%) of correctly forecasted funds with extreme inflows (outflows), with a standard deviation of 10% (8%). This indicates that our logistic regression approach that models separately funds with expected inflows and funds with expected outflows produces better tail flow forecasts than a model where the actual flows of all funds are modeled jointly.

2.3.2 Expected Fire-sales

Forecasting fund flows can tell us which funds are potentially going to be involved in flow-driven transactions. To identify where exactly to expect price pressures, we need to look at the funds' portfolio holdings. Following Coval and Stafford (2007), we expect to observe more price pressure among commonly held stocks. The more-widely a stock is held by funds with expected high outflows, the more likely it is that this stock will experience a strong selling pressure. Therefore, the anticipated flow-induced sales should be concentrated among the most-widely held holdings of funds with high expected outflows.

Lou (2012) points out that around 60 cents of each dollar invested in a mutual fund is used for scaling up current positions. Thus, despite the opportunity to invest in other stocks or to hold cash, a substantial number of money flow in successful funds is used for scaling positions, potentially causing buying pressure in prices. Therefore, in order to estimate the selling pressure on the stock level, we follow Coval and Stafford (2007) and subtract the selling pressure in a given stock from the buying pressure in the same stock. The differences should net out any buying pressure effects from the selling pressure of funds in distress and hence provide us with a better estimate of where to expect downward selling pressure.

For each stock i that is held by the funds with expected high inflows and outflows, we sum the holdings of all funds with expected high inflows and subtract the holdings of all funds with expected high outflows. We scale this expected pressure variable using the average stock trading volume between months $t-12$ and $t-6$. More specifically,

$$E_t(Pressure\_1_{i,t+1}) = \frac{\sum_j (N_{j,i,t}|E_t(high\_inflows) - \sum_j (N_{j,i,t}|E_t(high\_outflows)}{AvgVolume_{i,t-12:t-6}} \tag{4}$$

where $N_{j,i,t}$ refers to the number of stocks i held by fund j, based on the most recent publicly available holdings information.

The Investment Company Act of 1940 historically requires funds to disclose the composition of their portfolios on semi-annual basis, via the N-Q (prior to May 2004) and N-CSR forms (after May 2004). Since

May 2004 all mutual funds were required to report their holdings quarterly although around two thirds of them voluntarily reported to the SEC or data providers on a quarterly basis prior to 2004. Importantly, funds are required to disclose their holdings to the public with a delay of no more than 60 days. For example, if a fund reports a portfolio snapshot for the end of January it needs to make the holdings report available to the public by no later than the end of March. Our study attempts to construct a front-running trading strategy which uses publicly available information only and we therefore start using the reported fund holdings two months after the true portfolio snapshot date. In the hypothetical example of a fund which reports holdings for the end of January, we start using its reported holdings at the end of March and include them for calculating the expected stock level pressure in (4) for the months of April, May, and June (taking into account stock splits and other stock adjustments). For July we start using the newly publicly disclosed holdings at the end of June, which refer to fund level holdings for the end of April. Since a large number of funds report on a semi-annual basis during our sample period, we include those funds' holdings in (4) if they are disclosed to the public at most 6 months ago.

A potential concern with this empirical setup is that the holdings data is delayed between 2 to 8 months, depending on the frequency of the reported fund holdings. Given that the median turnover of a fund in our sample is 66% per year, 11 to 44 % of holdings of the median fund are already outdated. We have repeated our analysis using portfolio holdings for at most 3 months after the 2 month delay. Results remain qualitatively similar and we therefore proceed using at most 6 months of the data coming from the same report, in order to make sure we have continuous time-series even for the funds reporting semi-annually.

This stock level expected price pressure variable is very similar to the one constructed by Coval and Stafford (2007). The main difference between our measure and theirs is that we use publicly available information only. The flow forecast of Coval and Stafford (2007) is based on Fama-Macbeth estimates spanning the entire sample while we use real-time data. More importantly, they do not employ a delay of two months to account for portfolio information becoming publicly available. While their analysis shows that there is predictability of flow-driven trades, it can not show whether this can be exploited by investors relying on public information only. Similarly, Lou (2012) shows that there is price pressure predictability in stock prices following aggregate flows in the mutual fund industry, but this does not imply that this predictability can be exploited by investors.

The stocks with the highest expected downward price pressure are the ones with the highest probability of being commonly sold by funds in distress. Therefore, we select the stocks in the lowest decile of (4), which are the stocks ex-ante most likely to be in an outflow-driven sale in the next month. We take an equal-weighted average of all stocks in that portfolio. We call the stocks in that portfolio $Expected\ Fire-sales$. Thus, estimating the expected price pressure in (4) takes place at the beginning of the event month when we select the $Expected\ Fire-sales$. Rebalancing happens at the end of the $Holding\ Period$. We link the rebalanced portfolio returns and form a time-series of returns of our portfolio of expected fire-sales stocks, which constitutes our front-running strategy.

Table 2.5 reports the characteristics of the stocks expected to be fire-sales during the holding period. On average, we select 252 stocks in the expected fire-sale portfolio. The total number of months for testing the fire-sale front-running strategy is 246. In only two of them we have less than 25 stocks in the portfolio. We further subdivide the sample along the NYSE mean size, which is month-specific. The majority of the stocks are below the mean - on average there are 194 below mean stocks per month (79%) and 58 above mean stocks. There are 244 months with more than 25 stocks below the mean and only 156 months with more than 25 stocks above the mean. Yet, stocks below the NYSE mean size are not illiquid stocks. Since the size distribution is highly skewed to the left, the mean size is located in quintile 5. Less than 15% of the stocks included in the front-running strategy are in the first two size quintiles, which implies that shorting the expected fire sale stocks should not be hindered by short sale constraints or illiquidity. In terms of book-to-market ratio, we observe a tilt towards low book-to-market stocks among the below-mean stocks. This is consistent with fire-sales being stocks that are already in distress. Yet, the past 12-month return distribution does not reveal any particular tilt towards past losers or winners.

Table 2.5. Characteristics of the Expected Fire-sales.

This table provides summary statistics for the expected fire-sale stocks. For each stock held by mutual funds at the end of month t between 1990 and 2010 we construct an expected pressure score by summing all mutual fund holdings by funds expected to experience extreme inflows in month $t+1$ and subtracting all mutual fund holdings by funds expected to experience extreme outflows, scaling the difference with the average trading volume between months $t-12$ and $t-6$. We label the stocks in the bottom decile of the expected pressure distribution as "expected fire-sales". We rebalance the portfolio of expected fire-sales at the end of each month. In Panel A, we report the average number of observations, the number of months for which we have observations, and the number of months for which we have more than 25 observations in the expected fire-sales portfolio. In Panels B, C, and D we report the distribution of stocks along five book-to-market, size, and last 12 month return month specific NYSE quintiles. We report numbers for all stocks in the "expected fire-sale portfolio" as well as for the subsamples of stocks below and above the mean NYSE stock size at the time of portfolio construction.

			Panel A: Frequencies		
	Observations Average	Months	Months|obs>25		
All stocks	252	246	244		
Below mean size	194	246	244		
Above mean size	58	238	156		
			Panel B: B/M		
	Q1 (low) (%)	Q2 (%)	Q3 (%)	Q4 (%)	Q5 (high) (%)
All stocks	22.63	24.27	21.82	18.70	12.58
Below mean size	19.01	22.72	22.52	21.05	14.70
Above mean size	36.21	30.05	19.22	9.91	4.61
			Panel C: Size		
	Q1	Q2	Q3	Q4	Q5
All stocks	2.84	11.50	23.18	30.22	32.26
Below mean size	3.59	14.57	29.37	38.30	14.16
Above mean size					100.00
			Panel D: PrRet		
	Q1	Q2	Q3	Q4	Q5
All stocks	17.44	21.02	20.36	22.14	19.04
Below mean size	19.85	20.80	18.66	20.83	19.86
Above mean size	8.41	21.86	26.74	27.01	15.98

2.4 Performance of the Expected Fire-sales

We evaluate the performance of the strategy based on anticipated fire-sales using a five-factor model, including the excess return of the market, SMB, HML, MOM and the traded liquidity factor of Pastor and Stambaugh (2003). Throughout this paper, we require at least 25 stocks per month, otherwise we drop that month's portfolio observation. Results are reported in Table 2.6. Overall, the expected fire-sale stocks generate a negative alpha which is not statistically different from zero. The SMB loading indicates that the front-running strategy is slightly tilted towards small stocks. Since the front-running strategy covers expected fire-sales, we observe a negative loading on MOM. Systematic liquidity, proxied by Pastor and Stambaugh's traded liquidity factor, has a very low loading indicating little connection between the returns of the strategy and systematic liquidity.

The results in Panel A of Table 2.6 indicate that going short in all stocks with high expected flow-induced outflows cannot be profitable. This happens because the performance of the strategy is blurred by the most liquid stocks who revert before the front-running strategy can detect the flow-induced selling pressure. The results in Panels B and C hint in this direction. The five-factor alpha of the below mean stocks is -50 basis points, which is statistically highly significant and economically very large. However, the alpha of the strategy based on the anticipated fire-sales of stocks above the mean NYSE size is highly positive and amounts to 86 basis points per month. These results remain consistent if we use a reduced version of the five-factor model.

To investigate this sharp difference in returns between the two type of stocks in greater detail, we look at the five-factor alphas of the expected fire-sale stocks before and after the holding period month. Results over the 1990 – 2000 period are presented in Table 2.7. We can see that the positive alpha of large stocks, shown in Panel C of Table 2.6, is because reversals in those stocks start before the front-running algorithm can detect the price pressures. We observe a sharp negative alpha in the month preceding the holding period and a very quick reversal during the event month. Thus, liquidity has already arrived on the market before we can exploit the flow-induced trading. The smaller stocks have a more gradual price pressure pattern – pressure starts a few months before they are included in the front-running strategy and reverts in the 3 months following the holding period. Bessembinder et al. (2013) present a simple theoretical model which implies that front-running is profitable in less resilient markets, consistent with our findings that the success of the front-running strategy is driven by stocks below the mean size.

Our results indicate that liquidity arrives faster for larger stocks which prevents the front-running algorithm from exploiting the price pressure effects caused by funds in distress. Large stocks are subject to a greater analyst coverage which diminishes information asymmetries – liquidity providers can more easily attribute the price decline to a non-informed shock and step in the market to restore prices to fundamentals. Another reason why price pressure effects might be stronger for smaller stocks is that institutional investors prefer to hold larger, more liquid stocks (for example, see Gompers and Metrick (2001)). Greater institutional coverage implies that fresh liquidity arrives faster for larger stocks and consequently their prices restore faster to fundamentals.

Table 2.6. Five Factor Alphas of Expected Fire-sales During the Holding Period.

This table reports the risk-adjusted performance of the fire-sale front-running strategy. For each stock held by mutual funds at the end of month t between 1990 and 2010 we construct an expected pressure score by summing all mutual fund holdings by funds expected to experience extreme inflows in month $t+1$ and subtracting all mutual fund holdings by funds expected to experience extreme outflows, scaling the difference with the average trading volume between months $t-12$ and $t-6$. We label the stocks in the bottom decile of the expected pressure distribution as "expected fire-sales" and construct an equal-weighted average of the return of the "expected fire-sales" in month $t+1$. We rebalance the portfolio every month and obtain a time-series of equally-weighted portfolio returns. In Panel A we select all expected fire-sales. In Panel B we select expected fire sales that are below the mean NYSE stock size at the time of portfolio construction, and in Panel C we select the expected fire sales that are above the mean NYSE stock size at the time of portfolio construction. The risk factors included in the model are excess market returns (Mkt), SMB, HML, MOM, and the traded liquidity factor of Pastor and Stambaugh (2003). In all panels we drop months where we have less than 25 observations. Results are expressed as percentage per month.

	Alpha	Mkt	Smb	Hml	Mom	Liq
			A: All stocks			
Est	-0.18	1.18				
StdE	0.21	0.05				
Est	-0.38	1.18	0.42	0.36		
StdE	0.18	0.04	0.06	0.06		
Est	-0.19	1.09	0.44	0.28	-0.22	
StdE	0.17	0.04	0.05	0.06	0.03	
Est	-0.22	1.09	0.45	0.29	-0.22	0.05
StdE	0.17	0.04	0.05	0.06	0.03	0.04
			B: Below mean size			
Est	-0.49	1.22				
StdE	0.24	0.05				
Est	-0.74	1.20	0.52	0.40		
StdE	0.21	0.05	0.06	0.07		
Est	-0.48	1.08	0.55	0.30	-0.31	
StdE	0.18	0.04	0.05	0.06	0.03	
Est	-0.50	1.08	0.56	0.31	-0.31	0.04
StdE	0.18	0.04	0.05	0.06	0.03	0.04
			C: Above mean size			
Est	0.83	1.06				
StdE	0.27	0.06				
Est	0.77	1.08	-0.04	0.08		
StdE	0.28	0.06	0.08	0.09		
Est	0.83	1.06	-0.04	0.07	-0.05	
StdE	0.28	0.07	0.08	0.09	0.05	
Est	0.86	1.06	-0.04	0.07	-0.05	-0.09
StdE	0.28	0.07	0.08	0.09	0.05	0.08

The results in Table 2.6 suggest that it is possible to benefit from the selling pressure of mutual funds in distress using publicly available information only. Using a relatively-straightforward approach to forecast fund flows and to identify stocks with expected selling pressure, an equally-weighted short portfolio of stocks with expected high selling pressure produces an alpha of 50 basis points per month, provided that the largest stocks (above the mean size) are excluded.

We have to keep in mind the reported alpha of 50 basis points does not take into account the impact of transaction costs. Our front-running strategy is characterized with very high turnover – 71.78% per month, which implies relatively low break-even transaction costs of 0.35%. Consequently, the trading strategy may only be implementable by sophisticated traders who can afford to trade at low cost. On the other hand, sophisticated market participants may be able to obtain more accurate and more timely forecasts of the fire-sales of mutual funds than our econometric model based on publicly available information only.

In the rest of the paper, we examine the robustness of our main finding, including differences in prof-

Table 2.7. Five Factor Alphas of Expected Fire-sales Around the Holding Period.

This table reports the risk-adjusted performance of the fire-sale front-running strategy around the holding period. For each stock held by mutual funds at the end of month t between 1990 and 2010 we construct an expected pressure score by summing all mutual fund holdings by funds expected to experience extreme inflows in month $t+1$ and subtracting all mutual fund holdings by funds expected to experience extreme outflows, scaling the difference with the average trading volume between months $t-12$ and $t-6$. We label the stocks in the bottom decile of the expected pressure distribution as "expected fire-sales" and construct an equal-weighted average of the return of the "expected fire-sales" in month $t+1$ (the "holdings month"). We further construct equally-weighted portfolio returns for 6 months prior and after the "holding month". We rebalance the portfolio every month and obtain a time-series of equally-weighted portfolio returns. We report results using all stocks, and two subsets, according to mean NYSE stock size at the time of portfolio construction. The risk factors included in the model are excess market returns (Mkt), SMB, HML, MOM, and the traded liquidity factor of Pastor and Stambaugh (2003). We drop months where we have less than 25 observations. Results are expressed as percentage per month.

Month	All stocks		Below mean size		Above mean size	
	Est	StdE	Est	StdE	Est	StdE
-6	0.64	0.17	0.50	0.18	1.38	0.29
-5	0.68	0.19	0.44	0.19	1.14	0.25
-4	0.34	0.18	-0.02	0.19	1.22	0.26
-3	-0.49	0.19	-0.75	0.20	0.17	0.26
-2	-0.95	0.18	-1.18	0.19	-0.06	0.27
-1	-1.46	0.19	-1.43	0.20	-1.02	0.29
Holding Month	-0.22	0.17	-0.50	0.18	0.86	0.28
1	0.38	0.17	0.48	0.18	0.04	0.24
2	0.36	0.16	0.35	0.17	0.27	0.23
3	0.26	0.17	0.22	0.17	0.49	0.29
4	-0.01	0.17	0.01	0.17	-0.30	0.24
5	0.06	0.15	0.09	0.17	-0.26	0.23
6	0.15	0.16	0.20	0.17	0.31	0.29

itability over time (Section 2.5), alternative information-based economic sources of profitability (Section 2.6), and sensitivity to the number of funds and stocks used for portfolio construction (Section 2.7).

2.5 Time-variation in Returns

In this section we examine time-variation in the return of the expected fire-sales. A number of studies document important changes in the equity markets in the USA with an overall positive impact on market liquidity. Regulation Fair Disclosure (Reg FD), effective October 2000, limits the selective access of firm information to analysts and other investment professionals. Eleswarapu et al. (2004) show that due to decreases in asymmetric information, trading costs have decreased after the implementation of Reg FD. Another major regulatory change – The Sarbanes-Oxley Act (SOX), passed in 2002, includes provisions aimed at mitigating broker-agency conflicts.[5] Cumming et al. (2011) and Cumming et al. (2012) show that introducing new exchange rules that prohibit specific manipulative practices, such as ones arising from broker-agency conflicts, positively affect market liquidity and decrease insider trading incidences. In line with this conjecture Jain et al. (2008) find that liquidity has improved in the post-SOX period.

In a few steps between August 2000 and April 2001, the NYSE and NASDAQ replaced the historical system of fractional pricing with new decimal pricing. Bessembinder (2003) shows that the reduced tick size

[5] The SOX was enacted to promote accountability of public companies and restore investor confidence following a number of financial scandals.

resulted in decreased quoted and effective bid-ask spreads. The rise of algorithmic trading is another major recent technological change. Hendershott et al. (2011) provide causal evidence that algorithmic evidence improves liquidity. Finally, due to the growth in the hedge fund industry it is possible that the number of sophisticated investors engaging in front-running has increased over time, thus driving profits to zero. Shive and Yun (2013) provide evidence that hedge funds buy stocks in anticipation of mutual fund stock purchases. The theoretical model of Bessembinder et al. (2013) further suggests that the front-running strategy delivers better performance before these important changes took place, when markets were less resilient.

Having in mind these recent developments, we expect to find a decrease in the performance of the trading strategy over time. We first plot the 120 month moving two-factor alpha of the expected fire-sales and of the subset of below mean size stocks. The graph, plotted in Figure 2.1, suggests that by the end of 2010 the monthly profitability of the trading strategy has already evaporated. Next, we split our sample roughly in half and examine the performance of the trading in both subsamples. The breakpoint in 2001 roughly corresponds to the beginning of the regulatory and technological changes described above.

Figure 2.1. Rolling 120 Month Alphas of the Front-Run Fire-sales.

This figure reports the rolling 120 month risk-adjusted performance of the fire-sale front-running strategy. For each stock held by mutual funds at the end of month t between 1990 and 2010 we construct an expected pressure score by summing over all mutual fund holdings by funds expected to experience extreme outflows in month t+1 and subtracting all mutual fund holdings by funds expected to experience extreme inflows, scaling the difference with the average trading volume between months t-12 and t-3. We label the stocks in the bottom decile of the expected pressure distribution as "expected fire-sales" and construct an equal-weighted average of the returns of the "expected fire-sales" in month t+1 (the "holding month"). We rebalance the portfolio every month and obtain a time-series of equally-weighted portfolio returns in month t+1. We plot rolling 120 month alphas of the performance of the "expected fire-sales" and report results for all stocks included in the portfolio (solid line) and for the subset of stocks below the mean NYSE stock size at the time of portfolio construction (dashed line). The risk factors included in the model are excess market returns (Mkt), SMB, HML, UMD, and the traded liquidity factor of Pastor and Stambaugh (2003). We drop months where we have less than 25 observations. The horizontal axis indicates the final month of the 120-month investment window. Results are expressed in percentage points per month.

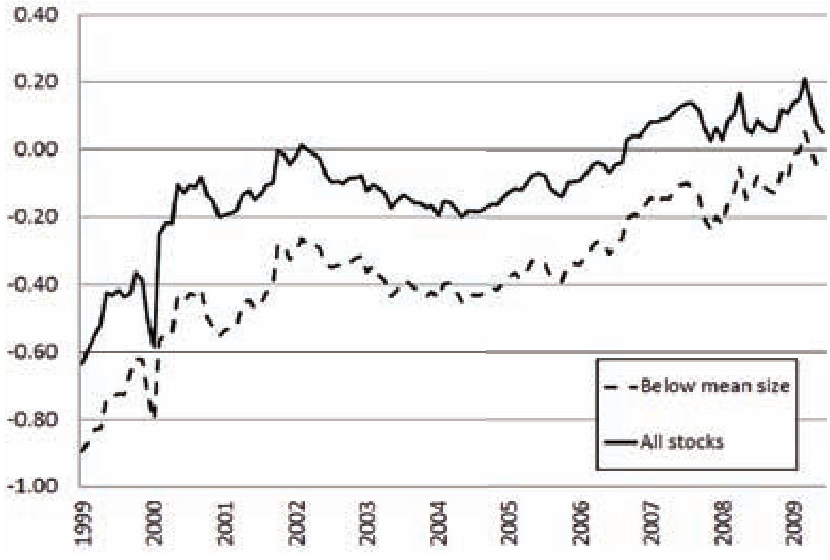


Table 2.8. Five Factor Alphas of Expected Fire-sales Around the Holding Period – Subsample Analysis.

This table reports the risk-adjusted performance of the fire-sale front-running strategy around the holding period. For each stock held by mutual funds at the end of month t between 1990 and 2010 we construct an expected pressure score by summing all mutual fund holdings by funds expected to experience extreme inflows in month $t+1$ and subtracting all mutual fund holdings by funds expected to experience extreme outflows, scaling the difference with the average trading volume between months $t-12$ and $t-6$. We label the stocks in the bottom decile of the expected pressure distribution as "expected fire-sales" and construct an equal-weighted average of the return of the "expected fire-sales" in month $t+1$ (the "holdings month"). We further construct equally-weighted portfolio returns for 6 months prior and after the "holding month". We rebalance the portfolio every month and obtain a time-series of equally-weighted portfolio returns. We report results using all stocks, and two subsets, according to mean NYSE stock size at the time of portfolio construction. The risk factors included in the model are excess market returns (Mkt), SMB, HML, MOM, and the traded liquidity factor of Pastor and Stambaugh (2003). In Panel A we show results for the period 1990-2000 and in Panel B we show results for the period 2001-2010. In both panels we drop months where we have less than 25 observations. Results are expressed as percentage per month.

Month	All stocks		Below mean size		Above mean size	
	Est	StdE	Est	StdE	Est	StdE
	Panel A: 1990 - 2000					
-6	0.71	0.27	0.45	0.29	1.41	0.43
-5	0.71	0.28	0.27	0.28	1.14	0.36
-4	0.60	0.27	0.10	0.29	1.33	0.35
-3	-0.64	0.28	-1.11	0.30	0.32	0.35
-2	-0.91	0.28	-1.30	0.28	0.07	0.43
-1	-1.35	0.27	-1.34	0.27	-1.02	0.38
Holding Month	-0.44	0.25	-0.62	0.24	0.42	0.34
1	0.20	0.26	0.48	0.28	0.11	0.33
2	0.57	0.22	0.71	0.25	0.36	0.30
3	0.14	0.23	0.15	0.26	-0.09	0.32
4	0.02	0.23	0.11	0.24	-0.42	0.31
5	-0.20	0.19	-0.14	0.22	-0.55	0.26
6	-0.05	0.21	0.04	0.24	-0.46	0.34
	Panel B: 2001 - 2010					
-6	0.41	0.20	0.41	0.21	1.08	0.36
-5	0.60	0.23	0.47	0.22	1.13	0.40
-4	-0.05	0.21	-0.20	0.22	0.72	0.36
-3	-0.50	0.26	-0.57	0.27	-0.38	0.41
-2	-1.02	0.21	-1.12	0.23	-0.25	0.32
-1	-1.52	0.26	-1.41	0.27	-0.97	0.48
Holding Month	-0.11	0.22	-0.08	0.23	1.02	0.49
1	0.47	0.23	0.45	0.24	0.17	0.39
2	0.17	0.21	0.07	0.22	0.33	0.37
3	0.33	0.24	0.21	0.23	1.09	0.50
4	0.01	0.25	-0.03	0.25	-0.09	0.40
5	0.10	0.23	0.07	0.25	-0.12	0.38
6	0.30	0.25	0.26	0.24	1.14	0.50

We present the subsample analysis in Table 2.8. The average pattern among above and below mean size stocks in columns 2 and 3 show that the identifiable pressure effects were stronger before 2001. This is especially the case for below mean size stocks. Columns 4 and 5 show that in the first half of the sample, there were economically very large price drops in the 3 months preceding portfolio construction and the whole holding period. After 2001, the size of the price pressure effects before the holding period has decreased, but during the holding period returns are zero, followed by reversals in the following month. Columns 6 and 7 report that the magnitude of the reversals among large stocks during the holding period has increased.

Both Table 2.7 and Figure 2.1 are based on a monthly holding period. We take a closer look in the daily returns during the holding month and report daily average cumulative returns in excess of a value-weighted portfolio of all stocks in CRSP in Table 2.9. We also plot the cumulative average abnormal returns (CAARs) in Figure 2.2. The results reported in Panels A of Table 2.9 and Figure 2.2 concur the evidence from the previous section, documenting substantial price drops for stocks that are below the mean NYSE size, and a clear upward trend for stocks above the mean NYSE size. In Panels B, we see that the price drops among below mean size stocks are more severe during the first half of the sample. The CAAR during the holding month follows a steady downward pattern, reaching -0.85% at the end of the month. The within month decreasing trend in the CAAR implies that the price pressures in the earlier half of our sample continue throughout the whole month and that reversals start after portfolio rebalancing.

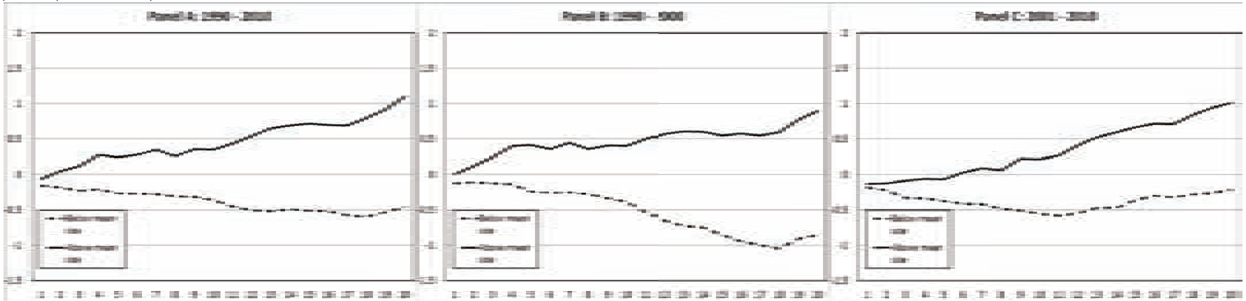
Table 2.9. CAARs During the Holding Period.

This table reports the daily cumulative average abnormal returns (CAARs) of the fire-sale front-running strategy during the holding month. For each stock held by mutual funds at the end of month t between 1990 and 2010 we construct an expected pressure score by summing all mutual fund holdings by funds expected to experience extreme inflows in month t+1 and subtracting all mutual fund holdings by funds expected to experience extreme outflows, scaling the difference with the average trading volume between months t-12 and t-6. We label the stocks in the bottom decile of the expected pressure distribution as "expected fire-sales" and construct an equal-weighted average of the daily return of the "expected fire-sales" in excess of a value-weighted return of all stocks in CRSP on that day for each trading day in month t+1. We rebalance the portfolio every month and obtain a time-series of equally-weighted daily portfolio returns. We report CAARs separately for the first 5, 10, 15, and 20 trading days during month t+1 and report results separately for two subsets of the "expected fire-sales", according to mean NYSE stock size at the time of portfolio construction. Results are expressed in percentage points per holding period.

		Days 1 - 5	Days 1 - 10	Days 1 - 15	Days 1 - 20
		A: 1990 - 2010			
Below mean size	CAAR (%)	-0.27	-0.36	-0.51	-0.46
	StdE	0.10	0.14	0.16	0.17
Above mean size	CAAR (%)	0.24	0.35	0.72	1.10
	StdE	0.11	0.13	0.22	0.33
		B: 1990 - 2000			
Below mean size	CAAR (%)	-0.24	-0.38	-0.85	-0.85
	StdE	0.12	0.16	0.31	0.54
Above mean size	CAAR (%)	0.41	0.40	0.55	0.89
	StdE	0.12	0.14	0.34	0.63
		C: 2001 - 2010			
Below mean size	CAAR (%)	-0.37	-0.55	-0.36	-0.21
	StdE	0.15	0.22	0.40	0.64
Above mean size	CAAR (%)	-0.07	0.22	0.66	1.01
	StdE	0.18	0.21	0.34	0.48

Figure 2.2. CAARs During the Holding Period.

This figure reports the CAARs of the front-running strategy during the holding month. The front-running strategy is defined in section 2.3.3. Abnormal returns are defined as stock returns minus value-weighted return of all stocks in CRSP on the day. We plot the CAARs for two subsets of stocks, according to mean NYSE stock size. For each stock held by mutual funds at the end of month t between 1990 and 2010 we compute an expected pressure score by summing all mutual fund holdings by funds expected to experience extreme outflows in month t and dividing all mutual fund holdings by funds expected to experience extreme outflows, scaling the difference with the average trading volume between months t-12 and t-3. We label the stocks in the bottom decile of the expected pressure distribution as "expected fire-sales" and compute an equal-weighted average of the daily returns of the "expected fire-sales" in excess of a value-weighted return of all stocks in CRSP on that day for each trading day in month t+1. We rebalance the portfolio every month and obtain a time-series of equally-weighted daily portfolio returns. We plot average daily CAARs during month t+1 and report results separately for two subsets of the "expected fire-sales", according to mean NYSE stock size at the time of portfolio construction. Results are expressed in percentage points per holding period.



In contrast, after 2000, reversals among the small stocks start much earlier - around 10 trading days after the estimation of the expected pressure variable. At that point, the CAAR reaches its lowest cumulative weakly value of -0.55% and prices start to revert. This explains why the monthly alpha estimate of the small stocks in the second half of our sample is roughly zero. Although reversals start earlier in the second half of the sample, the price pressure seems to be profitable even in this period. However, an investor willing to exploit the price pressure would need to rebalance more frequently (possibly every two weeks) after year 2000.

2.6 Alternative Information-based Explanations

Despite the transitory price pressure patterns reported in the previous sections, one might still conjecture that the success of the anticipated fire-sale strategy is driven by the incorporation of information. For example, an analyst forecast error, predicting higher than the actual earnings of a company might result in a very negative stock price reaction, once the earnings are announced and the error has been comprehended by market participants. This would result in a negative price reaction that could potentially drive the high abnormal returns documented earlier.

To test such information based explanations, we perform a Fama-MacBeth regression, regressing the returns of all stocks in the universe on common stock characteristics known in the literature to forecast returns, and two information variables. The dependent variable is stock returns in month t. Following Jiang et al. (2009), we include lagged size and book-to-market (both in logs), the previous 12 month return, the most recently available leverage ratio, and two dummy variables indicating whether the stock is a below or above mean NYSE size stock included in the front-running strategy. The two information variables that we include are standardized unexpected earnings (SUE) and analyst forecast error (FER). SUE is defined as reported quarterly earnings per share (EPS) in excess of EPS four quarters ago, scaled by the standard deviation of EPS over the past eight quarters or a minimum of four quarters (data is from Compustat). We include SUE in the regression if the EPS were announced in months $t-2$, $t-1$, or t. FER is defined as the realized quarterly EPS in excess of the mean of analysts EPS forecasts for that quarter, scaled by the previous year's book value of equity per share (data comes from IBES). We include FER in the regressions if the EPS were announced in months $t-2$, $t-1$, or t. We correct for possible autocorrelation and heteroscedasticity using Newey-West standard errors with 3 lags.

The results, reported in Table 2.10, cannot provide support for the alternative information based explanations. In the first specification, we do not include the two variables related to unexpected earnings. Consistent with our previous findings, the small stock dummy is negative and significant, while the large stock dummy is positive and significant. Including SUE and FER in the second specification, we still observe a positive value for the short_big dummy and a negative value for the short_small dummy. Thus, unexpected earnings and realization of analysts' forecast error cannot explain the pattern we observe in the

Table 2.10. Alternative Information Explanations.

This table reports the results of Fama-Macbeth regressions, where each the returns of all stocks in the universe are regressed on a number of variables, known in the literature to predict stock returns. Log(size), defined as log of the market cap of the stock in month $t-1$; Log(B/M), defined as the book to market ratio at the most recent fiscal year-end, assuming a four month reporting lag (i.e. the most recent data used is from month $t-4$); PrRet, defined as the average 12 month stock return as of the end of month $t-1$; Lev, defined as the ratio of book value of assets to debt value of assets as of the most recent fiscal year end, assuming a four month reporting lag (i.e. the most recent data used is from month $t-4$); Short_large, defined as a dummy variable equal to 1 if the stock is above the mean NYSE stock size and the stock is included in the short portfolio of "expected fire-sales" and 0 otherwise; and Short_small, defined as a dummy variable equal to 1 if the stock is below the mean NYSE stock size and the stock is included in the short portfolio of "expected fire-sales" and 0 otherwise. Standardized unexpected earnings (SUE) is defined as reported quarterly earnings per share (EPS) in excess of EPS four quarters ago, scaled by the standard deviation of EPS over the past eight quarters or a minimum of four quarters (data is from Compustat). We include SUE in the regression if the EPS were announced in months $t-2$, $t-1$, or t. Analyst forecast error (FER) is defined as the realized quarterly EPS in excess of the mean of analysts EPS forecasts for that quarter, scaled by the previous year's book value of equity per share (data comes from IBES). We include FER in the regression if the EPS were announced in months $t-2$, $t-1$, or t. We correct for possible autocorrelation and heteroscedasticity using Newey-West standard errors with 3 lags.

	Model 1		Model 2	
	Est	StdE	Est	StdE
Intercept	2.79	1.21	2.83	1.20
Log(size)	-0.13	0.07	-0.13	0.06
Log(b/m)	0.15	0.11	0.14	0.11
PrRet	1.71	3.44	0.56	3.43
Lev	-0.03	0.44	-0.06	0.44
Short_small	-0.32	0.15	-0.33	0.15
Short_large	1.35	0.33	1.35	0.33
Sue			0.06	0.01
Fer			1.17	0.36

previous section. Combined with the strong reversals documented in Table 2.7, we can rule out alternative information based explanations and conclude that our front-running strategy captures the transitory price pressure associated with the outflows of mutual funds in distress.

2.7 Robustness Checks

To test the robustness of our results, we investigate the sensitivity of the returns of the front-running strategy with respect to different expected fund flow and expected price pressure breakpoints of the expected pressure variable in equation (4). We select funds in the top (bottom) 15 and 5 % of estimated probabilities of experiencing extreme flows (instead of the original 10%), and the top 15 and 5 % of stocks with expected price pressure (instead of the original 10%). For brevity, we focus on the subset of stocks below the mean NYSE size during the whole sample period and compare five-factor alphas before, during, and after the holding month in Table 2.11.

The results indicate that the front-running strategy is robust to different specifications. Expanding the set of stocks (columns 6 and 7), we obtain very similar results to the baseline specification. However, decreasing the number of stocks (columns 4 and 5) renders the profits statistically insignificant. Given that the expected price-pressure phenomenon is present over a substantial number of stocks (as indicated in columns 6 and 7), decreasing the number of stocks implies a possibly greater effect of outliers, that is, stocks that were incorrectly assigned to the expected fire-sale portfolio. Furthermore, decreasing the number of stocks drives

Table 2.11. Robustness Checks Using Below Mean Size Stocks and Various Expected Fund Flow and Expected Stock Price Pressure Breakpoints.

This table reports the risk-adjusted performance of various definitions of the the fire-sale front-running strategy around the holding period. For each stock held by mutual funds at the end of month t between 1990 and 2010 we construct an expected pressure score by summing all mutual fund holdings by funds expected to experience extreme inflows in month $t+1$ and subtracting all mutual fund holdings by funds expected to experience extreme outflows, scaling the difference with the average trading volume between months $t-12$ and $t-6$. We consider different expected fund flow breakpoints ('EFF') in order to define funds as funds expected to experience extreme inflows or outflows. We label the stocks below certain level of expected stock price pressure ('EPP') of the expected pressure distribution as "expected fire-sales" and construct an equal-weighted average of the return of the "expected fire-sales" in month $t+1$ (the "holdings month"). For example, a front-running strategy with 'EFF'=0.10 and 'EPP'=0.05 selects funds in the top 10% of estimated probabilities of experiencing extreme inflows (outflows) and the top 5% of stocks with highest expected price pressure. We further construct equally-weighted portfolio returns for 6 months prior and after the "holding month". We rebalance the portfolios every month and obtain a time-series of equally-weighted portfolio returns. We report results only for the subset of "expected fire-sales" below the mean NYSE stock size at the time of portfolio construction. The risk factors included in the model are excess market returns (Mkt), SMB, HML, MOM, and the traded liquidity factor of Pastor and Stambaugh (2003). We drop months where we have less than 25 observations. Results are expressed as percentage per month.

Month	EPP=0.10		EPP=0.05		EPP=0.15	
	Est	StdE	Est	StdE	Est	StdE
	A: Below mean size, 1990 - 2010, EFF=0.10					
-6	0.50	0.18	0.49	0.21	0.53	0.17
-5	0.44	0.19	0.55	0.23	0.43	0.19
-4	-0.02	0.19	0.09	0.21	-0.03	0.18
-3	-0.75	0.20	-0.70	0.23	-0.87	0.19
-2	-1.18	0.19	-1.20	0.23	-1.04	0.18
-1	-1.43	0.20	-1.82	0.23	-1.44	0.18
Holding Month	-0.50	0.18	-0.25	0.22	-0.51	0.17
1	0.48	0.18	0.32	0.21	0.35	0.17
2	0.35	0.17	0.41	0.21	0.35	0.16
3	0.22	0.17	0.18	0.21	0.16	0.16
4	0.01	0.17	0.05	0.20	0.12	0.17
5	0.09	0.17	0.05	0.21	0.05	0.16
6	0.20	0.17	0.23	0.19	0.16	0.16
	B: Below mean size, 1990 - 2010, EFF=0.05					
-6	0.61	0.18	0.51	0.20	0.60	0.17
-5	0.53	0.19	0.55	0.23	0.56	0.17
-4	0.20	0.18	0.23	0.21	0.15	0.16
-3	-0.66	0.20	-0.56	0.23	-0.71	0.18
-2	-1.11	0.19	-0.99	0.23	-1.06	0.17
-1	-1.40	0.20	-1.64	0.23	-1.31	0.18
Holding Month	-0.38	0.17	-0.21	0.23	-0.42	0.16
1	0.30	0.18	0.27	0.21	0.25	0.17
2	0.37	0.17	0.37	0.21	0.31	0.16
3	0.33	0.17	0.11	0.21	0.26	0.16
4	0.06	0.17	-0.13	0.18	0.09	0.16
5	0.11	0.16	0.03	0.20	0.06	0.15
6	0.23	0.16	0.22	0.19	0.16	0.15
	C: Below mean size, 1990 - 2010, EFF=0.15					
-6	0.40	0.18	0.40	0.20	0.40	0.18
-5	0.34	0.20	0.46	0.23	0.37	0.20
-4	-0.04	0.20	0.05	0.22	-0.08	0.19
-3	-0.86	0.21	-0.76	0.23	-0.85	0.19
-2	-1.12	0.20	-1.18	0.23	-0.99	0.20
-1	-1.51	0.20	-1.83	0.24	-1.52	0.18
Holding Month	-0.52	0.19	-0.40	0.23	-0.51	0.18
1	0.42	0.18	0.34	0.22	0.34	0.18
2	0.28	0.17	0.34	0.21	0.26	0.17
3	0.17	0.17	0.17	0.22	0.09	0.16
4	0.00	0.18	-0.08	0.20	0.13	0.17
5	0.04	0.17	0.13	0.21	0.10	0.17
6	0.17	0.17	0.25	0.19	0.10	0.16

the size of the short portfolio particularly small in the first few years of our sample when there were fewer mutual funds and stocks. However, this problem is mitigated if we increase the threshold for funds and select the top (bottom) 15 % of estimated probabilities of experiencing extreme flows (Panel C). Then, even if we select only the top 5% of stocks with expected flow-induced selling pressure, the front-running strategy remains significant. In sum, the robustness checks offered in Table 2.11 indicate that our results are not driven by one particular specification.

2.8 Conclusion

This paper investigates the returns of a real-time trading strategy which front-runs the anticipated fire-sales by mutual funds experiencing extreme capital outflows. Our results indicate that publicly available information on flows and holdings of funds in distress offers viable investment opportunities. We show that the profitability of the strategy comes from the price pressure caused by funds in distress and identify important cross-sectional difference in the duration of those reversals. Despite a decreasing trend in the duration of price pressures that could be exploited, the trading strategy still offers substantial returns.

The trading strategy has two-building blocks. First, fund flows can be reasonably well-predicted due to the alpha chasing behavior of investors. Generally, investors' investments are directed towards funds with recent successful records, and money is redeemed out of funds with recent poor records. This allows the anticipation of selling pressure on the fund level. Second, stocks most-widely held by funds in distress are the ones with an ex-ante highest probability of experiencing outflow-induced selling pressure.

Our paper demonstrates that front-running of mutual fund flow-induced sales is a viable option, but it does not show whether it is actually implemented by sophisticated investors. This is hard to test due to unavailability of trading data – we do not really observe who trades what. Chen et al. (2008) investigate whether hedge funds engage in such front-running activities but due to this unavailability of data they can only provide an indirect evidence. They show that the average return on long/short strategies by hedge funds increases with a larger fraction of the mutual fund industry being in distress. Shive and Yun (2013) investigate the reported long positions of hedge funds and show that their holdings change in the direction of expected future flow-induced mutual fund trading. Nevertheless, they do not observe the short positions of hedge funds and cannot quantify the economic effect of trading in the direction of anticipated price-pressure. To our knowledge, the only paper that provides more direct evidence of actual front-running activities in general is by Cai (2003). She shows that during the LTCM crash, market makers front-ran customer orders coming from a particular clearing firm. Although Cai does not observe the identity of the firm, its orders closely match various features of LTCM's trades through Bear Stearns.[6]

We should keep in mind that the profits of the front-running strategy do not necessarily have to be at the expense of mutual funds in distress. We borrow a numerical example from Chen et al. (2008) to illustrate

[6] For a textbook discussion on different forms of front-running, please see Chapter 11 in Harris (2002).

this point. Consider that the front-running algorithm anticipates a substantial selling pressure in 100 shares of stock A 2 periods from now. Current price of stock A is \$100 per share. Without front-running, risk-averse investors would absorb the selling demand at time 2 for \$98 per share. Alternatively, the front-runner might short-sell 50 units of stock A at time 1 at price \$99 per share and risk-averse liquidity providers would absorb the 100 selling pressure at time 2 at price \$98 per share. In essence, this implies that the distressed fund(s) still sell stock A at \$98 per share at time 2, but the rest of the market buys 50 shares at time 1 for \$99 per share and another 50 shares at time 2 for \$98. This simple example illustrates that the front-running profits might come from the general public and not the distressed funds.

Yet, one might easily provide numerous counter-examples where front-running can actually harm funds in distress. For instance, in the above example, if the fund's need to sell 100 shares at time 2 is exacerbated by the price effect of the front-runner's short-sale at time 1, then the distressed mutual funds suffer from front-runners. This implies that our study might have important implications for funds in distress that experience substantial outflows. We do not directly show the potential negative consequences on funds in distress that could be caused by front-runners, but our results indicate that funds with substantial outflows are exposed to predatory trading and might suffer from the short-selling activities of front-runners. In times of distress, the last thing that fund managers need is predatory short selling that might drive down the value of their assets even further. Regulators are then left with the task to think how to protect funds in distress from the potentially destructive front-running of other market participants.

Appendix A: Data Selection

We start by selecting all US open-ended mutual funds from the CRSP mutual fund database and Thomson Financial CDA database from January 1990 till June 2010. To ensure that we cover the universe of domestic diversified equity funds, for which the holdings data is most reliable, we select in our sample only funds with one of the following objective codes, provided by Lipper, Wiesenberger, and Strategic Insight and available in the CRSP Mutual Fund Database:

- Lipper: 'EI', 'EIEI', 'EMN', 'FLX', 'G', 'GI', 'I', 'LCCE', 'LCGE', 'LCVE', 'LSE', 'MC', 'MCCE', 'MCGE', 'MCVE', 'MLCE', 'MLGE', 'MLVE', 'SCCE', 'SCGE', 'SCVE', 'SESE', 'SG'
- Wiesenberger:'SCG', 'AGG', 'G', 'G-S', 'S-G', 'GRO', 'LTG', 'I', 'I-S', 'IEQ', 'ING', 'GCI', 'G-I', 'G-I-S', 'G-S-I', 'I-G', 'I-G-S', 'I-S-G', 'S-G-I', 'S-I-G', 'GRI', 'MCG'
- Strategic Insight: 'SCG','GRO','AGG','ING','GRI','GMC'

Furthermore, we include funds only if they have one of the following investment objective codes in the Thomson Financial database: aggressive growth, growth, growth and income, or unclassified, thus excluding any international, bond, asset allocation, precious metal and sector funds. Then, we drop funds that hold less than 80% or more than 105% in common stocks, as reported by CRSP. We also drop index funds by removing funds that contain in their CRSP-reported fund name the strings 'INDEX', 'INDE', 'INDX', 'S&P', or 'MSCI'. From Thomson Financial database, we remove overlapping report dates and file dates caused by fund mergers and name changes. We also delete funds that hold less than 10 stocks or manage less than $5 million.

If a fund offers multiple share classes to investors, we aggregate across different share classes. For total net assets (TNA) under management, we sum the TNAs of individual shares. For funds's age, we select the age of the oldest share class. For the other fund attributes (expenses, turnovers, etc.), we take the weighted average of the attributes of the individual share classes, where the weights are the lagged TNAs of the individual share classes.

We link the two mutual fund databases, using the MFLINKS database provided by WRDS. More information on how MFLINKS assigns a unique fund identifier to each fund in the two databases can be found in Wermers (2000). We manually check the MFLINKS databases for assigning reports from different Thomson Financial funds to the same fund in MFLINKS, and resolve such problems manually.

Chapter 3

Do Investors Use Fund Holdings to Infer Managerial Skill?

3.1 Introduction

With currently more than $5 trillion assets under management[1], the equity mutual fund industry holds a substantial amount of the total market portfolio in the USA. Understanding how investors move capital across the plenitude of funds available is therefore important for studying the allocative efficiency of capital markets. Past studies have shown that investors make decisions primarily based on past performance[2], which may not be informative about future performance. In order to decrease the information asymmetries between managers and investors, the SEC requires mutual fund managers to report a snapshot of their portfolio holdings on a quarterly basis. Starting with Grinblatt and Titman (1989), a vast body of research has suggested that disclosed portfolio holdings contain valuable information for inferring managerial skill.[3] Yet, we know very little about whether investors use portfolio holdings data (in addition to return-based

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[1] According to data from the Investment Company Institute for December 2011.

[2] See, for example, Ippolito (1992), Chevalier and Ellison (1997), and Sirri and Tufano (1998).

[3] See, for instance, Grinblatt and Titman (1993), Daniel et al. (1997), Wermers (1999), Chen et al. (2000), Wermers (2000), Gompers and Metrick (2001), Cohen et al. (2005), Kacperczyk et al. (2005), Sias et al. (2006), Alexander et al. (2007), Jiang et al. (2007), Kacperczyk and Seru (2007), Cremers and Petajisto (2007), Baker et al. (2010).

performance indicators) to distinguish skilled from unskilled fund managers.

A priori, the answer to this question is unclear. On the one hand, there is much evidence pointing that investors are naive and inexperienced in their investment decisions. For example, Barber et al. (2005) show that investors are sensitive to only salient information and pay little attention to fund information which may not be immediately observable. Similarly, Choi et al. (2010) show that investors fail to minimize fees in the simplest possible context – choosing between otherwise identical index funds with different fee levels. These results suggests that investors pay little attention to information from fund holdings, which albeit publicly available, may be costly to obtain and difficult to process. On the other hand, most of the theoretical literature assumes a significant degree of investor sophistication. For example, Berk and Green (2004) model investor learning and suggest that investors can make optimal capital allocation decisions. Furthermore, Gruber (1996) and Zheng (1999) document a "smart money effect" – the tendency of investors to allocate capital to future winners. This evidence potentially suggests that investors may be sophisticated enough to use the information embedded in fund holdings when making their investment decisions.

This paper demonstrates that investors use information stemming from fund holdings in order to infer managerial skill. In particular, we study the sensitivity of fund flows to a simple, but powerful portfolio-based measure of managerial skill – the difference between fund returns and the hypothetical return of the most recently disclosed fund holdings. This difference, termed "the return gap" by Kacperczyk, Sialm, and Zheng (2008), captures the impact of interquarterly actions not directly observed by investors. Since the unobservable interquarterly actions of fund managers affect only the return of a fund without affecting the return of its most recently disclosed holdings, the return gap is a direct measure of the value-added of unobserved managerial actions. Consistent with Kacperczyk et al. (2008), we show that the return gap contains information about future performance which cannot be inferred from past performance and alpha. Therefore, the return gap stands as an ideal candidate for a decision-making variable.

Using a large panel of nearly 2500 actively managed US equity mutual funds over the period 1990 to 2010, this study documents that investors use the return gap (over and above other performance measures) when making their capital allocation decisions. More specifically, a one standard deviation increase in the return gap during the last four quarters is followed by a 0.96% or 1.34% increase in money flows in the following quarter, depending on the specification used. Consistent with the notion that the use of the return gap requires a certain degree of sophistication, we show that the presumably more sophisticated, institutional investors respond stronger to the return gap than do retail investors. Furthermore, we find that almost all of the sensitivity of fund flows is driven by a response to the funds in the top return gap quintile. In line with the theoretical framework of Huang et al. (2007), investors decide to invest in high return gap funds if and only if the expected utility of doing so outweighs the costs associated with processing information about fund holdings, which may drive the convexity documented in this paper. We also find that the sensitivity of fund flows to the return gap is stronger when there is less cross-sectional dispersion in fund performance, implying that the information content embedded in the return gap becomes more important when there is less information in past net performance.

Further, we investigate whether the documented response to the return gap helps investors enhance their returns. First, for each fund, we calculate the difference between the expected fund flows from a flow-performance model including the return gap with those from a flow-performance model excluding the return gap. This difference captures the capital allocated to mutual funds because of investors' response to the return gap. Next, we sort funds into 10 deciles based on this difference and investigate their performance over time. We demonstrate that funds that receive capital because of investors' response to the return gap perform better in the future than funds that experience redemptions because of investors' response to the return gap. More specifically, the four-factor alpha of the spread between the top and bottom portfolios amount to 17bp to 20bp per month, depending on the specification. This implies that the actual response to the return gap is "smart" because it helps investors enhance their returns.

Last, we implement additional tests to rule out alternative explanations for the findings in this paper. One possibility is that instead of basing decisions on the return gap, investors are guided towards skilled funds through brokers and financial advisors. We reject this conjecture by showing that there are no differences in the sensitivity of fund flows to the return gap across investors using financial advisors and brokers and those who do not. Another potential problem might be that the results are driven by the correlation of the return gap with other performance measures. To mitigate this concern, we study the determinants of the return gap and include them as additional controls in the flow-performance relationship. The results indicate that the sensitivity of investor flows to the return gap remains strong and statistically significant even after controlling for the effect of variables potentially correlated with the return gap.

The main contribution of this paper is to show that mutual fund investors can process publicly disclosed information on fund holdings and employ this to separate skilled from unskilled fund managers. Despite the recent findings that mutual fund investors are naive and inexperienced[4], there appears to be a sophisticated mass of investors who infer managerial skill from portfolio holdings data and invest in funds likely to add value in the future. Not only do fund holdings contain important information about managerial skill, but investors appear to actually use that information to enhance their returns. This paper also contributes to the literature on the "smart money effect". We show that at least part of the tendency of investors to allocate capital to future winners, documented by Gruber (1996) and Zheng (1999), is driven by investors' evaluation of skill-related information contained in disclosed quarterly fund holdings. Last, we contribute to the recent debate on whether the benefits of disclosed fund holdings outweigh the costs[5] by showing that at least some investors use reported fund holdings for mitigating information asymmetries.

This paper has the following structure. In Section 3.2 we introduce the data sample, construct the return gap and discuss its relevance. Section 3.3 provides the main evidence showing that investors use the return gap as an information variable. Section 3.4 investigates whether the actual response of investors to the return

[4]See, for example Barber et al. (2005) and Choi et al. (2010).

[5]A number of papers have shown that disclosing portfolio holdings may harm mutual funds. See, for example, Dyakov and Verbeek (2013) and Shive and Yun (2013).

gap helps them to enhance their returns. Section 3.5 provides additional analyses and robustness checks to rule out alternative hypotheses for our main findings, while Section 3.6 concludes.

3.2 Data Selection and the Return Gap

This study combines a number of commonly used databases - CRSP Mutual Fund Database, Thomson Financial/CDA equity holdings database, and the CRSP monthly stock files. The CRSP Mutual Fund Database provides monthly fund net investor returns, total net assets and annual data on expenses, fees, proportion of assets invested in common stocks, bonds, cash and other securities, and other fund characteristics. The Thomson Financial/CDA database covers quarterly/semi-annual holdings of mutual funds, as reported to the SEC or voluntarily reported by the funds, which we link to the monthly and daily CRSP stock files in order to obtain information on holdings' prices and returns (adjusting for stock splits and other share adjustments). Both mutual fund databases are free of survivorship bias and linked via the MFLINKS tool provided by WRDS. This study focuses on US domestic actively-manged equity mutual funds, for which the data is most complete and reliable. Thus, we exclude index, balanced, bond, money market, sector, and international funds, as well as funds that do not invest primarily in common stocks. Since most actively managed US equity funds offer different share classes to investors, we sum the net assets over different share classes and take asset-weighted share class averages of different attributes such as returns and expense ratios. More details on the merging process and sample selection is available in Appendix A.

Following standard procedures in the literature, we define flows for fund i during quarter t as the return-adjusted difference in total net assets (TNA) between the start and end date of quarter t, scaled by the fund's total net assets at the start of the quarter:[6]

$$Flow_{i,t} = (TNA_{i,t} - TNA_{i,t-1} * (1 + Return_{i,t}))/TNA_{i,t-1} \tag{1}$$

where TNA stands for total net assets and $Return$ for net fund return.

The summary statistics of the sample are presented in Table 3.1. In total, the sample covers 2486 equity mutual funds, ranging from 373 in 1990 to 1691 in 2006. Over time, the median amount of assets has increased from $137 million to $309 million. We also observe a tendency for mutual funds to hold a larger number of stocks in more recent times. Generally, the first half of our sample period (before 2000) is characterized with larger mean flows and higher returns than the second half. We further note that the mean annual expense ratios have remained about the same throughout the sample period.

The key variable in this study is the return gap of Kacperczyk, Sialm, and Zheng (2008), which is

[6] Consistent with Coval and Stafford (2007), we exclude funds whose information is too different between CRSP and CDA ($1/1.3 < TNA^{CRSP}_{i,t}/TNA^{CDA}_{i,t,}$) and funds with too extreme changes in TNA ($-0.5 < \Delta TNA_{i,t}/TNA_{i,t-1} < 2.0$).

Table 3.1. Summary Statistics of the Sample.

This Table summarizes the main summary statistics of the sample.

	# of funds	# of stocks	Net Assets, \$mil	Flow, % per quarter	Return, % per quarter	Expense Ratio, % per year
		(median)	(median)	(mean)	(mean)	(mean)
1990	373	56	137.19	0.73	-1.18	1.26
1991	420	56	130.83	3.61	8.33	1.27
1992	502	58	142.66	5.17	2.53	1.29
1993	536	63	173.26	5.18	3.73	1.26
1994	678	67	197.58	2.85	-0.11	1.26
1995	809	68	169.89	3.37	6.96	1.25
1996	920	71	185.53	3.94	4.48	1.24
1997	1000	74	222.20	3.61	5.58	1.23
1998	1160	73	229.57	1.99	4.27	1.26
1999	1201	70	233.10	0.62	6.95	1.26
2000	1374	72	272.15	2.87	0.15	1.27
2001	1408	75	276.30	2.66	-1.23	1.29
2002	1517	76	227.60	1.03	-5.39	1.33
2003	1595	75	171.00	2.24	8.25	1.36
2004	1691	81	214.00	1.22	3.12	1.33
2005	1679	78	232.30	1.32	1.86	1.30
2006	1691	78	261.65	0.77	3.13	1.27
2007	1621	77	306.10	-0.15	1.84	1.22
2008	1603	76	320.25	-1.23	-11.01	1.20
2009	1504	76	239.40	0.19	7.63	1.20
2010	1274	82	309.20	-0.43	-2.11	1.14
1990 – 2010	2486	74	229.17	1.54	2.03	1.26

constructed as the difference between the performance of the fund and the performance of the portfolio based on the fund's most recently reported holdings. More specifically, for each fund i in quarter t, the return gap is constructed as:

$$ReturnGap_{i,t} = Return_{i,t} - (HoldingsReturn_{i,t} - ExpenseRatio_{i,t}) \quad (2)$$

For each fund i, $HoldingsReturn_{i,t}$ refers to the quarter t return of the portfolio holdings disclosed at the end of quarter $t-1$ and $ExpenseRatio_{i,t}$ is the most recently available fund expense ratio at the beginning of quarter t. We use the stockholdings information provided by Thomson Financial in order to identify each common stock in a fund's portfolio. The data come from mandatory reports to the SEC as well as voluntary reports by the mutual funds. After 2004, all funds are required to report their holdings quarterly to the SEC. Before then, they were required to file their holdings semiannually, but about two thirds of the funds already reported quarterly. Even though we select funds with average percentage of assets invested in common stocks above 80% and below 105%, funds still have a proportion of their portfolio invested in other assets. We cannot identify the precise portfolio composition in those other assets and we proxy their returns with the returns of suitable indices. We proxy returns of bonds and preferred stocks with the Barclays Aggregate Bond Index (formerly known as the Lehman Brothers Aggregate Bond Index) and the return of cash and other assets with the Treasury Bill rate.[7] Since a number of funds included in the Thomson Financial/CDA

[7] The bond index data comes from Datastream and the return of Treasuries comes from Kenneth French's

database have long periods of missing data, we require the latest fund holdings used for calculating the return gap in quarter t to be no-older than 6 months as of the beginning of quarter t. The expense ratio used is the most recently reported as of the end of quarter t and reported no earlier than two years before the end of quarter t, and is calculated as one fourth of the actually reported yearly expense ratio.

The procedure for calculating the return gap follows Kacperczyk et al. (2008). The impact of unobserved actions is reflected in the net return of the fund, without affecting the hypothetical return of the fund's most recently disclosed holdings. Consequently, the difference between the fund's return and the return of the hypothetical portfolio, measured by the return gap, captures the value added (or subtracted) by fund managers via their unobserved actions. For example, value-adding unobserved trades would increase the return of the fund relative to the return of the previously disclosed holdings. On the other hand, trading costs and commissions and other value-decreasing unobserved actions affect negatively the return gap. Kacperczyk et al. (2008) show that unobserved actions of some funds persistently create value, while the unobserved actions of other funds persistently destroy value. Furthermore, they show that return gap helps predict performance – funds with hight return gap perform better in the future than funds with low return gap.

We provide summary statistics for the return gap in Table 3.2. In Panel A, we examine the distribution of the quarterly return gap. The mean return gap is negative, which implies that on average, the gains of the unobserved interquarterly actions of fund managers do not outweigh the trading costs. This skill measure is characterized with a substantial cross-sectional dispersion – the standard deviation of the return gap is 1.65% per quarter. In Panel B, we construct a cumulative yearly return gap for the funds in the sample and examine its correlation with other performance measures and its lagged value. Similarly to Kacperczyk et al. (2008), we find that the return gap is highly correlated with its past realizations. We find a positive and statistically significant correlation with fund size, though the economic magnitude is low. Furthermore, the return gap is negatively correlated with fund expenses, which implies that fees, on average, are not compensating for value-enhancing unobserved actions. Not surprisingly, the return gap is positively correlated with past returns and alpha because the return gap contributes to both net returns and alpha.

An important driver of the return gap is transaction costs. These costs affect fund performance negatively, without affecting the return of the previously disclosed fund holdings. Thus, funds paying high brokerage fees will typically have more negative return gaps than their peers. Grinblatt and Titman (1989) are the first to use the difference between fund return and the return of the most recently disclosed holdings for approximating transaction costs. Later, the same approximation for inferring transaction costs has been used by Wermers (2000) and Bollen and Busse (2006).

However, the return gap captures more than the effect of trading costs. The return gap may reflect informational advantages, or optimal timing of trades (Kacperczyk et al. (2008)). For example, a mutual fund manager may process news faster than the market and trade before her private information is incorporated

Data Library `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`.

Table 3.2. Summary Statistics of the Return Gap.

This Table summarizes the main summary statistics of the Return Gap. In Panel A, we provide distributional statistics of the quarterly return gap, expressed in percentages per quarter. In Panel B, we cumulate four consecutive return gap measures to form a Yearly Return Gap score. We provide Pearson and Spearman correlations with the lagged value of the Yearly Return Gap, the most recently available yearly Expense Ratio, contemporaneous fund alpha (estimated using past 12 months of data and the excess return on the market, SMB, HML, and Momentum as risk factors contemporaneous fund alpha), contemporaneous cumulative one-year fund return, and contemporaneous fund size. * denotes statistical significance on the 10% level, ** denotes statistical significance on the 5% level, and *** denotes statistical significance on the 1% level.

A: Distribution of Quarterly Return Gap				
Mean	Median	Stdev	Skewness	Kurtosis
-0.49	-0.50	1.65	0.04	3.52
B: Pearson/Spearman Correlations of Yearly Return Gap with				
Lagged Yearly Return Gap	Expense Ratio	Alpha	Net Return	Size
0.12***/0.19***	-0.12***/-0.23***	0.22***/0.21***	0.19***/0.17***	0.02***/0.07***

into prices. A manager may sell an overvalued stock in January, before the rest of the market brings the price of the stock closer to fundamentals in February. Consider also that the manager reported holdings at the end of December and will report next at the end of March (a realistic quarterly disclosure policy). In this case, the asset sale positively affects the return of the fund without affecting the return of the most recently disclosed holdings, driving upwards the return gap in that quarter. Using daily fund returns, Bollen and Busse (2005) demonstrate that stock selection and market-timing are short-lived phenomena whose effect on fund performance disappear within a quarter.

To understand how the return gap is different from alpha, consider the case when there is a shock to a stock in a quarter when the stock is not traded by the fund manager. In that case, the shock affects equally the most recently disclosed holdings and net return of the fund, and therefore does not affect the return gap. Yet, this shock is reflected in the overall risk-adjusted performance. In the hypothetical fund setup above, a manager may receive a private signal in February that a stock will experience surprisingly high earnings in April. The information content of the trade does not affect the return gap in quarter 1, because the net return is not affected until April. Furthermore, the trade does not affect the return gap in quarter 2, because it is not traded in quarter 1 and consequently it does not change the net return in quarter 2 relative to the most recent holdings disclosed at the end of quarter 1.[8]. This explains why we find the positive but less than perfect correlation between the return gap and alpha in Table 3.2

We conjecture that the information content embedded in the return gap is used by fund investors for three main reasons. First, it contains predictive power about future performance over and above other performance measures. Second, the return gap is highly persistent, which suggests that investors are likely to infer its future value from past realizations. Last, the return gap is relatively simple to construct and easy to interpret which makes it likely to be used by fund investors. Below we elaborate on each of those arguments separately.

The return gap can add value to fund investors if it provides them with an indication of future performance

[8]Empirical evidence on such trading behavior comes from, for example, Baker et al. (2010) who demonstrate that mutual fund quarterly trades predict next quarter's unexpected stock earnings

which is not already contained in other performance indicators. To show this, at the end of each quarter we double-sort funds on past returns or alpha and the return gap. Next, we collect the returns of the portfolios and rebalance. This way we obtain a time-series of double-sorted portfolios and examine their performance. Results are summarized in Table 3.3. In Panel A (B), we first sort on the cumulative fund net return (alpha) in the previous year, and then on the cumulative return gap in the previous year. Going from left to right in both panels, there is an increasing pattern in abnormal post-ranking performance. The spreads between the top and bottom quintile of funds sorted on return gap ranges between 6bp and 31bp per month. This indicates that the return gap contains predictive power about fund performance which complements the information in past net returns and alpha, rather than substituting it. The return gap is particularly informative about the future performance of the funds with the best/worst past performance, where the spread between funds with the highest and lowest realizations of the return gap ranges between 15bp and 31bp per month is significantly different from zero at conventional levels.

Next, we show that the return gap is highly persistent. At the end of each quarter we sort funds on their return gaps over the previous 1, 3, and 5 years, and find that it helps predict their return gap in the following quarter. The results, summarized in Table 3.4, show that the spread between the average return gaps of

Table 3.3. Fund Return Predictability Based on the Return Gap.

At the end of each quarter we sort funds in 5 quintiles based on past one year cumulative net return (Panel A) or past alpha (Panel B). Alpha is estimated using past 12 months of data and the excess return on the market, SMB, HML, and Momentum as risk factors. Next, we sort each of the quintiles in 5 quintiles based on past one year cumulative return gap. We collect the returns of the portfolios over the next three months and repeat the procedure. This way we obtain a time-series of quarterly return gap scores for each portfolio. Next, we evaluate the performance of each time-series of portfolio returns using a four-factor asset pricing model, where I use the excess return on the market, SMB, HML, and Momentum as risk factors. For each time-series of portfolio returns, we report the alpha and the corresponding t-statistic. * denotes statistical significance on the 10% level, ** denotes statistical significance on the 5% level, and *** denotes statistical significance on the 1% level.

A: Two-way Sorts on Net Return and the Return Gap							
Net Return		Yearly Return Gap					
		Q1	Q2	Q3	Q4	Q5	Q5-Q1
Q1	Alpha	−0.15	−0.19*	−0.02	−0.01	0.00	0.15*
	t-stat	−1.15	−1.90	−0.20	−0.10	0.00	1.67
Q2	Alpha	−0.06	−0.07	−0.08	−0.02	0.05	0.11
	t-stat	−0.86	−1.17	−1.33	−0.33	0.56	1.57
Q3	Alpha	−0.08	−0.07*	−0.06	−0.03	0.02	0.10*
	t-stat	−1.60	−1.75	−1.50	−0.75	0.33	1.67
Q4	Alpha	−0.14*	−0.06	−0.10**	−0.08	0.02	0.16***
	t-stat	−1.75	−1.00	−2.00	−1.60	0.33	2.67
Q5	Alpha	−0.14	−0.14	−0.05	−0.05	0.00	0.15*
	t-stat	−1.08	−1.17	−0.38	−0.42	0.00	1.88
B: Two-way Sorts on Alpha and the Return Gap							
Alpha		Yearly Return Gap					
		Q1	Q2	Q3	Q4	Q5	Q5-Q1
Q1	Alpha	−0.41***	−0.22***	−0.18**	−0.17**	−0.10	0.31***
	t-stat	−3.15	−2.75	−2.57	−2.13	−0.91	2.82
Q2	Alpha	−0.19***	−0.13***	−0.10**	−0.05	−0.11	0.09
	t-stat	−3.17	−2.60	−2.00	−1.00	−1.57	1.50
Q3	Alpha	−0.12**	−0.07	−0.05	−0.03	0.00	0.11**
	t-stat	−2.00	−1.40	−1.00	−0.75	0.00	2.20
Q4	Alpha	−0.08	−0.06	0.00	−0.02	−0.01	0.06
	t-stat	−1.14	−1.20	0.00	−0.40	−0.14	1.00
Q5	Alpha	−0.01	0.10	0.13	0.19*	0.17	0.17**
	t-stat	−0.08	1.25	1.44	1.90	1.13	2.13

Table 3.4. Persistence of the Return Gap.

At the end of each quarter we sort funds in 10 portfolios based on past 1, 3, or 5 year cumulative return gap. Next, we track the return gap of the portfolios over the next one quarter and repeat the procedure. This way we obtain a time-series of quarterly return gap scores for each portfolio. In Panel A, we use equal weights to aggregate returns and in Panel B we use fund net assets. We report portfolio means in percentages per quarter with t-statistics based on corresponding standard error of the mean. * denotes statistical significance on the 10% level, ** denotes statistical significance on the 5% level, and *** denotes statistical significance on the 1% level.

			A: Equally-weighted			
	1 year		3 year		5 year	
	Mean	t-stat	Mean	t-stat	t-stat	t-stat
1 (lowest)	−0.48***	−5.96	−0.53***	−8.41	−0.55***	−6.83
2	−0.44***	−10.39	−0.44***	−8.57	−0.43***	−8.80
3	−0.37***	−8.89	−0.38***	−9.21	−0.40***	−8.70
4	−0.28***	−8.16	−0.29***	−6.26	−0.32***	−6.23
5	−0.26***	−6.90	−0.22***	−6.66	−0.23***	−5.78
6	−0.13**	−1.99	−0.16***	−4.34	−0.20***	−4.67
7	−0.13***	−3.58	−0.13***	−3.10	−0.18***	−3.18
8	−0.08**	−2.08	−0.07	−1.41	−0.12**	−2.00
9	−0.02	−0.42	−0.07	−0.81	−0.09	−1.42
10 (highest)	0.20**	2.37	0.14*	1.95	0.04	0.47
High - Low	0.68***	7.91	0.67***	10.44	0.59***	6.86
			B: Value-weighted			
	1 year		3 year		5 year	
	Mean	t-stat	Mean	t-stat	Mean	t-stat
1 (lowest)	−0.53***	−4.92	−0.63***	−4.24	−0.65***	−5.86
2	−0.39***	−5.02	−0.40***	−4.92	−0.46***	−4.23
3	−0.32***	−4.39	−0.27***	−4.02	−0.36***	−5.12
4	−0.20***	−3.46	−0.16**	−2.26	−0.29***	−3.98
5	−0.16***	−3.66	−0.22***	−3.33	−0.15**	−2.03
6	−0.10	−1.61	−0.11**	−2.38	−0.14**	−2.00
7	−0.06	−1.31	−0.11*	−1.92	−0.14**	−2.01
8	−0.07	−1.32	−0.07	−1.11	−0.03	−0.54
9	0.04	0.86	0.00	0.07	−0.06	−0.92
10 (highest)	0.08	0.95	0.08	1.01	0.01	0.13
High - Low	0.61***	5.39	0.70***	4.70	0.66***	5.63

funds with the highest return gap and those with the lowest return gaps remains economically substantial even after 5 years. Using both equal and value-weighting schemes, the return gaps of the spread portfolios range between 60 and 70bp per quarter, depending on the time-frame used for sorting.[9] These results imply that past realizations of the return gap provide investors with a strong signal about its future values.

Last, the return gap is relatively simple to construct and easy to interpret. It requires the comparison of the return of a fund with the return of its holdings, making it easier to construct than other skill measures proposed in the literature which require non-public information or more stock-level information. For example, the active share measure of Cremers and Petajisto (2007) requires non-publicly available data on the composition of stock indices and the public information measure of Kacperczyk and Seru (2007) requires information on analysts' stock recommendations. On the contrary, the return gap requires only the composition of the fund's portfolio whose performance needs to be tracked over time. The information about fund portfolio composition is available free of charge on SEC's EDGAR system. Note that this need not imply that all investors collect information about fund holdings and construct the return gap themselves. Many data vendors provide investors with analyses on the performance of mutual fund holdings, which may be used

[9] The methodology used and the results obtained are very similar to those of Kacperczyk et al. (2008).

by investors as a benchmark for inferring the added value of unobserved managerial actions. For example, Morningstar provides free of charge data on the performance of each fund's top 25 holdings, with the rest of the holdings' performance data available under subscription. Last, the return gap is economically intuitive since any unobserved interquarterly action by fund managers is reflected in the net return, without affecting the hypothetical return of the most recently disclosed fund holdings. As a result, value enhancing positively actions reflect the return gap, while value-decreasing actions reflect the return gap negatively.

In sum, the return gap contains information about future performance which is not already contained in fund net returns and alpha, is highly persistent, and is relatively easy to construct and interpret. Consequently, investigating investors' response to the return gap provides us with a powerful setup for testing whether investors use disclosed portfolio holdings to infer skill. We perform the empirical analysis in the following Section.

3.3 Investors' Response to the Return Gap

In this section we investigate investors' response to the return gap and provide a number of empirical patterns consistent with the hypothesis that investors use the return gap as an information variable for inferring managerial skill.

3.3.1 Main Effect

We regress quarterly fund flows in quarter t on lagged variables, known to influence investors' capital allocation decisions, and four lagged return gap measures. More specifically,

$$Flow_{i,t+1} = \boldsymbol{\beta}' \boldsymbol{X_{i,t}} + \epsilon_t \tag{3}$$

The vector of explanatory variables $\boldsymbol{X_{i,t}}$ consists of an intercept, past net returns and fund flows, alpha, the most recently available expense ratio, and past return gap realizations. The alpha is estimated at the end of quarter t using monthly data over the preceding 12 months from a four factor model, including the return of the market, SMB, HML, and Mom.[10] We include the most recently available expense ratio because the return gap is calculated using fund's expenses. This way, we rule out a mechanical relation between fund flows and the return gap that may be due to a response to the expense ratio. We use two methodological alternatives – Fama-Macbeth regressions (Fama and Macbeth (1973)) with Newey-West standard errors and pooled regressions with time-fixed effects and standard errors clustered on the fund level.

[10]The risk factors are obtained from Kenneth French's data library: `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`.

Table 3.5. Investors' Response to the Return Gap.

The dependent variable in each regression specification is fund flow in quarter t. In each specification, we include an intercept, alpha (estimated using past one year of monthly fund returns and the excess return on the market, SMB, HML, and Momentum as risk factors), the most recently available expense ratio, four lagged quarterly fund flow measures, and four lagged fund net return measures. In specifications (2) and (4) we add four lagged return gap scores, calculated according to the procedure described in Section 3.2. In specifications (1) and (2) we estimate the models using Fama-Macbeth regressions where I report t-statistics based on Newey-West standard errors with 3 lags. In specifications (3) and (4) we estimate the models using a panel regression approach where we include time-fixed effects and cluster standard errors on the fund level. * denotes statistical significance on the 10% level, ** denotes statistical significance on the 5% level, and *** denotes statistical significance on the 1% level.

	Fama-Macbeth				Pooled			
	(1) $Flow_t$		(2) $Flow_t$		(3) $Flow_t$		(4) $Flow_t$	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
Intercept	−0.02***	−2.91	−0.02**	−2.39	−0.01***	−2.82	−0.01*	−1.82
Alpha	1.19***	4.66	0.97***	3.57	1.40***	8.34	1.29***	7.97
Exp Ratio	0.83***	3.65	1.13***	4.24	0.31	1.23	0.43	1.44
$Flow_{t-1}$	0.18***	9.86	0.17***	10.01	0.07***	2.71	0.07***	2.72
$Flow_{t-2}$	0.08***	5.74	0.10***	7.28	0.06***	5.74	0.06***	5.74
$Flow_{t-3}$	0.08***	4.17	0.09***	4.89	0.02***	3.67	0.02***	3.66
$Flow_{t-4}$	0.01***	2.92	0.02***	3.77	0.01***	3.55	0.01***	3.52
$Return_{t-1}$	0.36***	7.86	0.31***	5.52	0.35***	17.38	0.34***	17.03
$Return_{t-2}$	0.25***	6.45	0.20***	5.44	0.17***	9.86	0.15***	9.00
$Return_{t-3}$	0.25***	6.17	0.22***	5.49	0.17***	11.12	0.16***	10.35
$Return_{t-4}$	0.11***	3.29	0.07**	2.18	0.10***	6.18	0.09***	5.56
$ReturnGap_{t-1}$			0.21***	3.39			0.11***	3.08
$ReturnGap_{t-2}$			0.23***	3.85			0.18***	5.96
$ReturnGap_{t-3}$			0.22***	3.22			0.14***	4.27
$ReturnGap_{t-4}$			0.15**	2.50			0.15***	4.13
R^2	0.22		0.24		0.12		0.13	
Observations	85914		85914		85914		85914	
Time-Period	Q1.1990 – Q3.2010		Q1.1990 – Q3.2010		Q1.1990 – Q3.2010		Q1.1990 – Q3.2010	

The results, using the whole dataset between 1990 and 2010, are consistent across the two methodologies and summarized in Table 3.5. In the restricted models 1 and 3, where we do not include the lagged return gap variables, we find results largely consistent with previous studies on the flow-performance relationship, such as Ippolito (1992) and Chevalier and Ellison (1997). Investors strongly chase past returns and alpha, putting higher weight on more recently available data. The estimated coefficients on lagged fund returns range from above 0.3 for the most recently available quarterly fund return to about 0.1 for fund returns that are four quarters old. Consequently, a 1% fund return in each of the four preceding quarters translates to about 1% quarterly fund flows. Similarly, the estimated coefficients on lagged fund alpha imply that a 1% yearly alpha translates to a 0.97% to 1.40% increase in fund flows in the following quarter, depending on the specification.

Next, in specifications 2 and 4, we include four past realizations of the return gap measure as explanatory variables. We find a strong, positive response of flows to the past return gaps. The estimated coefficients of the four lagged return gap measures range between 0.15 and 0.21, with t-stats between 2.50 and 3.39. The results are economically important. More specifically, a one standard deviation increase in the return gap in each of the last four quarters is followed by a 0.96% or 1.34% increase in flows in the following quarter, depending on the estimation method. To position this in perspective, a one standard deviation increase in alpha is followed by an increase in expected flows of 0.78% or 1.03% during the next quarter, depending on the estimation method. The results further show that a one standard deviation increase in net returns brings 8.10% or 7.40% expected flows in the following quarter, depending on the specification. The evidence presented in Table 3.5 suggests that the economic impact of investors' response to the return gap is important, in order of magnitude similar to investors' response to past alpha.

We also find a positive response of investors to the lagged expense ratio. At first sight, this may appear a bit surprising since previous studies document a negative response to management fees (see, for example, Sirri and Tufano (1998)). Yet, the specifications include total expense ratio, which also contains the marketing and distribution expenses, known as 12b-1 fees. Jain and Wu (2000) and Barber et al. (2005) point that marketing by fund managers seems to work – higher marketing expenses attract investors. Furthermore, Barber et al. (2005) show that investors tend to avoid load funds and Haslem (2009) points that fund managers mask payments to brokers and advisors in the 12b-1 fees and market themselves as no-load funds in order to attract naive investors. Thus, 12b-1 fees appear to be positively related to fund flows. Note that we include the total expense ratio in our specifications since we are interested in ruling out a mechanical relation between the return gap and investor flows that is due to a response to the expense ratio. Therefore, it is beyond the scope of this study to examine the response of investors to different fund fees.

3.3.2 Response to the Return Gap, Conditional on Investor Sophistication

The above estimations of the impact of unobserved actions are solely based on public information. Nevertheless, this information may be costly to obtain and difficult to process. Thus, we expect more sophisticated investors to respond stronger to the return gap than less sophisticated investors. To empirically test this hypothesis, we repeat the analysis in Section 3.3.1, conditional on investor type, where institutional investors are assumed to be more sophisticated than retail investors.

Since 1999, the CRSP database reports whether a share class was distributed to institutional or retail investors, which provides the main identification mechanism in this section. The share class distinction allows us to aggregate separately flow and return data for the retail and institutional part of a fund. Consequently, we obtain flow and return data separately for the institutional and retail investors in a fund. Note that if a fund does not distribute share classes to institutional (retail) investors, then it drops out of the institutional (retail) sub-sample. In total, the institutional investors subsample has 25706 fund-period observations and the retail investor subsample has 49653 fund-period observations.

We estimate the restricted and unrestricted flow performance specifications in Section 3.3.1, separately for the institutional and retail subsamples. The dependent variable, the lagged net return, expense ratio, and alpha are calculated separately for the institutional and retail subsamples. The lagged flows and return gap variables are calculated the same way as in the previous analysis, using information on the whole fund level (i.e both retail and institutional). We report results aggregating lagged flow measures on the whole fund level, but results remain qualitatively the same if we aggregate the flows separately for the institutional and retail subsamples.

The estimation results covering the period 2000 – 2010 are summarized in Table 3.6. In specifications (1) and (2) we report results for the institutional subsample, and in specifications (3) and (4) we report results for the retail subsample. Comparing the results in specifications (1) and (3) which do not include the lagged return gap variables, we do not observe a differential response to past performance data. Although retail investors respond slightly stronger to past flows, institutions respond stronger to past alpha. The main difference comes with respect to the expense ratio variable – institutions avoid funds with high expenses, while individual investors prefer them, possibly due to the effect of advertisement fees (see Jain and Wu (2000) and Barber et al. (2005)).

The findings in specifications (2) and (4) suggest that the results in Table 3.5 presented earlier are mainly driven by the more sophisticated clientèle. All four lagged return gap variables in the subset of institutional investors enter the performance-flow relationship with statistically significant coefficients. On the other hand, the statistical significance using the subset of retail investors is much weaker. Moreover, most of the estimated coefficients using the institutional investor subset are statistically higher than the estimated coefficients using the retail subset. Furthermore, the magnitude of the estimated return gap coefficients using the subset of institutional investors is two to three times higher the magnitude of the estimated return gap coefficients using the subset of retail investors. The last two columns of Table 3.5 compare the estimated return gap coefficients between institutional and retail investors. A one standard deviation in the return gap in each of the last four quarters is followed by a 1.56% or 0.96% increase in the capital allocated by institutional investors, depending on the estimation method. In contrast, under a similar scenario, the expected fund flow increase allocated by retail investors is 0.61% or 0.48%, depending on the estimation method. Overall, the results are consistent with the notion that the use of the return gap requires some degree of investors sophistication.

3.3.3 Asymmetric Response to the Return Gap

A large number of empirical papers have documented that investors reward highly successful funds, but they tend not to withdraw money from poorly performing funds (for example, Ippolito (1992), Chevalier and Ellison (1997), and Sirri and Tufano (1998)). Huang et al. (2007) attribute this pattern to investors' participation costs, such as the costs of collecting and analyzing fund specific information before investing. In their model, new investors choose to invest in a fund if and only if the expected utility of investing in the fund offsets the costs associated with acquiring information about the expected performance of the fund. This, in turn, leads to the documented convexity of the flow-performance relationship.

Even though mutual funds disclose the composition of their portfolios to the public on a quarterly basis, investors face costs in acquiring and processing that information. Such costs may include downloading holdings data from the EDGAR system and constructing portfolio returns, or buying analysis on portfolio

Table 3.6. Investors' Response to the Return Gap - Institutional vs Retail Investors.

We use the identification of retail and institutional share classes introduced by CRSP at the end of 1999 and aggregate the flow, expenses, and return data separately for the retail and institutional part of a fund. The dependent variable in specifications (1) and (2) is institutional flow in quarter t, and in specifications (3) and (4) – retail flow in quarter t. In each specification we include an intercept, alpha (estimated using past one year of monthly fund returns to institutional (specifications (1) and (2)) or retail (specifications (3) and (4)) investors and the excess return on the market, SMB, HML, and Momentum as risk factors), the most recently available expense ratio, specific to institutional (specifications (1) and (2)) or retail (specifications (3) and (4)) investors, four lagged quarterly fund-specific flow measures, and four lagged fund net return measures, specific to institutional (specifications (1) and (2)) or retail (specifications (3) and (4)) investors. In specifications (2) and (4) we add four lagged return gap scores, calculated according to the procedure described in Section 3.2. In the last two columns we compare the estimated return gap coefficients in specifications (2) and (4) and report the corresponding t-stats. In Panel A we estimate the models using Fama-Macbeth regressions where I report t-statistics based on Newey-West standard errors with 3 lags. In Panel B we estimate the models using a panel regression approach where we include time-fixed effects and cluster standard errors on the fund level. * denotes statistical significance on the 10% level, ** denotes statistical significance on the 5% level, and *** denotes statistical significance on the 1% level.

	A: Fama-Macbeth									
	Institutional				Retail				Difference in RG	
	(1) $Flow_t$		(2) $Flow_t$		(3) $Flow_t$		(4) $Flow_t$		(2) - (4)	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Diff	t-stat
Intercept	0.01	0.63	0.02	0.90	−0.01	−0.48	0.00	−0.36		
Alpha	1.63***	3.17	1.48***	2.80	1.39***	4.01	1.38***	4.04		
Exp Ratio	−0.97***	−3.03	−0.62*	−1.79	0.08	0.31	0.27	1.16		
$Flow_{t-1}$	0.09***	3.30	0.09***	3.31	0.11***	4.78	0.11***	4.77		
$Flow_{t-2}$	0.03***	5.40	0.03***	5.44	0.07***	6.07	0.07***	6.06		
$Flow_{t-3}$	0.03***	3.21	0.03***	3.17	0.04***	4.47	0.04***	4.41		
$Flow_{t-4}$	0.01**	2.25	0.01**	2.25	0.02***	4.33	0.02***	4.29		
$Return_{t-1}$	0.35***	3.67	0.39***	3.88	0.50***	8.62	0.49***	8.19		
$Return_{t-2}$	0.39***	4.32	0.37***	4.13	0.26***	5.85	0.24***	5.84		
$Return_{t-3}$	0.46***	4.39	0.45***	4.29	0.18***	4.65	0.16***	4.53		
$Return_{t-4}$	0.31***	4.24	0.32***	4.42	0.12***	2.80	0.10**	2.17		
$ReturnGap_{t-1}$			0.28**	2.54			0.12**	2.18	0.15**	2.14
$ReturnGap_{t-2}$			0.22**	1.98			0.08	1.61	0.14*	1.94
$ReturnGap_{t-3}$			0.22**	2.22			0.06*	1.81	0.16**	2.53
$ReturnGap_{t-4}$			0.24***	2.60			0.11	1.18	0.12	1.59
R^2	0.14		0.15		0.19		0.20			
Observations	25706		25706		49653		49653			
Time-Period	Q1.2000 – Q3.2010		Q1.2000 – Q3.2010		Q1.2000 – Q3.2010		Q1.2000 – Q3.2010			

Table 3.6 – continued from previous page

	B: Pooled									
	Institutional				Retail				Difference in RG	
	(1) $Flow_t$		(2) $Flow_t$		(3) $Flow_t$		(4) $Flow_t$		(2) - (4)	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Diff	t-stat
Intercept	0.02***	8.91	0.02***	9.68	0.00	−1.32	0.00	−1.24		
Alpha	2.19***	7.87	2.09***	7.65	1.60***	10.37	1.54***	10.33		
Exp Ratio	−0.28**	−2.48	−0.23**	−2.36	0.09	0.44	0.24	1.17		
$Flow_{t-1}$	0.12***	3.78	0.12***	3.78	0.04**	1.96	0.04**	1.97		
$Flow_{t-2}$	0.05***	4.75	0.05***	4.75	0.06***	3.87	0.06***	3.87		
$Flow_{t-3}$	0.03**	2.04	0.03**	2.05	0.01**	2.53	0.01**	2.52		
$Flow_{t-4}$	0.01**	2.40	0.01**	2.41	0.01***	2.70	0.01***	2.70		
$Return_{t-1}$	0.21***	5.08	0.20***	4.93	0.37***	17.12	0.37***	17.07		
$Return_{t-2}$	0.18***	5.45	0.17***	5.10	0.17***	8.95	0.16***	8.68		
$Return_{t-3}$	0.16***	4.71	0.15***	4.43	0.14***	8.23	0.14***	8.09		
$Return_{t-4}$	0.08**	2.47	0.07**	2.11	0.09***	5.37	0.08***	4.96		
$ReturnGap_{t-1}$			0.19**	2.27			0.09**	2.03	0.10*	1.92
$ReturnGap_{t-2}$			0.16**	2.31			0.08**	2.34	0.08*	1.68
$ReturnGap_{t-3}$			0.10*	1.83			0.05	1.25	0.06	1.46
$ReturnGap_{t-4}$			0.13**	2.08			0.07*	1.64	0.06	1.43
R^2	0.06		0.06		0.12		0.12			
Observations	25706		25706		49653		49653			
Time-Period	Q1.2000 – Q3.2010		Q1.2000 – Q3.2010		Q1.2000 – Q3.2010		Q1.2000 – Q3.2010			

holdings from data providers, such as Morningstar. Following the theoretical model of Huang et al. (2007), the information acquisition costs that investors face suggest that the response to the return is highly non-linear. In this Section, we investigate this hypothesis in further detail.

In order to test for potential non-linearities in investors' response to the return gap, we follow Sirri and Tufano (1998) and employ a piece-wise linear approach. First, we aggregate the four lagged return gap variables in one cumulative yearly return gap score ($\mathrm{RG_t}$). Next, we calculate each fund's fractional rank $\mathrm{RG\_Rank_t}$ which represents the fund's cumulative return gap percentile relative to the rest of the funds in that period and ranges from 0 to 1. Then, we spread each fund's $\mathrm{RG\_Rank_t}$ over five different quintiles in the following way.

$$RG\_Q1 = \min(0.2, RG\_Rank_t)$$
$$RG\_Q2 = \min(0.2, RG\_Rank_t - RG\_Q1)$$
$$RG\_Q3 = \min(0.2, RG\_Rank_t - RG\_Q1 - RG\_Q2)$$
$$RG\_Q4 = \min(0.2, RG\_Rank_t - RG\_Q1 - RG\_Q2 - RG\_Q3)$$
$$RG\_Q5 = RG\_Rank_t - RG\_Q1 - RG\_Q2 - RG\_Q3 - RG\_Q4$$

We also calculate RG_mid, which combines the middle three quintiles:

$$RG\_mid = \min(0.6, RG\_Rank_t - RG\_Q1)$$

Furthermore, we aggregate the past net returns in one cumulative yearly net fund return value ($\mathrm{FR_t}$), and split it into 5 quintiles FR_Q1-5 and combine the middle three quintiles in an additional bucket, FR_mid. Similarly to most of our previous analysis, we include lagged flows, expense ratio, and alpha in the performance flow relationship. For brevity, we do not report their estimated coefficients.

The results are summarized in Table 3.7. Panel A offers the results for all funds for the period 1990 – 2010. In specifications (1) and (4), we include the yearly cumulative fund return and return gap and find results consistent with the analysis in Section 3.3. In the rest of the specifications, we introduce the piecewise linear break and report a highly non-linear response of investors to the return gap. The sensitivity of flows to past return gap appears to be very strong for funds with high return gaps. For funds in the top quintile of past year gap, a 1 percentile increase in the cumulative return gap is followed by an increase in flows of 13.37 to 14.96 basis points in the following quarter, depending on the specification. However, investors appear to not respond to funds with particularly poor and even average return gaps. The pattern is similar to investors' response to net returns and is even more pronounced. The results are consistent with the predictions of Huang et al. (2007). Investors decide to invest in funds where the expected payoff from investing in those funds is higher than the costs of acquiring and processing information about disclosed mutual fund holdings.

In Panels B and C, we investigate the asymmetries in response to the return gap, separately for the institutional and retail investors. We find similar patterns as in Panel A. Both retail and institutional investors respond non-linearly to the return gap, over the 2000 – 2010 period. However, institutional investors respond stronger to past poor performance and put lower weight on stellar past performance. Consistent with the findings in Table 3.6, the response of institutional investors to the return gap is stronger than the response of retail investors. Again, due to the costs associated with analyzing disclosed funds holdings, we find the pattern among both retail and institutional investors to be highly non-linear. A 1 percentile increase in the cumulative gap among the funds in the top quintile is followed by an increase in institutional flows in the following quarter by 10.63 to 12.50 basis points, depending on the specifications. Under the same scenario, the increase in retail flows is expected to be 6.67 to 8.73 basis points, depending on the specification.

The results from Table 3.7 are visualized in Figure 3.1. For each value of RG_Rank we calculate the expected flow in the following quarter, using the estimated return gap bucket coefficients from the non-linear

Table 3.7. Asymmetric Response to the Return Gap.

The dependent variable is fund flows in quarter t, institutional flow in quarter t in Panel B, and retail flow in quarter t in Panel C. We use the identification of retail and institutional share classes introduced by CRSP at the end of 1999 and aggregate the flow, expenses, and return data separately for the retail and institutional part of a fund. Each quarter we calculate four lagged return gap scores according to the procedure described in Section 3.2 and cumulate them to form a yearly return gap score (RG_{t-1}). We calculate each fund's fractional rank RG_Rank_{t-1} which represents the fund's cumulative return gap percentile relative to the rest of the funds in that period and ranges from 0 to 1. We spread each fund's RG_Rank_{t-1} over five different quintiles: $RG\_Q1_{t-1} = \min(0.2, RG\_Rank_t)$, $RG\_Q2 = \min(0.2, RG\_Rank_t - RG\_Q1)$, $RG\_Q3 = \min(0.2, RG\_Rank_t - RG\_Q1 - RG\_Q2)$, $RG\_Q4 = \min(0.2, RG\_Rank_t - RG\_Q1 - RG\_Q3 - RG\_Q4)$, and $RG\_Q5 = RG\_Rank_t - RG\_Q1 - RG\_Q3 - RG\_Q4 - RG\_Q5$. We also combine the middle three quintiles in $RG\_mid = \min(0.6, RG\_Rank_t - RG\_Q1)$. We cumulate the last four lagged fund return scores and form a yearly return gap score (FR_{t-1}). In Panel A we use total return, in Panel B – return specific to institutional investors, and in Panel C – return specific to retail investors. We similarly split (FR_{t-1}) in FR_Q1_{t-1}, FR_Q2_{t-1}, FR_Q3_{t-1}, FR_Q4_{t-1}, FR_Q5_{t-1}, and FR_mid_{t-1}. In each specification we include an intercept, alpha (estimated using past one year of monthly fund returns to all investors (Panel A), institutional investors (Panel B), or retail investors (Panel C) and the excess return on the market, SMB, HML, and Momentum as risk factors), the most recently available expense ratio to all investors (Panel A), institutional investors (Panel B), or retail investors (Panel C), four lagged quarterl total fund flow measures. In specifications (1), (2), and (3) we estimate the models using Fama-Macbeth regressions where we report t-statistics based on Newey-West standard errors with 3 lags. In specifications (4), (5), and (6) we estimate the models using a panel regression approach where I include time-fixed effects and cluster standard errors on the fund level. * denotes statistical significance on the 10% level, ** denotes statistical significance on the 5% level, and *** denotes statistical significance on the 1% level.

	A: All Funds, Q1.1990 – Q3.2010											
			Fama-Macbeth						Pooled			
	(1) $Flow_t$		(2) $Flow_t$		(3) $Flow_t$		(4) $Flow_t$		(5) $Flow_t$		(6) $Flow_t$	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
FR_{t-1}	0.19***	8.38					0.18***	15.09				
FR_Q1_{t-1}			2.52	1.24	2.84	1.41			4.64**	2.13	5.61***	2.87
FR_Q2_{t-1}			6.87***	5.91					8.66***	8.01		
FR_Q3_{t-1}			4.42***	5.33					4.86***	4.57		
FR_Q4_{t-1}			7.50***	4.52					8.26***	5.96		
FR_mid_{t-1}					6.04***	9.48					6.91***	17.08
FR_Q5_{t-1}			20.39***	5.27	21.25***	6.23			29.54***	9.39	30.16***	10.46
RG_{t-1}	0.18***	4.85					0.14***	5.94				
RG_Q1_{t-1}			2.90*	1.85	1.47	0.87			1.52	0.84	−0.11	−0.07
RG_Q2_{t-1}			−1.73**	−2.11					−1.72	−1.38		
RG_Q3_{t-1}			0.72	0.90					0.20	0.17		
RG_Q4_{t-1}			1.15	1.09					2.04	1.59		
RG_mid_{t-1}					0.14	0.49					0.18	0.48
RG_Q5_{t-1}			13.75***	4.40	14.91***	4.91			13.37***	5.35	14.96***	6.88
Controls	Yes		Yes		Yes		Yes		Yes		Yes	
R^2	0.22		0.24		0.23		0.12		0.13		0.13	
Observations	85914		85914		85914		85914		85914		85914	

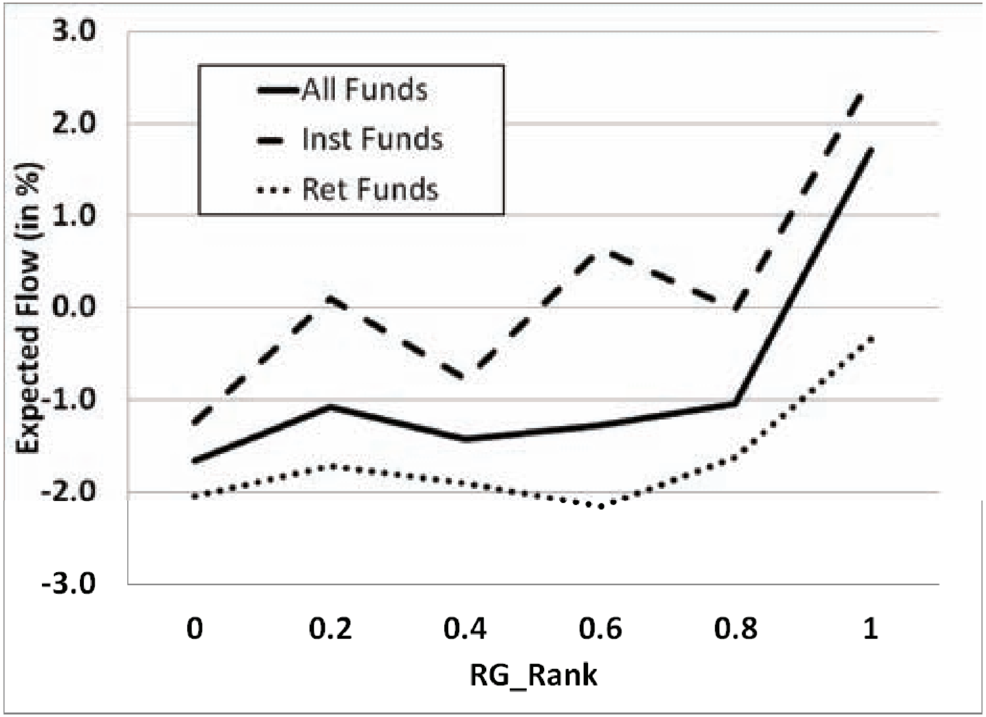
Table 3.7 – continued from previous page

	B: Institutional Funds, Q1.2000– Q3.2010											
	Fama-Macbeth						Pooled					
	(1) Flow$_t$		(2) Flow$_t$		(3) Flow$_t$		(4) Flow$_t$		(5) Flow$_t$		(6) Flow$_t$	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
FR$_{t-1}$	0.21***	4.69					0.15***	6.63				
FR_Q1$_{t-1}$			6.15	1.14	6.30	1.20			12.71***	3.05	12.51***	3.21
FR_Q2$_{t-1}$			5.96**	2.15					6.99**	2.48		
FR_Q3$_{t-1}$			3.43*	1.69					4.72	1.58		
FR_Q4$_{t-1}$			7.27***	2.92					9.14***	2.64		
FR_mid$_{t-1}$					5.25***	5.06					6.61***	7.28
FR_Q5$_{t-1}$			11.76**	2.05	13.28***	2.90			16.64***	3.05	18.40***	3.85
RG$_{t-1}$	0.22***	3.37					0.14***	3.36				
RG_Q1$_{t-1}$			6.70	1.43	4.46	0.93			5.62	1.38	3.66	1.05
RG_Q2$_{t-1}$			−4.36	−1.49					−2.87	−0.91		
RG_Q3$_{t-1}$			7.02**	2.20					5.89*	1.91		
RG_Q4$_{t-1}$			−3.21	−1.10					−2.81	−0.86		
RG_mid$_{t-1}$					0.84	0.91					0.93	1.09
RG_Q5$_{t-1}$			12.50***	3.55	10.63***	3.42			14.79***	2.89	12.88***	2.79
Controls	Yes		Yes		Yes		Yes		Yes		Yes	
R^2	0.13		0.14		0.14		0.06		0.07		0.07	
Observations	25706		25706		25706		25706		25706		25706	
	C: Retail Funds, Q1.2000– Q3.2010											
	Fama-Macbeth						Pooled					
	(1) Flow$_t$		(2) Flow$_t$		(3) Flow$_t$		(4) Flow$_t$		(5) Flow$_t$		(6) Flow$_t$	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
FR$_{t-1}$	0.21***	4.26					0.19***	12.56				
FR_Q1$_{t-1}$			3.04	0.91	3.33	1.10			6.62***	2.98	6.63***	3.32
FR_Q2$_{t-1}$			6.54***	3.24					7.45***	5.49		
FR_Q3$_{t-1}$			3.70***	3.97					5.26***	3.79		
FR_Q4$_{t-1}$			7.51***	5.04					8.90***	4.98		
FR_mid$_{t-1}$					5.62***	7.53					6.93***	13.96
FR_Q5$_{t-1}$			19.42***	5.08	20.46***	4.79			31.33***	7.46	32.58***	8.48
RG$_{t-1}$	0.07**	2.51					0.08***	3.21				
RG_Q1$_{t-1}$			1.63	0.65	0.78	0.33			2.02	0.80	1.00	0.47
RG_Q2$_{t-1}$			−0.91	−0.97					−0.93	−0.55		
RG_Q3$_{t-1}$			−1.29	−1.32					−1.51	−1.01		
RG_Q4$_{t-1}$			2.66	1.39					2.70	1.61		
RG_mid$_{t-1}$					−0.05	−0.12					−0.15	−0.30
RG_Q5$_{t-1}$			6.42**	2.29	8.36***	3.90			6.67**	2.29	8.73***	3.44
Controls	Yes		Yes		Yes		Yes		Yes		Yes	
R^2	0.21		0.22		0.22		0.12		0.13		0.13	
Observations	49653		49653		49653		49653		49653		49653	

specifications (2). Since RG_Rank is sliced into different buckets, an expected flow for a fund is calculated as the sum of that fund's allocations to each bucket times the estimated sensitivities from Table 3.7. The Figure shows the large economic importance of the funds with high return gaps. We see that the highest expected fund flows are attributed to funds with the highest return gap scores, while funds with low or medium level return gaps are expected to receive negative or close to zero fund flows.

Figure 3.1. Expected Flow Due to Asymmetric Response to the Return Gap.

This figure presents expected flows (in % of total net assets) corresponding to different levels of funds' [illegible] based on relative return gap, based on the results in Table ??. All variables, methodology and estimated coefficients are described in Table ??. Results are reported for all funds, institutional funds and retail funds, using the results in specification 3.



3.3.4 Time-varying Response to the Return Gap

In this paper we hypothesize that investors can extract skill information from fund holdings using the return gap. Of course, past returns and alpha are other performance measures, which are widely used for the same purpose. Given that the information content embedded in each of those measures may change with time, we expect to find an increasing fund flow sensitivity to the return when the information in other performance measures decreases. In other words, in times when other performance measures are less informative about the skill of mutual fund managers, the economic importance of the return gap ought to increase.

We use the cross-sectional standard deviation of fund returns to proxy for the amount of information embedded in fund returns. When the cross-sectional dispersion of fund returns is relatively low, investors have less information content in fund returns to distinguish skilled from unskilled managers than in periods when the dispersion is relatively high. Consequently, when the cross-sectional dispersion of fund returns is low, investors have to rely relatively more on other skill identifiers. Empirically, we include the interaction of the lagged return gap with the standard deviation of fund returns in their respective quarters as explanatory variables in the flow-performance relationship. We estimate the models using pooled regressions where we include quarter fixed effects and cluster the standard errors on the fund level.

The results from this exercise are summarized in Table 3.8. Specifications (1) and (2) have already been

Table 3.8. Investors' Response to the Return Gap – Time-Dimension.

The dependent variable in each regression specification is fund flow in quarter t. In each specification we include an intercept, alpha (estimated using past one year of monthly fund returns and the excess return on the market, SMB, HML, and Momentum as risk factors), the most recently available expense ratio, four lagged quarterly fund flow measures, and four lagged fund net return measures. In specifications (2) we add four lagged return gap scores, calculated according to the procedure described in Section 3.2. In specification (3) we further add interactions between the lagged return gap measures and the standard deviation of fund returns in that respective quarter. We estimate the models using a panel regression approach where we include time-fixed effects and cluster standard errors on the fund level. * denotes statistical significance on the 10% level, ** denotes statistical significance on the 5% level, and *** denotes statistical significance on the 1% level.

	(1) $Flow_t$		(2) $Flow_t$		(3) $Flow_t$	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
Intercept	−0.01***	−2.82	−0.01*	−1.82	−0.01	−1.54
Alpha	1.40***	8.34	1.29***	7.97	1.24***	7.83
Exp Ratio	0.31	1.23	0.43	1.44	0.50	1.59
$Flow_{t-1}$	0.07***	2.71	0.07***	2.72	0.07***	2.72
$Flow_{t-2}$	0.06***	5.74	0.06***	5.74	0.06***	5.73
$Flow_{t-3}$	0.02***	3.67	0.02***	3.66	0.02***	3.66
$Flow_{t-4}$	0.01***	3.55	0.01***	3.52	0.01***	3.51
$Return_{t-1}$	0.35***	17.38	0.34***	17.03	0.33***	16.36
$Return_{t-2}$	0.17***	9.86	0.15***	9.00	0.15***	8.65
$Return_{t-3}$	0.17***	11.12	0.16***	10.35	0.16***	10.07
$Return_{t-4}$	0.10***	6.18	0.09***	5.56	0.08***	5.27
$ReturnGap_{t-1}$			0.11***	3.08	0.33***	4.83
$ReturnGap_{t-2}$			0.18***	5.96	0.34***	5.29
$ReturnGap_{t-3}$			0.14***	4.27	0.32***	4.36
$ReturnGap_{t-4}$			0.15***	4.13	0.26***	3.92
$ReturnGap_{t-1}*\sigma(Return_{t-1})$					−0.03***	−3.58
$ReturnGap_{t-2}*\sigma(Return_{t-2})$					−0.02***	−3.31
$ReturnGap_{t-3}*\sigma(Return_{t-3})$					−0.02***	−3.08
$ReturnGap_{t-4}*\sigma(Return_{t-4})$					−0.01**	−2.34
R^2	0.12		0.13		0.13	
Observations	85914		85914		85914	
Time-Period	Q1.1990 – Q3.2010		Q1.1990 – Q3.2010		Q1.1990 – Q3.2010	

presented in Table 3.5 and point that investors respond positively to the return gap. The results associated with the time-variation in response to the return gap are presented in specification (3). Consistent with the hypothesis that the skill component captured by the return gap becomes more important when there is less information in total fund returns, we find the interactions between the return gap and the standard deviation of fund returns to be negative. Although the estimated coefficients are small, their economic magnitude is non-negligible. This is due to the large standard deviation of the quarterly dispersion of fund net returns – 2.6% per quarter. For example, a one standard deviation change in the quarterly dispersion of fund net returns in the quarter preceding changes the sensitivity of fund flows to last quarter's return gap by 0.08. The results suggests that there is substantial time-variation in investors' use of the return gap, which is in accordance with the hypothesis that the relative importance of the return gap depends on the informativeness of other performance measures.

3.4 Is the Response to the Return Gap "smart"?

In Section 3.2 we show that the return gap contains valuable information for predicting future performance. Even though Section 3.3 provide a number of empirical patterns consistent with the hypothesis that investors use the return gap as an information variable, it may not be immediately clear whether the response to the return gap actually helps investors increase their returns.

In this section we investigate whether investors actually benefit from taking into account the return gap in their capital allocation decisions. To test this, we first estimate a Fama-Macbeth flow-performance model using the 1990 – 2010 sample, where the dependent variable is Flow_t and on the right hand side there are an intercept, lagged alpha, lagged expense ratio, lagged four quarter flows, and FR_Q1, FR_mid, and FR_Q5. We call this the restricted model. For each fund in each quarter, we calculate an expected flow score using the estimated coefficients from the restricted model and the respective realizations of the independent variables. Next, we estimate an unrestricted Fama-Macbeth model, which expands the restricted with three additional explanatory variables – RG_Q1, RG_mid, and RG_Q5, which we orthogonalize with respect to the variables in the restricted model.[11] Again, for each fund in each quarter, we calculate expected flows, using the estimated coefficients from the unrestricted model and the respective realizations of the independent variables.

Then, for each fund in each quarter, we calculate the difference between the expected flow based on the unrestricted model and the expected flow based on the restricted model. We term this difference "Expected Flow Difference". At the end of each quarter, we sort funds in 10 portfolios based on that quarter's "Expected Flow Difference" and track their performance over the next one quarter. The top decile contains funds with the highest "Expected Flow Difference" and the bottom one – those with the lowest "Expected Flow

[11] We orthogonalize the return gap variables because we want to capture that part of investor flows which is attributed to the return gap only. Note that if we don't orthogonalize RG_Q1, RG_mid, and RG_Q5, the results remain qualitatively the same. Results are not reported, due to brevity, and available upon request.

Difference". This way we obtain a time-series of portfolio returns and evaluate their performance using a four-factor model, including the return on the market, SMB, HML, and Momentum. We report results using both equally and flow-weighted portfolios. For robustness, we repeat the analysis using pooled regressions with time fixed effects to estimate the restricted and unrestricted models.

This methodology allows us to evaluate the performance of fund flows that are due to response to the return gap. If the "Expected Flow Difference" score for a fund is positive (negative), investors' response to the return gap has increased (decreased) the assets under management for that particular fund. Consequently, if investors' reaction to the return gap helps them enhance their returns, we should find that performance is increasing in the "Expected Flow Difference".

The results, using the whole set of funds over 1990 – 2010, are summarized in Panel A of Table 3.9. In the whole sample, the excess return on each of the spread portfolios is positive and statistically significant at conventional levels, irrespective of the estimation method and the weighting scheme. The four-factor monthly alpha of the spread portfolio is economically important, ranging between 0.17% and 0.20% per month, depending on the specification. Yet, caution is needed in interpreting these results, because the pattern from portfolio 1 to portfolio 10 is not strictly monotonic. Nevertheless, results are consistent with the hypothesis that investors enhance their returns from allocating (withdrawing) capital from funds with high (low) return gaps.

The results are consistent with the hypothetical return of a trading strategy, documented by Kacperczyk et al. (2008). They sort funds in 10 deciles based on their average monthly return gap during the past 12 months, and examine their subsequent results. Their results indicate that a strategy long in the top decile and short in the bottom decile generates a subsequent four factor alpha of 0.22% per month, consistent with the 0.20% we find.

In Panel B and C of Table 3.9 we repeat the exercise of Panel A, using the subsets of institutional and retail investors. The only difference with respect to the exercise using all funds is that we estimate separately the restricted and unrestricted model for each subgroup of funds, on the basis of which we construct the expected flow measures. Even though there is a similar pattern of increasing performance from bottom to top deciles, the spread portfolio for both institutional and retail investors is not statistically different from zero. We attribute this to the lower statistical power of the test since the analysis of the institutional and retail subsamples is based on 10 years of data only.

The results in this section provide evidence that the actual response of investors to the return gap is "smart" – the capital allocated to mutual funds because of investors' response to the return gap helps predict performance. However, these results cannot reject the behavioral hypothesis that investors are naive and irrational in their investment decisions. The results point that there are some investors who can benefit from allocating capital to funds with high return gap, which does not imply that investors are, on average, sophisticated.

Table 3.9. Smart Money Effect.

We regress fund flows on an intercept, alpha (estimated using past one year of monthly fund returns and the excess return on the market, SMB, HML, and Momentum as risk factors), the most recently available expense ratio, four lagged quarterly fund flow measures, and FR_Q1$_{t-1}$, FR_mid$_{t-1}$, and FR_Q5$_{t-1}$ (defined in Table 3.7). We call this the restricted model. We also regress fund flows on the same set of variables and RG_Q1$_{t-1}$, RG_mid$_{t-1}$, and RG_Q5$_{t-1}$ (defined in Table 3.7), which I orthogonalize with respect to the variables in the restricted model. We call this the unrestricted model. At the end of each quarter t we use the estimated coefficients from the restricted and the unrestricted models and the respective time-specific realizations of the independent variables (i.e. fund flows in quarters t, t-1, t-2, and t-3) to construct two expected flow scores. We calculate "Expected Flow Difference" for each fund in quarter t+1 as the difference between the expected flow in quarter 1 based on the unrestricted model and the expected flow based on the restricted model. Next, we sort funds in 10 portfolios based on their "Expected Flow Difference" scores and track their performance until the end of quarter t+1 when I rebalance the portfolios. This way I obtain a time-series of quarterly return gap scores for each portfolio. Next, we evaluate the performance of each time-series of portfolio returns using a four-factor asset pricing model, where I use the excess return on the market, SMB, HML, and Momentum as risk factors. For each time-series of portfolio returns we report the alpha and the corresponding t-statistic. We report results estimating the restricted and unrestricted models via Fama-Macbeth regressions and pooled regressions with time-fixed effects. In Panel A the sample covers the whole data set. In Panels B and C we use the subsamples of institutional and retail investors (defined in Table 3.6). Note that the explanatory variables used for estimating the restricted and unrestricted are defined in the same way as in Table 3.6. * denotes statistical significance on the 10% level, ** denotes statistical significance on the 5% level, and *** denotes statistical significance on the 1% level.

	A: All Funds							
	Fama-Macbeth				Pooled			
	Equally-weighted		Flow-weighted		Equally-weighted		Flow-weighted	
	Alpha	t-stat	Alpha	t-stat	Alpha	t-stat	Alpha	t-stat
1 (lowest)	−0.14	−1.23	−0.14	−1.16	−0.16	−1.39	−0.16	−1.31
2	−0.14**	−2.36	−0.12**	−2.11	−0.10**	−2.38	−0.08	−1.49
3	−0.07	−1.43	−0.07	−1.47	−0.06	−1.39	−0.04	−1.01
4	−0.06	−1.41	−0.07*	−1.82	−0.07	−1.53	−0.06	−1.38
5	−0.05	−1.11	−0.05	−1.15	−0.05	−0.89	−0.04	−0.88
6	−0.08	−1.61	−0.08	−1.51	−0.05	−0.91	−0.08	−1.43
7	−0.02	−0.26	−0.04	−0.57	−0.05	−0.79	−0.08	−1.18
8	−0.10	−1.42	−0.09	−0.86	−0.03	−0.85	−0.08	−1.08
9	−0.08	−1.08	−0.07	−0.99	−0.06	−0.90	−0.04	−0.61
10 (highest)	0.03	0.32	0.05	0.44	0.02	0.21	0.04	0.37
10 − 1	0.17*	1.94	0.19*	1.91	0.18**	1.97	0.20**	2.04
Time-Period	Q2.1990 − Q4.2010		Q2.1990 − Q4.2010		Q2.1990 − Q4.2010		Q2.1990 − Q4.2010	

3.5 Additional Tests

In this part of the paper, we conduct a number of additional tests which rule out alternative explanations for the main finding that investors use portfolio holdings to calculate the return gap and in turn use the return gap when making capital allocating decisions (Sections 3.5.1 and 3.5.3). We further investigate the sensitivity of fund flows to the accuracy of the return gap in Sections 3.5.3.

3.5.1 Financial Advisors and Brokers Direct Investors to More Skillful Fund Managers

The empirical results in the previous sections suggest that investors can identify managers who add value via their interquarterly actions and allocate relatively more flows to their funds. An alternative explanation to this finding is that investors are directed towards skillful fund managers by financial advisors and brokers (see, for example, Bergstresser et al. (2009) and Del Guercio et al. (2010)). To test for this conjecture, we check if the previously documented response to the return gap is driven by investors who use financial advisors and

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	B: Institutional Funds							
	Fama-Macbeth				Pooled			
	Equally-weighted		Flow-weighted		Equally-weighted		Flow-weighted	
	Alpha	t-stat	Alpha	t-stat	Alpha	t-stat	Alpha	t-stat
1 (lowest)	−0.13	−1.37	−0.09	−0.88	−0.15	−1.49	−0.12	−1.12
2	−0.11	−1.62	−0.14**	−2.14	−0.17**	−2.50	−0.17**	−2.25
3	−0.06	−1.00	−0.08	−1.13	−0.06	−0.81	−0.09	−1.38
4	−0.08	−1.19	−0.08	−1.22	−0.08	−1.22	−0.07	−1.16
5	−0.08	−1.29	−0.07	−1.07	−0.05	−0.68	−0.02	−0.29
6	−0.08	−1.15	−0.10	−1.61	−0.05	−0.72	−0.08	−1.10
7	−0.05	−0.59	−0.03	−0.21	−0.03	−0.33	−0.05	−0.16
8	−0.07	−0.67	−0.02	−0.17	−0.04	−0.50	−0.01	−0.07
9	−0.03	−0.35	−0.01	−0.14	−0.07	−0.87	−0.01	−0.18
10 (highest)	−0.06	−0.69	0.03	0.31	−0.04	−0.47	0.03	0.38
10 − 1	0.07	1.01	0.12	1.47	0.11	1.46	0.15*	1.78
Time-Period	Q2.2000 − Q4.2010		Q2.2000 − Q4.2010		Q2.2000 − Q4.2010		Q2.2000 − Q4.2010	
	C: Retail Funds							
	Fama-Macbeth				Pooled			
	Equally-weighted		Flow-weighted		Equally-weighted		Flow-weighted	
	Alpha	t-stat	Alpha	t-stat	Alpha	t-stat	Alpha	t-stat
1 (lowest)	−0.10	−0.76	−0.10	−0.64	−0.12	−0.80	−0.09	−0.55
2	−0.15	−1.60	−0.11	−1.33	−0.11	−1.44	−0.07	−1.09
3	−0.03	−0.51	−0.07	−1.32	−0.01	−0.22	−0.08	−1.32
4	−0.07	−1.19	−0.07	−1.36	−0.06	−0.73	−0.04	−0.70
5	−0.05	−0.60	−0.05	−0.85	−0.02	−0.16	−0.04	−0.59
6	0.01	0.08	−0.09	−1.11	−0.04	−0.47	−0.06	−0.73
7	0.01	0.07	−0.03	−0.25	0.01	0.16	−0.05	−0.60
8	−0.07	−0.91	−0.03	−0.38	−0.10*	−1.71	−0.01	−0.11
9	−0.05	−0.86	−0.02	−0.25	−0.06	−1.02	−0.06	−0.81
10 (highest)	−0.02	−0.20	0.02	0.26	−0.03	−0.31	0.00	0.03
10 − 1	0.09	0.69	0.12	0.82	0.09	0.69	0.09	0.62
Time-Period	Q2.2000 − Q4.2010		Q2.2000 − Q4.2010		Q2.2000 − Q4.2010		Q2.2000 − Q4.2010	

brokers.

We split the data sample in two subsamples – load and no-load funds. We define load fund share class as a share class with a front-load or a back-end load or with 12b-1 fees above 25 basis points. Information on load fees is available in the CRSP database since 1999. Similarly to the split of institutional vs. retail investors in Section 3.3.2, we aggregate fund information separately for the load and no-load part of a fund and obtain separate flow and return data for investors using the services of brokers and financial advisors and those who do not. This allows us to separately estimate the flow-performance relationship for two subsamples – one for the subset of investors using the services of brokers and financial advisors, and one for the subset of investors who do not use such services.

If the return gap effect documented previously is entirely driven by the advise of brokers and financial advisors, we should observe no response to the return gap in the no-load subsample. The results in Table 3.10 suggest that this is not the case. Investors in no-load funds respond very strongly to the lagged return gap measures where almost all of the coefficients are larger in magnitude than those in the load sample. This indicates that investors' response to the return gap is not driven by the advise investors receive by financial advisors and brokers.

Table 3.10. Investors' Response to the Return Gap - Load vs No-load funds.

We define load share classes as share classes having front-end or rear-end load (CRSP reports this information from the end of 1999) or with a 12b-1 fee that is higher than 0.25% per year. Consequently, we aggregate the flow, expenses, and return data separately for the load and no-load part of a fund. The dependent variable in specifications (1) and (2) is load flow in quarter t, and in specifications (3) and (4) – no-load flow in quarter t. In each specification we include an intercept, alpha (estimated using past one year of monthly fund returns to load (specifications (1) and (2)) or no-load (specifications (3) and (4)) investors and the excess return on the market, SMB, HML, and Momentum as risk factors), the most recently available expense ratio, specific to load (specifications (1) and (2)) or no-load (specifications (3) and (4)) investors, four lagged quarterly fund-specific flow measures, and four lagged fund net return measures, specific to load (specifications (1) and (2)) or no-load (specifications (3) and (4)) investors. In specifications (2) and (4) we add four lagged return gap scores, calculated according to the procedure described in Section 3.2. In Panel A we estimate the models using Fama-Macbeth regressions where we report t-statistics based on Newey-West standard errors with 3 lags. In Panel B we estimate the models using a panel regression approach where we include time-fixed effects and cluster standard errors on the fund level. * denotes statistical significance on the 10% level, ** denotes statistical significance on the 5% level, and *** denotes statistical significance on the 1% level.

	A: Fama-Macbeth							
	Load				No Load			
	(1) $Flow_t$		(2) $Flow_t$		(3) $Flow_t$		(4) $Flow_t$	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
Intercept	−0.01*	−1.85	−0.01	−1.29	0.00	−0.14	0.01	0.48
Alpha	1.13***	3.29	0.95***	3.14	1.36***	2.95	1.31***	2.88
Exp Ratio	0.52	1.47	0.71**	2.19	−0.01	−0.02	0.32	0.67
$Flow_{t-1}$	0.18***	7.56	0.18***	7.43	0.21***	9.47	0.21***	9.64
$Flow_{t-2}$	0.10***	6.67	0.09***	6.70	0.09***	4.57	0.09***	4.35
$Flow_{t-3}$	0.09***	4.26	0.09***	4.27	0.09***	4.70	0.09***	5.07
$Flow_{t-4}$	0.02**	2.37	0.02**	2.48	0.04***	3.95	0.05***	4.08
$Return_{t-1}$	0.30***	4.55	0.28***	4.29	0.37***	5.65	0.34***	4.72
$Return_{t-2}$	0.24***	5.07	0.23***	4.97	0.35***	5.35	0.30***	5.45
$Return_{t-3}$	0.29***	6.24	0.28***	5.36	0.20***	3.16	0.17**	2.42
$Return_{t-4}$	0.11***	2.71	0.11**	2.49	0.12***	2.72	0.09**	2.04
$ReturnGap_{t-1}$			0.16*	1.73			0.29***	2.66
$ReturnGap_{t-2}$			0.14**	1.98			0.20**	2.22
$ReturnGap_{t-3}$			0.21***	3.76			0.16*	1.79
$ReturnGap_{t-4}$			0.13*	1.73			0.13**	2.04
R^2	0.24		0.26		0.23		0.25	
Observations	54955		54955		42731		42731	
Time-Period	Q1.2000 – Q3.2010		Q1.2000 – Q3.2010		Q1.2000 – Q3.2010		Q1.2000 – Q3.2010	
	B: Pooled							
	Load				No Load			
	(1) $Flow_t$		(2) $Flow_t$		(3) $Flow_t$		(4) $Flow_t$	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
Intercept	0.00	−1.22	0.00	−0.84	0.01	1.30	0.01	1.44
Alpha	1.22***	6.61	1.11***	6.26	2.26***	8.55	2.18***	8.31
Exp Ratio	0.19	0.79	0.42*	1.76	−0.25	−0.66	−0.11	−0.26
$Flow_{t-1}$	0.11***	5.59	0.11***	5.59	0.06	1.61	0.06	1.61
$Flow_{t-2}$	0.07***	6.40	0.07***	6.39	0.06***	9.02	0.06***	9.03
$Flow_{t-3}$	0.01***	2.86	0.01***	2.85	0.01*	1.88	0.01*	1.88
$Flow_{t-4}$	0.01***	3.32	0.01***	3.29	0.01**	2.20	0.01**	2.20
$Return_{t-1}$	0.32***	14.50	0.31***	13.70	0.28***	10.15	0.28***	9.91
$Return_{t-2}$	0.15***	8.36	0.14***	7.50	0.19***	7.99	0.18***	7.67
$Return_{t-3}$	0.18***	10.35	0.17***	9.59	0.17***	7.58	0.16***	7.27
$Return_{t-4}$	0.12***	7.20	0.10***	6.41	0.11***	4.86	0.11***	4.79
$ReturnGap_{t-1}$			0.16***	3.56			0.11**	2.42
$ReturnGap_{t-2}$			0.15***	3.94			0.12***	2.63
$ReturnGap_{t-3}$			0.16***	3.62			0.06	1.20
$ReturnGap_{t-4}$			0.16***	3.95			0.09*	1.82
R^2	0.12		0.12		0.08		0.08	
Observations	54955		54955		42731		42731	
Time-Period	Q1.2000 – Q3.2010		Q1.2000 – Q3.2010		Q1.2000 – Q3.2010		Q1.2000 – Q3.2010	

3.5.2 Investors Respond to a Correlated Skill Measure

Another potential concern is that the results might be driven by the correlation of the return gap with performance indicators, other than net return and alpha. In other words, investors might respond to a performance measure, such as trading costs, which influences both fund flows and the return gap. To dispel any doubts, we first investigate the determinants of the return gap and demonstrate that the sensitivity of fund flows is not driven by the response of investors to performance measures, correlated to the return gap.

We first regress the quarterly return gap on a number of variables, which might have an economic link to the return gap. The precise definition of each determinant of the return gap is presented in Appendix B. Results of the test are summarized in Table 3.11, and are similar to those in Kacperczyk et al. (2008). As expected, we find that transaction costs, estimated following Wermers (2000), have a negative impact on the return gap. This implies that the interquarterly benefits from trading, on average, cannot offset the trading costs of mutual funds. The next determinant we investigate is the weight of recent IPOs. The previous literature has shown that mutual fund families tend to assign IPOs strategically across the fund family, allocating high weight of recent IPOs to certain funds in the family (see Gaspar et al. (2006), Nanda et al. (2004), Nimalendran et al. (2007), and Reuter (2006)). Given that those IPOs tend to be significantly underpriced, it is not surprising that we find very strong positive relation between the weight of recent IPOs and the return gap.

Next, we look at the transparency of fund's investment strategy, proxied by the correlation between the fund's reported holdings and fund's net return. A low correlation might be due to agency problems, such as window dressing, or high turnover. Nevertheless, a low correlation might also result in realizing interquarterly informational advantages. The positive coefficient on the correlation variable that we present in Table 3.11 suggests that the opaqueness of the trading strategy is negatively related to the return gap. The negative

Table 3.11. The Determinants of the Return Gap.

The dependent variable is return gap in t. The independent variables are described in Appendix B. Observations with missing data are dropped. We estimate the model using a panel regression approach. * denotes statistical significance on the 10% level, ** denotes statistical significance on the 5% level, and *** denotes statistical significance on the 1% level.

	(1) ReturnGap_t	
	Coeff	t-stat
Intercept	−0.01*	−1.93
Trading costs_t	−0.58**	−2.17
Weight of recent IPOs_t	0.21***	10.65
ρ(holding return and net returns)$_{t-1}$	0.50**	2.04
Expense Ratio_t	−0.21**	−2.15
Yearly Turnover_t	0.00	0.22
log(fund TNA)$_{t-1}$	−0.02*	−1.73
log(family TNA)$_{t-1}$	0.04***	8.42
log(age)$_{t-1}$	−0.02*	−1.86
Flow_t	0.11**	2.19
$\sigma(\text{Return}_{t-5 \text{ to } t-1})$	0.03***	4.33
R^2	0.04	
Observations	78888	
Time-Period	Q2.1993 – Q3.2010	

coefficient on the expense ratio suggests that fund expenses are not compensation for the value-added of fund managers via their interquarterly actions. We further find no significant effect of fund turnover on the return gap, which suggests that either the effect of fund turnover is captured in the trading cost proxy, or that the benefits of frequent trading just offset the costs of trading frequently.

Similarly to Chen et al. (2004), we find that performance is negatively related to size, but positively related to fund family size. The strong positive relationship to fund family size is probably due to economies of scale associated with transaction costs and lending fees (Chen et al. (2004)). We further document a positive relationship between contemporaneous flows and the return gap which is consistent with the "smart money" effect documented by Gruber (1996) and Zheng (1999). Somewhat surprisingly, we find that funds with volatile returns have higher return gaps, though the effect is economically small.

In a next step, we include the determinants of the return gap in the flow-performance relationship. The results are summarized in Table 3.12. Specification (1) presents the baseline specification, where we do not include any of the determinants as explanatory variables. In specifications (2) to (9), we examine the separate effect of each of the determinants of the return gap in conjunction with the return gap. We document very small changes in the return gap coefficients, indicating that none of the determinants singlehandedly subsumes the effect of the return gap. In specification (10) we include all of the determinants on the right hand side. Again, all of the return gap coefficients remain significant. In sum, the results in Table 3.12 suggest that the main finding that investors use the return gap as an information variable is not erroneously driven by the correlation of the return gap with other performance measures.

3.5.3 Precision of the Return Gap

Our main results in Table 3.5 show that the sensitivity of fund flows to the return gap is positive. However, some of the calculated return gaps might be noisy indicators of managerial skills. For example, managers may manipulate their reported holdings in order to present themselves as more skilled. The managers may window dress their portfolios, which refers to buying (selling) stocks with past positive (negative) performance shortly before reporting the holdings to the public in order to convey stock-picking skills. Portfolio pumping, referring to buying shares in the stocks the fund already owns on the last day of the reporting period, is another practice used by some managers to inflate their performance.[12] Both practices would add noise to the return gap as an indicator for managerial skill.

Another reason why there might be noise in the return gaps we estimate comes from the data limitations of our sample. Although small, the share of non-equity holdings in the portfolios of the mutual funds in our sample is non-zero. The quarterly snapshots of the funds' portfolios do not include their non-equity holdings. Consequently, to calculate the quarterly return of the portfolio of fund holdings we assume that the fund's yearly asset class allocation provided by CRSP is constant over time. However, funds may decide to actively

[12] See, for instance, Lakonishok et al. (1991), Musto (1999), and Carhart et al. (2002).

Table 3.12. Investors' Response to the Return Gap, Controlling for Correlated Performance Measures.

The dependent variable in each regression specification is fund flow in quarter t. In each specification we include an intercept, alpha (estimated using past one year of monthly fund returns and the excess return on the market, SMB, HML, and Momentum as risk factors), the most recently available expense ratio, four lagged quarterly fund flow measures, four lagged fund net return measures, and four lagged return gap measures, calculated according to the procedure described in Section 3.2. In specifications (2) to (9) we include separately each of the determinants of the return gap and in specification (10) we include all of them together. Each of the determinants is defined in Appendix B. We estimate the models using Fama-Macbeth regressions where we report t-statistics based on Newey-West standard errors with 3 lags. * denotes statistical significance on the 10% level, ** denotes statistical significance on the 5% level, and *** denotes statistical significance on the 1% level.

	(1) $Flow_t$		(2) $Flow_t$		(3) $Flow_t$		(4) $Flow_t$		(5) $Flow_t$	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
$ReturnGap_{t-1}$	0.21***	3.39	0.21***	3.27	0.20***	3.20	0.22***	3.65	0.21***	3.48
$ReturnGap_{t-2}$	0.23***	3.85	0.22***	3.61	0.22***	3.57	0.23***	3.70	0.21***	3.46
$ReturnGap_{t-3}$	0.22***	3.22	0.21***	3.16	0.21***	3.28	0.22***	3.12	0.21***	3.29
$ReturnGap_{t-4}$	0.15**	2.50	0.14**	2.57	0.14**	2.37	0.15**	2.40	0.15**	2.40
Trading $costs_t$			0.01**	2.15						
Weight of recent $IPOs_t$					0.18	1.19				
ρ(holding return and net $returns)_{t-1}$							−0.17***	−4.31		
Yearly $Turnover_t$									0.01***	2.86
log(fund $TNA)_{t-1}$										
log(family $TNA)_{t-1}$										
$\log(age)_{t-1}$										
$\sigma(Return_{t\text{-}5 \text{ to } t\text{-}1})$										
R^2	0.24		0.25		0.25		0.25		0.25	
Observations	85914		85914		85914		85914		85771	
Time-Period	Q1.1990 – Q3.2010		Q1.1990 – Q3.2010		Q1.1990 – Q3.2010		Q1.1990 – Q3.2010		Q1.1990 – Q3.2010	

Table 3.12 – continued from previous page

	(6) $Flow_t$		(7) $Flow_t$		(8) $Flow_t$		(9) $Flow_t$		(10) $Flow_t$	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
$ReturnGap_{t-1}$	0.20***	3.29	0.22***	4.17	0.21***	3.37	0.21***	3.63	0.20***	3.92
$ReturnGap_{t-2}$	0.23***	3.77	0.19***	3.04	0.24***	3.89	0.24***	3.76	0.17**	2.46
$ReturnGap_{t-3}$	0.21***	3.14	0.12**	2.44	0.21***	3.25	0.20***	3.07	0.10**	2.09
$ReturnGap_{t-4}$	0.15**	2.41	0.17**	2.50	0.15**	2.40	0.16***	2.75	0.12**	2.31
Trading $costs_t$									0.01*	1.83
Weight of recent $IPOs_t$									0.01	0.08
ρ(holding return and net $returns)_{t-1}$									−0.09***	−2.78
Yearly $Turnover_t$									0.00	0.81
log(fund $TNA)_{t-1}$	−0.01***	−11.49							−0.01***	−7.52
log(family $TNA)_{t-1}$			0.00	0.14					0.00***	5.03
$\log(age)_{t-1}$					−0.01***	−9.31			−0.01***	−3.57
$\sigma(Return_{t\text{-}5\text{ to }t\text{-}1})$							0.11	0.58	−0.13	−0.74
R^2	0.25		0.24		0.25		0.25		0.26	
Observations	85914		79561		85914		85914		79374	
Time-Period	Q1.1990 − Q3.2010		Q1.1993 − Q3.2010		Q1.1990 − Q3.2010		Q1.1990 − Q3.2010		Q1.1993 − Q3.2010	

manage their asset class allocations and have, for example, lower cash holdings in some quarters, while higher cash holdings in other quarters. This, in turn, would add noise to return gap measures we calculate.

We therefore investigate whether the sensitivity of fund flows to the return gap depends on the accuracy of the return gap. We expect to find a stronger fund flow sensitivity to funds with more precisely estimated return gaps. We first calculate monthly return gaps in the 12 previous months. Next, we construct two measures for the precision of the return gap: t-statistic (RG_t) and standard deviation (RG_stdev). We include interactions of the return gap with RG_t and RG_stdev and report results in Table 3.13. The results in the Fama-Macbeth specifications (1) and (2) tells us little whether the precision of the return gap adds additional information. Some of the interactions are significant, but in the case of RG_stdev they are in the opposite direction. The pooled results in (3) and (4), however, provide some evidence that the sensitivity of fund flows to the precision of the return gap is significant. We find negative coefficients on the interactions of the return gap with its standard deviation, implying that investors allocate more capital towards funds with less volatile return gaps. Using the t-statistic of the return gap as a proxy for its precision, however, we do not find such evidence. In untabulated results we mitigate potential multicollinearity concerns by using an aggregate yearly return gap as an explanatory variable in place of the four quarterly realizations, but results remain inconclusive. Overall, we do not find strong evidence that investors respond stronger to funds with more precise return gaps.

Table 3.13. Precision of the Return Gap.

The dependent variable in each regression specification is fund flow in quarter t. In each specification we include four lagged return gap scores, calculated according to the procedure described in Section 3.2. In specifications (1) and (3) we include interactions of the four return gap scores with the t-statistic of the return gap, calculated from monthly return gap scores in the past 12 months. In specifications (2) and (4) we include interactions of the four return gap scores with the standard deviation of the monthly return gaps during the past 12 months. In each specification, we include an intercept, alpha (estimated using past one year of monthly fund returns and the excess return on the market, SMB, HML, and Momentum as risk factors), the most recently available expense ratio, four lagged quarterly fund flow measures, and four lagged fund net return measures. In specifications (1) and (2) we estimate the models using Fama-Macbeth regressions where I report t-statistics based on Newey-West standard errors with 3 lags. In specifications (3) and (4) we estimate the models using a panel regression approach where we include time-fixed effects and cluster standard errors on the fund level. * denotes statistical significance on the 10% level, ** denotes statistical significance on the 5% level, and *** denotes statistical significance on the 1% level.

	Fama-Macbeth				Pooled			
	(1) $Flow_t$		(2) $Flow_t$		(3) $Flow_t$		(4) $Flow_t$	
	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat	Coeff	t-stat
$ReturnGap_{t-1}$	0.24	3.40***	0.60	3.49***	0.13	2.62***	0.19	4.73***
$ReturnGap_{t-2}$	0.02	0.57	-22.40	-2.27**	0.15	4.07***	0.23	6.69***
$ReturnGap_{t-3}$	0.26	2.77***	0.33	2.40**	0.17	3.79***	0.21	5.43***
$ReturnGap_{t-4}$	0.03	0.64	-7.69	-1.06	0.18	3.60***	0.17	3.59***
$ReturnGap_{t-1}$*RG_t	0.23	3.02***			0.03	1.24		
$ReturnGap_{t-2}$*RG_t	0.01	0.42			-0.03	-1.67*		
$ReturnGap_{t-3}$*RG_t	0.15	2.09**			0.02	1.21		
$ReturnGap_{t-4}$*RG_t	0.01	0.42			0.03	1.57		
$ReturnGap_{t-1}$*RG_stdev			0.21	2.64***			-1.94	-4.58***
$ReturnGap_{t-2}$*RG_stdev			-1.27	-0.21			-1.40	-4.34***
$ReturnGap_{t-3}$*RG_stdev			0.22	2.43**			-1.47	-3.82***
$ReturnGap_{t-4}$*RG_stdev			-1.51	-0.22			-0.82	-0.78
Controls	Yes		Yes		Yes		Yes	
R^2	0.26		0.25		0.12		0.12	
Observations	85914		85914		85914		85914	

3.6 Conclusion

A large number of empirical papers document that disclosed portfolio holdings contain valuable information about the skill of fund managers. Yet, we know very little about how this information is used by investors. This is where this paper contributes. Following Kacperczyk et al. (2008), we construct the return gap – the difference between the net return of the fund and the return of the most recently disclosed portfolio holdings, and examine whether investors use it in their investment decisions.

The measure is very intuitive – it captures the effect of managerial actions, not directly observable by fund investors. A positive value implies that the fund manager has managed to add value during the quarter, but the action remains unobserved. Similarly, a negative value implies that the manager has done something to decrease the value of the fund. The measure is easy to construct, since a large number of data providers, such as Morningstar, offer analysis on the performance of disclosed fund holdings. Importantly, we show that the return gap contains predictive information about future performance over and above other performance measures. This makes the return gap an ideal portfolio-based decision-making variable.

The results in this paper point that investors use the return gap in order to distinguish skilled from unskilled fund managers. We provide a number of empirical patterns, consistent with this conjecture. We find a strong positive sensitivity of fund flows to past realizations of the return gap, which increases with investor sophistication. Furthermore, we find that the use of the return gap is highly non-linear, potentially due to the costs associated with analyzing disclosed fund holdings, and increases in times when the information content embedded in other performance measures decreases. In order to assess the economic importance of investors' response to the return gap, we analyze the the flow component associated with the return gap. The results show that disclosed mutual fund holdings help investors increase their returns.

This paper contributes to our understanding of investor behavior. Much of the empirical work has focused on showing that investors are naive and inexperienced in their investment decisions. On the contrary, we show that investors distinguish skilled from unskilled fund managers, using fund holdings information. Thus, this paper provides empirical evidence for the empirically contested assumption in most of the theoretical literature that there is a significant degree of investor sophistication.

Appendix A: Database Construction and Sample Selection

We start by selecting all US open-ended mutual funds from the CRSP mutual fund database and Thomson Financial/CDA database from January 1990 till June 2010. To ensure that we cover the universe of domestic diversified equity funds, for which the holdings data is most reliable, we select in our sample only funds with one of the following objective codes, provided by Lipper, Wiesenberger, and Strategic Insight and available in the CRSP Mutual Fund Database:

- Lipper: 'EI', 'EIEI', 'EMN', 'FLX', 'G', 'GI', 'I', 'LCCE', 'LCGE', 'LCVE', 'LSE', 'MC', 'MCCE', 'MCGE', 'MCVE', 'MLCE', 'MLGE', 'MLVE', 'SCCE', 'SCGE', 'SCVE', 'SESE', 'SG'
- Wiesenberger:'SCG', 'AGG', 'G', 'G-S', 'S-G', 'GRO', 'LTG', 'I', 'I-S', 'IEQ', 'ING', 'GCI', 'G-I', 'G-I-S', 'G-S-I', 'I-G', 'I-G-S', 'I-S-G', 'S-G-I', 'S-I-G', 'GRI', 'MCG'
- Strategic Insight: 'SCG','GRO','AGG','ING','GRI','GMC'

Furthermore, we include funds only if they have one of the following investment objective codes in the Thomson Financial database: aggressive growth, growth, growth and income, or unclassified, thus excluding any international, bond, asset allocation, precious metal and sector funds. Then, we drop funds that hold less than 80% or more than 105% in common stocks, as reported by CRSP. We also drop index funds by removing funds that contain in their CRSP-reported fund name the strings 'INDEX', 'INDE', 'INDX', 'S&P", or 'MSCI'. From Thomson Financial database, we remove overlapping report dates and file dates caused by fund mergers and name changes. We also delete funds that hold less than 10 stocks or manage less than $5 million.

If a fund offers multiple share classes to investors, we aggregate across different share classes. For total net assets (TNA) under management, we sum the TNAs of individual shares. For funds's age, we select the age of the oldest share class. For the other fund attributes (expenses, turnovers, etc.), we take the weighted average of the attributes of the individual share classes, where the weights are the lagged TNAs of the individual share classes.

We link the two mutual fund databases, using the MFLINKS database provided by WRDS. More information on how MFLINKS assigns a unique fund identifier to each fund in the two databases can be found in Wermers (2000). We manually check the MFLINKS databases for assigning reports from different Thomson Financial/CDA funds to the same fund in MFLINKS, and resolve such problems manually.

Definitions of the Determinants of the Return Gap

Trading Costs$_t$ Trading costs are calculated using the algorithm provided in Wermers (2000). The trading costs are calculated separately for buys and sales, where buys are defined as positive changes in disclosed net holdings across two quarters, and sales are defined as negative changes in disclosed net holdings across two quarters.

$$C^B_{j,t} = 1.098 + 0.336 * D^{Nasdaq}_{j,t} + 0.092 * Trsize_{j,t} - 0.084 * log(mcap_{j,t}) + 13.807 * P^{-1}_{j,t} \quad (4)$$

$$C^S_{j,t} = 0.979 + 0.058 * D^{Nasdaq}_{j,t} + 0.214 * Trsize_{j,t} - 0.059 * log(mcap_{j,t}) + 6.537 * P^{-1}_{j,t} \quad (5)$$

where $C^B_{j,t}$ ($C^S_{j,t}$) refer to the cost of buying (selling) stock j in quarter t, $D^{Nasdaq}_{j,t}$ is a dummy indicating whether stock j is traded on the Nasdaq during quarter t, $Trsize_{j,t}$ is the trade size, expressed as dollar value of trade divided by market capitalization, $log(mcap_{j,t})$ is the natural log of market capitalization of stock j expressed in thousands, and $P_{j,t}$ is the price of stock j. The total trading costs are then the sum of individual trading costs of all traded stocks by the mutual fund in quarter t. In case the fund did not disclose its portfolio holdings during that quarter, we use the estimated trading costs from the previous quarter.

Weight of recent IPOs$_t$ IPOs stocks in quarter t are defined as stocks whose IPO is conducted after the end of quarter $t-1$ and before the end of quarter t. The weight of recent IPOs in quarter t is defined as the percentage of the total fund portfolio held in IPO stocks in quarter t, i.e. the weight of the total portfolio allocated to stock with an IPO in the last three months.

Correlation between holdings return and fund net return$_t$ At the end of quarter t, we construct a time series of the performance of the most recently disclosed fund holdings over the last 12 months and calculate its correlation with the fund net return. We refer to this variable as $\rho(holdingsreturnandnetreturn)$.

Expense Ratio$_t$ The most recently available fund expense ratio as of quarter t.

Yearly Turnover$_t$ The most recently available fund turnover ratio as of quarter t.

Log(fund TNA)$_t$ The natural logarithm of fund total net assets, expressed in millions of dollars as of quarter t.

Log(family TNA)$_t$ The natural logarithm of the total net assets of the whole family, expressed in millions of dollars as of quarter t.

Log(age)$_t$ The natural logarithm of fund age, expressed in number of months since exception as of quarter t.

Standard deviation of fund returns between t-5 and t-1 The standard deviation of monthly fund return in the the 12 months ending in quarter t-1.

Chapter 4

Have Mutual Funds Lost Their Information Advantage? Reversal of Returns to Mutual Fund Trades.

4.1 Introduction

Despite the apparent confidence of investors in actively-managed mutual funds, the academic literature has found mixed evidence whether fund managers can beat their benchmarks. Starting from Jensen (1968), a large body of literature studying mutual fund returns has found that mutual fund managers underperform passive benchmarks.[1] However, studies using portfolio holdings are able to identify fund managers who can systematically pick stocks that have superior future performance.[2] Using quarterly reported data on mutual fund holdings, Chen et al. (2000) investigate the aggregate trades of actively-managed mutual funds and find that stocks bought by funds outperform stocks sold by them. Their findings suggest that mutual fund managers have an information advantage and can systematically pick stocks.

In this paper, we investigate changes in the information advantage of actively-managed mutual funds over time. We follow the approach of Chen et al. (2000) and examine the future performance of stocks traded by mutual funds in the aggregate. This method provides us with a powerful test for detecting managerial skill, for two main reasons. First, the active decision to trade a stock represents a stronger opinion than

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[1]See also Malkiel (1995), Carhart (1997), and Fama and French (2010), among others.

[2]See, for instance, Grinblatt and Titman (1993), Wermers (1999), Wermers (2000), Daniel et al. (1997), Cohen et al. (2005), Kacperczyk et al. (2005), Alexander et al. (2007), Jiang et al. (2007), Kacperczyk and Seru (2007), Cremers and Petajisto (2007), and Baker et al. (2010).

the passive decision to hold it. Second, trades of fund managers in the aggregate represent the consensus opinion of the entire fund industry about the future performance of stocks. As a result, if fund managers can systematically identify under/over-valued stocks, we should be likely to observe this in the performance of the aggregate mutual fund trades.

We document diminishing returns to the trades of the actively-managed mutual fund industry. For the 1980 to 2000 period, we find results consistent with Chen et al. (2000). Stocks widely bought by mutual funds significantly outperform stocks widely sold over the next quarter. The difference is 0.59% on a risk-adjusted basis. However, between 2001 and 2010 the risk-adjusted difference in performance between the aggregate buys and sales among the mutual fund industry amounts to -0.86% in the following quarter. The latter result, although of high economic magnitude, is statistically indistinguishable from zero, probably due to the low number of observations after 2001. Nevertheless, the difference of 1.45% of the trades (buys minus sells) between the two periods is statistically significant and is an economically substantial effect. We further examine the cumulative return of one dollar invested in the portfolio of mutual fund trades and find that by the end of 2010, all of the return due to the positive performance of the mutual fund trades prior to 2001 is offset by the negative performance following 2001.

We further show that most of the dynamics in the performance of the aggregate mutual fund trades is due to the purchasing decisions of fund managers. Prior to 2001, mutual fund buys have a significantly positive performance of 0.44% per quarter. After 2001, the effect size is similar, but with the opposite sign – -0.43% per quarter, albeit statistically not different from zero. The difference of 0.88% is marginally statistically significant and economically substantial. There are also diminishing returns to the performance of the sales of mutual funds, although the magnitude of the change in performance across the two periods is smaller (0.57% per quarter). The aggregate effect is concentrated among the stocks most widely held by mutual fund managers – large and growth stocks. We also find that the reversal in the return of the trades is monotonically increasing in stocks' ownership by mutual funds and in the stocks' analyst coverage.

To understand what drives these results, we investigate the performance of the aggregate trades conditional on several fund characteristics. We show that fund size is an important determinant of our findings – the reversal in the performance of both quarterly buys and sales is most pronounced for the largest funds. We further investigate the performance of trades, conditional on managerial skill. We use two proxies for skill – past risk-adjusted performance and the return gap measure of Kacperczyk et al. (2008). Our findings point to an economically comparable decrease in the performance of the trades across both skilled and non-skilled funds. These findings suggest that our main results are not solely driven by a decreasing informational advantage among skilled fund managers.

We distinguish between two channels that may potentially drive the results. On the one hand, the stock-picking skills of fund managers might have decreased over time. On the other hand, mutual fund managers might suffer increasingly more from the price impacts of rebalancing their portfolios, for example after very high redemptions. We follow Alexander et al. (2007) and use fund flows as an identification mechanism for distinguishing information from liquidity driven trades. According to this approach, fund purchases (sales) when there are heavy outflows (inflows) are likely to be motivated by the belief that the stocks are undervalued (overvalued). On the other hand, purchases (sales) concurrent with investor inflows (outflows) are more likely to be made due to portfolio rebalancing needs and hence not related to future stock performance. We find no evidence for deteriorating performance of the liquidity motivated trades. However, we find an economic decrease in the valuation motivated trades, although statistical significance is weak.

We provide a further test for a potential liquidity-based explanation for our main findings. We investigate whether the performance of the trades of funds with volatile flows have worsened over time. If increasing costs of portfolio rebalancing are responsible for the diminishing returns to trades, we should find stronger effects among funds with more volatile flows. Our results do not indicate any significant changes in the performance of the trades among funds with volatile flows. Moreover, the main economic effects of diminishing returns to trades is not concentrated among such funds. Thus, we overall do not find support for the conjecture that the reason for the diminishing returns to the trades of actively managed mutual funds is increased cost of their liquidity driven trades.

Next, we take a closer look at the information-based hypothesis for the decrease in the performance of the aggregate mutual fund trades. We investigate the impact of a regulatory change, likely to decrease the private information of fund managers. Regulation Fair Disclosure (Reg FD), effective August 2000, limited the privileged access to firm information enjoyed by analysts and fund managers. Bhojraj et al. (2012) show that the effect of Reg FD is most pronounced for funds belonging to large fund families, since they are most likely to establish strong firm relations and command privileged access to information. Consistent with this hypothesis, we find that the drop in the performance of the aggregate purchases of mutual funds is driven by funds belonging to the largest fund families. However, we find a reversal in the performance of the sales only for funds belonging to medium-sized families. Consequently, we find that the decrease in the performance of the aggregate trades is significant for both fund belonging to large and medium sized families. Thus, it appears that Reg FD can at best only partially explain the diminishing returns to mutual fund trades.

This study builds on a large stream of literature studying the information content of mutual fund holdings and trades. Wermers (2000) uses mutual fund holdings to decompose fund returns into various components and finds that funds pick stocks which outperform their benchmarks, but this outperformance does not translate into superior investor returns due to fees and transaction costs. Baker et al. (2010) show that stocks traded by mutual funds positively predict future earning surprises. Kacperczyk et al. (2005), Kacperczyk and Seru (2007), Kacperczyk et al. (2008), and Cremers and Petajisto (2007), among others, construct managerial skill proxies using fund holdings data. Wermers et al. (2012) and Jiang et al. (2013) further show that there is predictability in stock returns based on information from fund holdings.

The paper closest to ours is by Chen et al. (2000). We follow their methodology and study changes in the performance of the aggregate mutual fund trades. Having a sample ending in 1995, Chen et al. (2000) find that stocks purchased by mutual funds outperform stocks they sell. Based on this evidence, they conclude that trades reveal important information about the presence of stock-picking skills in the actively-managed mutual fund industry. Our main contribution is to show that mutual funds appear to have lost the informational advantage. We further contribute by investigating the driving factors behind this finding. We show that the most likely explanation for this is limitation of selective access to firm information, following the implementation of Reg FD in 2001. Even though Reg FD may not fully explain the reversal in the performance of aggregate trades, our findings suggest that a large part of the informational advantage of active fund managers, documented in previous studies, may be driven by selective access to firm information.

4.2 Data Selection and Summary Statistics

This study combines a number of commonly used databases - Thomson Financial/CDA S12 equity holdings database, CRSP Mutual Fund Database, and the CRSP monthly stock files. The Thomson Financial/CDA database covers quarterly/ semi-annual holdings of mutual funds, as reported to the SEC or voluntarily reported by the funds. We select funds with an investment objective code of growth, aggressive growth, and growth and income. We further exclude all index funds. We link the Thomson Financial/CDA database to the CRSP Mutual Fund Database using the MFLINKS tool provided by WRDS. From the CRSP Mutual Fund Database we select active equity mutual funds only. Our final dataset covers funds included in both mutual fund databases, for which we have two consecutive quarterly reports in Thomson Financial/CDA. Since most actively managed US equity funds offer different share classes to investors, we sum the net assets over different share classes and take asset-weighted share class averages of different attributes such as returns and expense ratios. More details on the merging process and sample selection are available in Appendix A.

The summary statistics of the sample are reported in Table 4.1. We provide summary statistics separately for three subsamples of 10 years, as well as for the whole period. In total, our analysis is based on 1674 mutual funds, most of which were present in our sample between 1991 and 2000. The number of stocks in the portfolios of fund managers has been rising over time, with a mean of 109 and a median of 71. Similarly, funds have been growing in size over time and the mean size value is more than 4 times higher than the median. Means are higher than medians due to the presence of a few extremely large funds. We observe that net fund returns are much smaller in the last decade, which is driven by the crisis period after 2007. We investigate fund performance in greater details in Table 4.2. Despite the growth of the fund industry over time, average flows are on average negative after 2001. We further note an increase in the turnover and expenses charged by mutual funds from the 80s to the 90s, which remain on similar levels after 2001.

Table 4.1. Sample Summary Statistics.

This table provides the summary statistics of the sample.

Time-Period	# of funds	Stock holdings		Net Assets		Net Monthly Return		Monthly Flow		Yearly Turnover		Yearly Expense Ratio	
		Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
1980 - 1990	471	73	55	331	114	1.09	1.32	0.68	−0.02	78	59	1.15	1.00
1991 - 2000	1586	107	71	1088	188	1.42	1.58	3.08	0.24	90	68	1.30	1.21
2001 - 2010	1254	122	78	2017	382	0.23	0.82	−0.11	−0.56	87	67	1.32	1.21
1980 - 2010	1674	109	71	1394	237	0.85	1.19	1.37	−0.20	87	66	1.29	1.19

Table 4.2. Fund Performance – Summary Statistics.

This table provides individual fund performance summary statistics.

Time-Period	Quarterly Net Return		Monthly Alpha		Benchmark-adjusted Holdings Return		Benchmark-adjusted Trades Return	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median
1980 - 1990	3.72	4.62	0.05	0.04	0.23	0.13	0.00	0.07
1991 - 2000	3.54	3.36	0.10	−0.04	0.35	0.12	0.18	0.11
2001 - 2010	1.06	2.16	−0.12	−0.12	−0.04	−0.02	−0.21	−0.22
1980 - 2010	2.36	2.93	−0.01	−0.07	0.15	0.04	−0.03	−0.07

We analyze the performance of quarterly mutual fund trades. Similarly to Chen et al. (2000), we use benchmark-adjusted stock returns in the spirit of Daniel, Grinblatt, Titman, and Wermers (1997, henceforth DGTW). In the DGTW methodology, at the end of each June stocks are allocated to five size quintiles based on their market capitalization. Within each size quintile, stocks are further ranked in five quintiles based on their book-to-market ratios, yielding a total of 25 size and book-to-market sorted portfolios. Next, stocks within each of the 25 portfolios are further subdivided in 5 additional portfolios, based on their prior 12 month return. This procedure results in 125 stock portfolios. The benchmark returns are then computed as the returns of the 125 portfolios in the next 12 months, after which the portfolios are updated. The procedure is further explained in Daniel et al. (1997) and Wermers (2004). We obtain the stock allocation and the returns of the benchmark portfolios from Russ Wermers' webpage[3] and calculate benchmark-adjusted stock return as stock returns in excess of the return of their respective benchmark portfolio.

Summary statistics regarding individual fund performance are reported in Table 4.2. As in Table 4.1, we document that fund net returns are much lower in the last decade of our sample. However, it is interesting to see that risk-adjusted performance is also much lower after 2001. To calculate fund alphas, we first estimate a four factor model including the Excess Return on the Market, SMB, HML, and Momentum for each fund over a 12 month interval prior to the period when we compute the return of the funds' trades. Next, we calculate monthly alphas over the next three months subtracting the estimated coefficients times the respective realizations of the risk factors from the fund's excess return. This way we make sure we report alphas and calculate benchmark-adjusted trades returns over the same period. We document a mean alpha of -0.12% per month after 2001, while the average over the whole sample is -0.01%. This result, albeit descriptive, is the first evidence that the performance associated with stock-picking of fund managers might have decreased with time.

Next, we investigate the average holdings return. It is computed as the quarterly benchmark-adjusted return of each stock held, where the weights are based on the dollar amount of stock owned by the fund. Results are similar. Both the mean and median values have decreased in the last decade. The magnitude of

[3]The DGTW benchmarks are available via `http://www.smith.umd.edu/faculty/rwermers/ftpsite/Dgtw/coverpage.htm`.

the decrease is substantial: the mean benchmark-adjusted return has decreased with 0.39%, while the median one has decreased by 0.14%. We further look at the average benchmark-adjusted returns of the stocks traded by mutual funds. Buys (sales) at times t are stocks for which a fund increased its stock holdings between two consecutive quarters. We calculate benchmark-adjusted returns separately for the buys and sales portfolios, where we weigh the stocks using the dollar volume traded. We define dollar volume traded as the change in stock holdings times the share price at the end of quarter t. In Table 4.2 we report the average fund difference between the buys and sales portfolios, which we label trades. Again, we find a pronounced decrease in both the mean and median values. The difference in the mean (median) quarter-ahead performance between the 00s and the 90s amounts to 0.39% (0.33%) per quarter.

Overall, the descriptive statistics indicate that there is a sharp decrease in the performance of individual funds after 2001. The effect is substantial both for net and risk-adjusted performance, as well as for before and after-fee performance. In the rest of the paper, we investigate the stock-picking trades of fund managers by focusing on their aggregate quarterly trades.

4.3 Changes in the Performance of the Aggregate Mutual Fund Trades

This paper investigates the performance of stocks bought and sold in the aggregate by mutual funds. Prior to 2004, mutual funds were required to disclose the composition of their portfolios on a semi-annual basis, although most of them reported voluntarily every quarter. Starting from May 2004, all funds are required to disclose the composition of their portfolios on a quarterly basis. Since we do not observe any actual trading decisions, we use the disclosed portfolio holdings in order to approximate the aggregate buys and sales of mutual funds. We define "buys" ("sales") in quarter t as stocks for which there is an increase (decrease) in the aggregate holdings among the funds included in our sample for which we have a holdings report in quarters t and $t-1$.

We compute quarter $t+1$ benchmark-adjusted returns where we weigh again the stocks in the buys and sales portfolio using the dollar volume traded. This way we give higher weight to stocks for which there is a stronger trading consensus among mutual funds, represented by the difference among the buying and selling volume in those stocks (the aggregate change in holdings times the per share stock price). We define the "trades" portfolio as the difference between the "buys" and "sales" portfolios. This is the same procedure used for reporting descriptive statistics in Table 4.2, where buys, sales, and trades are calculated on an aggregate level.

We report the performance of the buys, sales, and trades portfolios over different time periods in Table 4.3. Over the whole sample period, the consensus buying and selling actions of the mutual fund industry do not add value. Panel A shows that the average benchmark-adjusted return of the trades portfolio is 0.14% per

Table 4.3. The Performance of the Stocks Traded by Mutual Funds.

For each stock owned by mutual funds in our sample we calculate the change in fund ownership between quarters t and $t-1$. We define BUYS (SALES) as stocks for which there is an increase (decrease) in the aggregate stock ownership between quarters t and $t-1$. We calculate benchmark-adjusted returns for the BUYS and SALES portfolios for quarter $t+1$, where we weight the stocks using the change in the number of shares owned by mutual funds times the per share price at the end of quarter $t-1$. TRADES are defined as the difference between BUYS and SALES. We report results separately for 1980-2010 (Panel A), 1980-2000 (Panel B), 2001-2010 (Panel C). In Panel D we calculate the differences between the 2001-2010 and the 1980-2000 periods. Results are expressed in percentage points per quarter. * denotes statistical significance on the 10% level, ** denotes statistical significance on the 5% level, and *** denotes statistical significance on the 1% level.

Buys	Sales	Trades	Buys	Sales	Trades
A: 1980-2010			B: 1980-2000		
0.17	0.03	0.14	0.44**	-0.15	0.59*
(0.22)	(0.20)	(0.31)	(0.20)	(0.25)	(0.32)
C: 2001-2010			D: (2001-2010) - (1980-2000)		
-0.43	0.42	-0.86	-0.88*	0.57	-1.45**
(0.40)	(0.31)	(0.64)	(0.45)	(0.40)	(0.71)

quarter, which is not statistically different from zero. However, these results miss important dynamics in the performance of the aggregate trades. In Panel B we report values for the 1980–2000 period and find results consistent with the study of Chen et al. (2000). The spread portfolio produces a significant abnormal return of 0.59% per quarter and the effect is driven by the buying decisions of fund managers. Chen et al. (2000) further show that the outperformance of the aggregate fund trades persists for one year. Thus, in the first two decades of our sample, changes in the portfolios of mutual fund managers were dominated by value-enhancing trades.

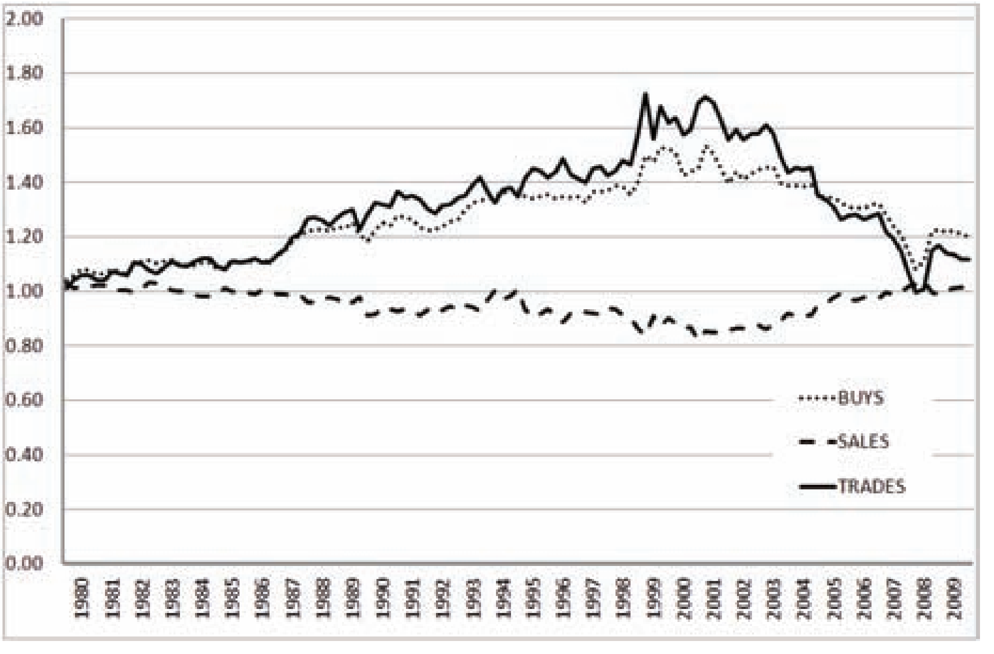
The results for the 2001–2010 period, presented in Panel C, indicate sizable reversals in the performance of the aggregate trades. Whereas prior to 2001 stocks widely bought by mutual fund outperformed their benchmark by 0.44% in the following quarter, they underperform by a similar amount after 2001 – -0.43%. A similar effect is present in the aggregate sales of mutual funds. This underperformance, however, is not statistically different from zero, possibly due to the small sample size (only 10 years). Yet, the change in performance between the two periods is statistically significant. In Panel D we report a very large economic magnitude in the reversal in the subsequent performance of the trades portfolio, which amounts to 1.45% per quarter. These results indicate that mutual funds may have lost the informational advantage they previously possessed.

We visualize the reversals in performance in Figure 4.1, where we plot the cumulative benchmark-adjusted return of 1 dollar invested in the buys, sales, and trades portfolios in 1980 during our sample period. The figure documents that the reversals in the performance of the cumulative aggregate trades portfolio start around year 2001. The peak in the hypothetical cumulative benchmark-adjusted return of the trades portfolio occurs in 1999. However, after 2001, we observe a clear downward trend. By 2008, all of the profits from the value-enhancing trades of the mutual fund industry have evaporated due to value-destroying trades.

In Table 4.4 we report changes in the performance of aggregate trades, conditional on several stock characteristics. We first examine stock size in Panel A. At the end of each June, we rank all NYSE, AMEX,

Figure 4.1. Cumulative Return of the Aggregate Trades.

For each stock owned by mutual funds in our sample we calculate the change in fund ownership between quarters t and t-1. We define BUYS (SALES) as stocks for which there is an increase (decrease) in the aggregate stock ownership between quarters t and t-1. We calculate benchmark-adjusted returns for the BUYS and SALES portfolios for quarter t+1, where we weight the stocks using the change in the number of shares owned by mutual funds times the per share price at the end of quarter t-1. TRADES are defined as the difference between BUYS and SALES.We plot the quarter $t+1$ cumulative benchmark-adjusted return of 1 dollar invested in the aggregate mutual funds buys, sales, and trades in quarter t.



and NASDAQ stocks having at least two years of book value of equity data in Compustat and stock return and market capitalization data in CRSP in 5 quintiles, using NYSE size quintile breakpoints. We keep the stock quintile allocation until the next June, when we repeat the ranking procedure. We do the ranking every June in order to remain consistent with the DGTW methodology. Using quarterly holdings data from quarters t and $t-1$, we identify the portfolios of buys, sales, and trades separately for each size bucket as identified at the end of quarter $t-1$, and track their benchmark-adjusted performance in quarter $t+1$. Note that this implies that the number of stocks in each quintile differs, since we base portfolio breakpoints on NYSE stock data while mutual funds have a preference for holding large stocks. We find that in the pre-2000 period managers had an information advantage among both large and small stocks – all but the smallest size quintile have a positive benchmark-adjusted trades. After 2000, the trades among the most widely held stocks, the ones with the largest size, have significantly negative returns. However, we find that the difference in the trades portfolio is significantly negative for the three largest size quintiles. Moreover, the magnitude of the reversal in performance between the two periods is increasing in fund size.

We perform a similar analysis using stocks' book-to-market ratio. Instead of conditioning on stock size, at the end of quarter $t-1$ we sort stocks based on industry-adjusted book-to-market ratio, where we follow Wermers (2004) and allocate each to stock to a book-to-market quintile at the end of June.[4] We report results in Panel B of Table 4.4. Again, we find that the decrease in the trades performance is concentrated among the most preferred stocks by fund managers – growth stocks. More specifically, we find significantly different change in the performance of the two portfolios with the lowest book-to-market ratio, and the economic effect is decreasing with the book-to-market ratio.

The next stock characteristic we examine is momentum. We perform a similar analysis where in the first step we rank stocks at the end of quarter $t-1$ based on their past 12 month return calculated at the end of previous June. Again, the reason why we keep the June rankings is to remain consistent with the DGTW methodology. Then, we proceed with computing the quarterly buys, sales, and trades portfolios. Results are reported in Panel C of Table 4.4. Our results point to a significant decrease in the performance of the aggregate mutual funds for three out of the five deciles, although there does not seem to be a more pronounced pattern among either past losers or winners.

We next investigate the performance of mutual fund trades, conditional on mutual fund ownership. At the end of quarter $t-1$ we sort stocks in 5 portfolios based on the number of mutual funds owning the stock. We drop stocks that are not owned by any mutual fund in our sample. Next, using quarterly holdings data from quarters t and $t-1$, we identify the portfolios of buys, sales, and trades separately for each bucket as identified at the end of quarter $t-1$, and track their benchmark-adjusted performance in quarter $t+1$. We report results in Panel D of Table 4.4. We find that the reversal in the performance of aggregate trades is monotonically increasing in stock ownership. This result is not surprising – our analysis on stock size and book-to-market ratio points that the decrease in the informational advantage of funds is increasing in fund size and decreasing in book-to-market ratio.

The last stock characteristic we investigate is analyst coverage. Similarly to the stock ownership analysis in Panel D, we sort stocks at the end of quarter $t-1$ base on the number of analysts covering them. The data comes from IBES. Then, we proceed with calculating the buys, sales, and trades portfolios in quarter t separately for each quintile and investigate their benchmark-adjusted returns in quarter $t-1$. Results are summarized in Panel E of In Table 4.4. We find that the reversals in the performance of aggregate trades are concentrated month the stocks with the highest analyst coverage. Only quintile 5 has significant changes in the performance of the buys between the two periods.

The results in this section point to a statistically significant and economically substantial reversal in the performance of the aggregate mutual fund trades. The effect is most pronounced among the most widely held stocks by mutual funds. This raises the possibility that after 2001 actively managed mutual funds might have lost the information advantage they previously had. In the next section we explore this finding in greater

[4] Note, however, that in contrast to Wermers (2004) and the DGTW methodology, we do not first rank funds based on firm size, since we are interested in capturing only the book-to-market dimension.

detail and suggest a few potential explanations.

Table 4.4. Stock Characteristics and Returns to Mutual Fund Trades.

At the end of each quarter $t-1$ we sort stocks in 5 buckets, based on a stock characteristic. In Panel A we sort stocks on stock size. Stock size is defined using NYSE size breakpoints as of the latest June. This way we effectively keep the same stock allocation from July until the next June. In Panel B we sort stocks on stock industry-adjusted book-to-market ratio. We follow the definitions in Wermers (2004) when computing the industry-adjusted book-to-market ratio and use allocations as of the latest June. This way we effectively keep the same stock allocation from July until the next June. In Panel C we sort stocks on stock momentum. Momentum is defined as the past 12 month return as of the latest June. This way we effectively keep the same stock allocation from July until the next June. In Panel D we sort stocks on mutual fund ownership. Mutual fund ownership is defined as the number of funds owning the stock at the end of quarter $t-1$. In Panel E we sort stocks on the number of analysts covering the stock at end of quarter $t-1$. Next, we calculate the change in mutual fund ownership between quarters $t-1$ and t, separately for each stock in each bucket. We define BUYS (SALES) as stocks for which there is an increase (decrease) in the aggregate stock ownership between quarters t and $t-1$, separately for each bucket. We calculate benchmark-adjusted returns for the BUYS and SALES portfolios for quarter $t+1$, where we weight the stocks using the change in the number of shares owned by mutual funds times the per share price at the end of quarter $t-1$. TRADES are defined as the difference between BUYS and SALES. We report results separately for 1980-2000, 2001-2010, and the differences between the 2001-2010 and the 1980-2000 periods. Results are expressed in percentage points per quarter. * denotes statistical significance on the 10% level, ** denotes statistical significance on the 5% level, and *** denotes statistical significance on the 1% level.

	A: Size								
	Buys	Sales	Trades	Buys	Sales	Trades	Buys	Sales	Trades
	1980-2000			2001-2010			(2001-2010) - (1980-2000)		
1 (low)	0.26	1.34***	-1.07**	0.40	0.82*	-0.42	0.14	-0.51	0.65
	(0.35)	(0.49)	(0.44)	(0.49)	(0.50)	(0.56)	(0.60)	(0.70)	(0.72)
2	0.84**	-0.09	0.93***	0.98**	0.69	0.30	0.14	0.77	-0.63
	(0.33)	(0.37)	(0.35)	(0.39)	(0.46)	(0.40)	(0.51)	(0.59)	(0.53)
3	0.54	-0.11	0.65*	0.43	1.26***	-0.83	-0.11	1.37**	-1.48**
	(0.39)	(0.38)	(0.38)	(0.55)	(0.43)	(0.57)	(0.68)	(0.58)	(0.69)
4	0.98**	0.04	0.94**	0.46	0.74	-0.29	-0.52	0.71	-1.23*
	(0.39)	(0.35)	(0.40)	(0.69)	(0.46)	(0.63)	(0.79)	(0.57)	(0.74)
5 (high)	0.28	-0.58**	0.86***	-0.63	0.43	-1.07*	-0.91	1.02**	-1.93***
	(0.21)	(0.28)	(0.28)	(0.53)	(0.37)	(0.57)	(0.57)	(0.46)	(0.63)
	B: Book-to-market								
	Buys	Sales	Trades	Buys	Sales	Trades	Buys	Sales	Trades
	1980-2000			2001-2010			(2001-2010) - (1980-2000)		
1 (low)	0.58	-0.66*	1.24***	-0.43	0.71	-1.14*	-1.01	1.37**	-2.38***
	(0.36)	(0.40)	(0.38)	(0.62)	(0.46)	(0.65)	(0.71)	(0.61)	(0.75)
2	0.53**	-0.06	0.60*	-0.49	0.76*	-1.25***	-1.02**	0.83	-1.85***
	(0.24)	(0.32)	(0.32)	(0.45)	(0.39)	(0.42)	(0.51)	(0.51)	(0.53)
3	0.37	0.35	0.03	-0.05	-0.23	0.18	-0.42	-0.57	0.15
	(0.41)	(0.32)	(0.36)	(0.84)	(0.49)	(0.76)	(0.93)	(0.59)	(0.84)
4	0.12	-0.96**	1.07***	0.45	-0.01	0.46	0.33	0.94	-0.61
	(0.29)	(0.48)	(0.40)	(0.89)	(0.66)	(0.69)	(0.94)	(0.82)	(0.80)
5 (high)	0.01	-0.16	0.17	2.15*	0.16	2.00*	2.14	0.32	1.82
	(0.53)	(0.44)	(0.53)	(1.26)	(1.24)	(1.03)	(1.37)	(1.32)	(1.16)
	C: Momentum								
	Buys	Sales	Trades	Buys	Sales	Trades	Buys	Sales	Trades
	1980-2000			2001-2010			(2001-2010) - (1980-2000)		
1 (low)	0.69	0.71	-0.03	-0.67	-0.01	-0.66	-1.35	-0.72	-0.63
	(0.59)	(0.75)	(0.67)	(1.24)	(1.02)	(0.87)	(1.37)	(1.27)	(1.10)
2	0.66**	-0.51	1.16***	-0.29	0.45	-0.74	-0.95	0.96	-1.91***
	(0.33)	(0.40)	(0.35)	(0.74)	(0.54)	(0.64)	(0.82)	(0.67)	(0.73)
3	0.55**	0.60*	-0.05	-0.75	0.90**	-1.65**	-1.30*	0.30	-1.59**
	(0.23)	(0.31)	(0.31)	(0.68)	(0.39)	(0.73)	(0.72)	(0.50)	(0.79)
4	0.33	-0.20	0.52	0.89*	0.24	0.65	0.57	0.44	0.13
	(0.25)	(0.37)	(0.36)	(0.49)	(0.50)	(0.60)	(0.55)	(0.62)	(0.70)
5 (high)	0.48	-0.18	0.66	-0.34	0.80	-1.15*	-0.83	0.98	-1.81**
	(0.39)	(0.45)	(0.47)	(0.63)	(0.85)	(0.64)	(0.74)	(0.96)	(0.80)

Table 4.4 – continued from previous page

	D: Mutual Fund Ownership								
	Buys	Sales	Trades	Buys	Sales	Trades	Buys	Sales	Trades
	1980-2000			2001-2010			(2001-2010) - (1980-2000)		
1 (low)	0.15	0.01	0.13	0.00	-0.10	0.09	-0.15	-0.11	-0.04
	(0.40)	(0.37)	(0.44)	(0.73)	(1.06)	(0.84)	(0.83)	(1.12)	(0.95)
2	0.25	-0.29	0.53	0.40	0.57	-0.17	0.16	0.86	-0.70
	(0.34)	(0.45)	(0.40)	(0.54)	(0.68)	(0.58)	(0.64)	(0.82)	(0.71)
3	0.39*	-0.06	0.45	-0.43	0.04	-0.47	-0.82*	0.10	-0.92*
	(0.23)	(0.33)	(0.32)	(0.36)	(0.33)	(0.36)	(0.43)	(0.46)	(0.49)
4	0.58	0.35	0.23	0.36	1.19***	-0.83*	-0.22	0.83*	-1.06*
	(0.41)	(0.29)	(0.39)	(0.48)	(0.36)	(0.43)	(0.63)	(0.46)	(0.58)
5 (high)	0.45**	-0.26	0.70***	-0.55	0.35	-0.91*	-1.00*	0.61	-1.61***
	(0.19)	(0.25)	(0.24)	(0.57)	(0.32)	(0.55)	(0.60)	(0.41)	(0.60)
	E: Analsyt Coverage								
	Buys	Sales	Trades	Buys	Sales	Trades	Buys	Sales	Trades
	1980-2000			2001-2010			(2001-2010) - (1980-2000)		
1 (low)	-0.37	-0.03	-0.33	-0.91	0.00	-0.90	-0.54	0.03	-0.57
	(0.45)	(0.58)	(0.65)	(0.57)	(0.78)	(0.95)	(0.73)	(0.97)	(1.15)
2	-0.02	-0.20	0.18	-0.73	0.65	-1.39*	-0.72	0.85	-1.57
	(0.40)	(0.57)	(0.65)	(0.63)	(0.63)	(0.78)	(0.75)	(0.86)	(1.01)
3	0.01	-0.27	0.28	0.06	0.62	-0.56	0.05	0.89	-0.84
	(0.48)	(0.43)	(0.56)	(0.82)	(0.55)	(0.90)	(0.94)	(0.70)	(1.06)
4	0.38	0.69	-0.31	0.47	-0.19	0.66	0.08	-0.88	0.96
	(0.41)	(0.56)	(0.72)	(0.68)	(0.55)	(0.79)	(0.80)	(0.79)	(1.07)
5 (high)	0.43**	-0.28	0.71**	-0.63	0.50	-1.13	-1.06*	0.77*	-1.83**
	(0.20)	(0.27)	(0.34)	(0.61)	(0.34)	(0.77)	(0.64)	(0.44)	(0.84)

4.4 Explanations for the Decrease in the Performance of the Aggregate Fund Trades

To better understand the driving factors behind the reversal in the trades of mutual fund managers, we examine the performance of the trades, conditional on several fund characteristics. We fist look at fund size. Chen et al. (2004) point that larger funds have higher liquidity costs that their smaller counterparts and note that organizational diseconomies may further drag the performance of large funds. Another often put argument why larger funds may perform worse than smaller funds is that managers of larger funds spread their informational advantages "too thin" (see, for example, Berk and Green (2004)). Therefore, investigating the impact of fund size on the performance of the aggregate trades can help us to better understand what drives the decrease in the informational advantage documented in the previous section.

We again use a portfolio sorting approach, according to which we first rank the funds in our sample in five buckets based on their size at the end of quarter $t-1$. Next, we identify the portfolios of buys, sales, and trades separately for each bucket, based on quarterly holdings data from quarters t and $t-1$, and track their benchmark-adjusted performance in quarter $t+1$. This procedure allows to investigate the consensus opinion about the performance of stocks separately for each size category of mutual funds.

Results are summarized in Table 4.5. We find that prior to 2001 the stock purchases among most size groups generated positive risk-adjusted returns. Interestingly though, during that period only the largest funds have a significantly positive value of their trades. This pattern completely reverts after 2000, where we document that the trades among the largest funds perform the worst. Even though there are economically seizable decreases in the returns of the trades among all fund size groups, the reversals are strongest among the quintile containing the largest funds – 1.50% per quarter on a risk-adjusted basis. Sales among portfolios 2 and 4 have positive future benchmark-adjusted performance, indicating that managers are selling stocks in quarters before they appreciate in value. Overall, the findings in Table 4.5 suggest that the pattern of decreasing returns to mutual fund trades is mainly driven by the largest funds.

Table 4.5. Fund Size and Returns to Mutual Fund Trades.

At the end of quarter $t-1$ we sort funds in our sample in 5 buckets based on their net assets under management. For each stock owned by mutual funds in our sample we calculate the change in fund ownership between quarters t and $t-1$, separately for each bucket. We define BUYS (SALES) as stocks for which there is an increase (decrease) in the aggregate stock ownership between quarters t and $t-1$, separately for each bucket. We calculate benchmark-adjusted returns for the BUYS and SALES portfolios for quarter $t+1$, where we weight the stocks using the change in the number of shares owned by mutual funds times the per share price at the end of quarter $t-1$. TRADES are defined as the difference between BUYS and SALES. We report results separately for 1980-2000, 2001-2010 and for the differences between the 2001-2010 and the 1980-2000 periods. Results are expressed in percentage points per quarter. * denotes statistical significance on the 10% level, ** denotes statistical significance on the 5% level, and *** denotes statistical significance on the 1% level.

	Buys	Sales	Trades	Buys	Sales	Trades	Buys	Sales	Trades
	1980-2000			2001-2010			(2001-2010) - (1980-2000)		
1 (low)	0.47**	0.22	0.25	0.22	0.26	-0.04	-0.25	0.04	-0.29
	(0.20)	(0.30)	(0.28)	(0.35)	(0.20)	(0.33)	(0.41)	(0.36)	(0.44)
2	0.32	0.19	0.13	0.37	0.38**	-0.02	0.04	0.19	-0.15
	(0.21)	(0.19)	(0.23)	(0.37)	(0.16)	(0.33)	(0.43)	(0.25)	(0.40)
3	0.46**	0.31	0.16	0.06	0.32	-0.26	-0.40	0.02	-0.42
	(0.22)	(0.19)	(0.23)	(0.32)	(0.22)	(0.29)	(0.39)	(0.30)	(0.37)
4	0.44**	0.03	0.41**	0.55	0.46**	0.09	0.10	0.42	-0.32
	(0.20)	(0.19)	(0.20)	(0.48)	(0.21)	(0.43)	(0.52)	(0.29)	(0.48)
5 (high)	0.42**	-0.18	0.59***	-0.53	0.37	-0.91**	-0.95**	0.55*	-1.50***
	(0.16)	(0.20)	(0.21)	(0.41)	(0.25)	(0.41)	(0.44)	(0.32)	(0.46)

4.4.1 Managerial Skill

Some papers document the presence of (short-term) persistence in performance among both skilled and unskilled mutual fund managers.[5] One possibility for our findings is worsening performance among the least skilled funds. Under this conjecture we should still find positive returns to the trades amongst the most skilled funds and a widening gap between skilled and less skilled funds. Alternatively, the decrease in the trades performance documented in the previous section might be attributable to the most skilled funds losing their competitive edge. Thus, to better understand the driving factors behind our main findings, we investigate the aggregate performance of quarterly trades among groups composed on the basis of proxies for managerial skill.

We use two proxies for managerial skill. The first one is four-factor alpha. Even though past alpha is affected by luck and may not predict future performance very well, it contains a noisy signal about managerial skill (see, for example, Berk and Green (2004) and Huang et al. (2007)). Consequently, we perform similar

[5] See, for example, Hendricks et al. (1993), Gruber (1996), and Bollen and Busse (2005).

tests as in Table 4.5, but instead of sorting funds on fund size, we sort funds on their past alpha, estimated from 12 month of returns where we use Excess Market Return, SMB, HML, and Momentum as risk factors.

We report results in Panel A of Table 4.6. In the pre-2001 period we find some evidence for return persistence. The benchmark-adjusted performance of the trades of funds belonging to the top quintile trades amounts to 1.34% in the following quarter. In the post-2001 period the return of the trades among funds with best past performance is still positive, but statistically not significantly different from zero. During that period there is a negative benchmark-adjusted performance of the trades of funds belonging to the lowest three quintiles. In terms of statistical significance, there is a decrease among the return to trades for four out of the five groups. Nevertheless, the decrease in the performance of the trades is economically most substantial among the funds with worse past performance and is largest for the funds in quintile one – -1.67%.

The second proxy for managerial skill we use is the return gap measure of Kacperczyk et al. (2008). It compares the actual fund return with the hypothetical return of the fund's most recently disclosed holdings. The measure captures the impact of unobserved managerial actions. Kacperczyk et al. (2008) show that the return gap captures a persistent skill component and funds with past high return gap outperform their benchmarks in the future. Empirically, we sort funds on the basis of their past 4 quarter cumulative return gap values in quarter $t-1$, construct the buys, sales, and trades portfolios using holdings data in quarters t and $t-1$ separately for each portfolio, and track their benchmark-adjusted performance in quarter $t+1$.[6]

Results are reported in Panel B of Table 4.6. Prior to 2001 and consistent with Kacperczyk et al. (2008), we find evidence that the return gap is related to skill. We report a significantly positive return to the buys of funds in quintile five and the trades of funds in quintile 4. However, there are economically large and statistically significant reversals in the post 2001 for all but the two lowest quintiles. The magnitude of the reversals among the top three return gap buckets range between 0.99% and 1.11% per quarter on a risk-adjusted basis. The results in Panel B imply that skilled fund managers might have lost their competitive edge.

However, the overall evidence in this section is mixed. Our analysis using the two proxies of managerial skill does not provide consistent results. When we proxy skill with past performance, we find uniform decreases among both funds with good and bad past performance. Moreover, the deterioration in the returns of the trades seems to be strongest for the worst performing funds. However, proxying skill with the return gap measure of Kacperczyk et al. (2008), we find that reversals are strongest among the most skilled funds, both in terms of statistical significance and economic magnitude.

[6] We construct quarterly return gaps the same way as in Kacperczyk et al. (2008).

Table 4.6. Managerial Skill and Returns to Mutual Fund Trades.

At the end of quarter $t-1$ we sort funds in our sample in 5 buckets based on an estimate of managerial skill. In Panel A we proxy managerial skill with past 12 month alpha. The risk facrors we use include the Market Return, SMB, HML, and Momentum. In Panel B, we proxy managerial skill with past 12 month cumulative return gap. The return gap calculations follow Kacperczyk et al. (2008). Next, for each stock owned by mutual funds in our sample we calculate the change in fund ownership between quarters t and $t-1$, separately for each bucket. We define BUYS (SALES) as stocks for which there is an increase (decrease) in the aggregate stock ownership between quarters t and $t-1$, separately for each bucket. We calculate benchmark-adjusted returns for the BUYS and SALES portfolios for quarter $t+1$, where we weight the stocks using the change in the number of shares owned by mutual funds times the per share price at the end of quarter $t-1$. TRADES are defined as the difference between BUYS and SALES. We report results separately for 1980-2000, 2001-2010 and for the differences between the 2001-2010 and the 1980-2000 periods. Results are expressed in percentage points per quarter. * denotes statistical significance on the 10% level, ** denotes statistical significance on the 5% level, and *** denotes statistical significance on the 1% level.

	A: Sorting on Alpha								
	Buys	Sales	Trades	Buys	Sales	Trades	Buys	Sales	Trades
	1980-2000			2001-2010			(2001-2010) - (1980-2000)		
1 (low)	0.12	0.01	0.12	-1.45*	0.10	-1.55***	-1.57**	0.09	-1.67**
	(0.26)	(0.28)	(0.31)	(0.75)	(0.34)	(0.59)	(0.80)	(0.44)	(0.66)
2	0.10	0.02	0.08	-0.28	0.74**	-1.02***	-0.38	0.72*	-1.10**
	(0.21)	(0.24)	(0.24)	(0.39)	(0.31)	(0.35)	(0.44)	(0.40)	(0.43)
3	0.40**	-0.02	0.42*	-0.52	0.40*	-0.91***	-0.91**	0.42	-1.33***
	(0.18)	(0.25)	(0.23)	(0.42)	(0.24)	(0.33)	(0.46)	(0.34)	(0.41)
4	0.09	0.07	0.02	-0.10	0.19	-0.29	-0.19	0.12	-0.31
	(0.18)	(0.25)	(0.26)	(0.39)	(0.26)	(0.39)	(0.42)	(0.36)	(0.47)
5 (high)	1.00***	-0.34	1.34***	0.43	0.03	0.40	-0.58	0.37	-0.94*
	(0.27)	(0.34)	(0.29)	(0.53)	(0.34)	(0.41)	(0.60)	(0.48)	(0.51)
	B: Sorting on Return Gap								
	Buys	Sales	Trades	Buys	Sales	Trades	Buys	Sales	Trades
	1980-2000			2001-2010			(2001-2010) - (1980-2000)		
1 (low)	0.37	0.17	0.20	0.33	-0.04	0.36	-0.04	-0.21	0.17
	(0.30)	(0.34)	(0.30)	(0.64)	(0.30)	(0.51)	(0.71)	(0.46)	(0.59)
2	0.36	-0.19	0.55	0.12	0.07	0.06	-0.24	0.25	-0.49
	(0.31)	(0.37)	(0.41)	(0.47)	(0.20)	(0.39)	(0.57)	(0.42)	(0.56)
3	0.15	0.32	-0.17	-0.64	0.64**	-1.28**	-0.79	0.32	-1.11*
	(0.25)	(0.28)	(0.29)	(0.61)	(0.27)	(0.53)	(0.66)	(0.39)	(0.60)
4	0.17	-0.37	0.54*	-0.30	0.31	-0.61*	-0.48	0.68*	-1.16***
	(0.28)	(0.30)	(0.30)	(0.36)	(0.20)	(0.33)	(0.45)	(0.36)	(0.44)
5 (high)	0.64**	0.18	0.46	-0.16	0.37	-0.53	-0.80	0.19	-0.99*
	(0.29)	(0.36)	(0.34)	(0.40)	(0.39)	(0.39)	(0.49)	(0.53)	(0.52)

4.4.2 Liquidity vs Information

Broadly speaking, there are two reasons for mutual fund managers to trade. First, fund managers may have information about the future performance of stocks. A number of papers provide results consistent with the notion that managers possess stock-picking skills. For example, Baker et al. (2010) find that mutual fund trades predict earnings surprises. However, a large portion of the trades may be liquidity driven, for example due to portfolio rebalancing following fund flows. Coval and Stafford (2007) and Lou (2012) point that liquidity motivated trades have the potential to move prices away from fundamentals. Consequently, in order to better understand what drives our main results, we separate the trades of the mutual fund managers based on whether they are information or liquidity driven.

Our approach follows Alexander et al. (2007). According to their identification strategy, buys concurrent with heavy investor outflows are likely to be motivation driven. On the other hand, mutual fund purchases happening when there are heavy inflows are more likely to be liquidity driven. A similar argument can be made about investor sells. For each fund in each point in time calculate the portfolios of buys and sells. Next, we calculate the following metrics:

$$BF_t^i = \frac{Buys_t^i - Flow_t^i}{TNA_{t-1}^i} \tag{1}$$

$$SF_t^i = \frac{Sells_t^i + Flow_t^i}{TNA_{t-1}^i} \tag{2}$$

where i indexes funds and t indexes time. $Flow_t^i$ is the investors flow for fund i in quarter t and TNA_{t-1}^i stands for fund i's total net assets at the end of quarter $t-1$. All three variables are measured in dollar terms. According to this procedure, buy portfolios with a high (low) BF score are characterized with high (low) stock purchases when there are high outflows (inflows). Similarly, the ranking procedure assigns high (low) SF scores to sell portfolios with high (low) stock sells when there are high inflows (outflows). Alexander et al. (2007) show that high BF buys outperform low BF buys. This happens because high BF portfolios consist of purchases happening at the same time with heavy outflows are thus likely to be valuation driven. On the other hand, low BF portfolios consist of purchases concurrent with heavy inflows which are more likely to be driven by the need to work off excess liquidity. Their results on the sell side is weaker, potentially due to the short-sell constraints imposed on mutual fund managers.

We investigate whether our main results are driven by a decreasing informational advantage or by a deterioration in the performance of liquidity driven trades using the approach of Alexander et al. (2007). For each fund we sort the quarterly buy and sell portfolios into quintiles based on the BF and SF metrics and examine their performance in the next quarter. We do this separately for the pre-2001 and post-2001 periods. The results are summarized Table 4.7. Consistent with Alexander et al. (2007), we find that the information-motivation purchases of mutual fund managers outperform those driven by liquidity needs. The effect is stronger in the pre-2001 sample. We find that the information-motivated purchases in quintile 1 generate 0.45% risk-adjusted return per quarter before 2001 and 0.29% after 2001, both of which are statistically different from zero. The difference of 16bp, however, does not reach conventional levels of statistical significance. We further don't find evidence for a deteriorating performance of the liquidity motivated trades in quintile 5 – there is in fact a small improvement of 0.10% per quarter, albeit statistically not different from zero. Keeping in mind the caveat of low statistical significance, these results point in the direction of decreasing informational advantage rather than a deterioration in the performance of the liquidity driven trades.

To further investigate whether the liquidity driven trades of fund managers have decreased over time, we analyze the performance of fund trades, conditional on the volatility of their flows. Funds experiencing volatile flows are likely to have a larger number of potentially value-destroying non-informational trades. To

Table 4.7. Information vs Liquidity.

For each fund in each quarter we calculate the change in fund ownership between two consecutive quarters. We define buys (sells) as stocks for which there is an increase (decrease) in the fund ownership between the two quarters. Next, we calculate the BF and SF metrics as in 1 and 2. For each fund we sort the quarterly buy and sell portfolios into quintiles based on the BF and SF metrics and calculate benchmark-adjusted returns in the following quarter. We report results separately for 1980-2010 (Panel A), 1980-2000 (Panel B), 2001-2010 (Panel C). In Panel D we calculate the differences between the 2001-2010 and the 1980-2000 periods. Results are expressed in percentage points per quarter. * denotes statistical significance on the 10% level, ** denotes statistical significance on the 5% level, and *** denotes statistical significance on the 1% level.

	BF	SF	BF	SF	BF	SF	BF	SF
	A: 1980 - 2011		B: 1980 - 2000		C: 2001 - 2011		D: (01 - 11) - (80 - 00)	
1 (low)	0.32***	-0.08	0.45***	-0.01	0.29***	0.04	-0.16	0.05
	(0.05)	(0.08)	(0.08)	(0.09)	(0.07)	(0.08)	(0.11)	(0.12)
2	0.25***	-0.07	0.27***	0.12	0.10	0.04	-0.17	-0.09
	(0.05)	(0.08)	(0.08)	(0.09)	(0.07)	(0.07)	(0.11)	(0.11)
3	0.11**	-0.07	0.28***	-0.14**	0.06	0.03	-0.22**	0.17*
	(0.05)	(0.07)	(0.07)	(0.07)	(0.06)	(0.06)	(0.09)	(0.09)
4	0.14**	-0.12*	0.21**	-0.18**	0.14**	0.08	-0.07	-0.10
	(0.06)	(0.07)	(0.08)	(0.08)	(0.07)	(0.07)	(0.11)	(0.11)
5 (high)	0.09	0.13*	-0.04	0.11	0.06	0.14**	0.10	0.03
	(0.06)	(0.07)	(0.09)	(0.08)	(0.07)	(0.07)	(0.11)	(0.10)

test this conjecture, we sort on the standard deviation of the fund's flows over the previous 12 months. Results are reported in Table 4.8. We find that prior to 2001 funds with the least volatile flows produced the best performing purchases, while those with the most volatile flows had the best performing sales. If deteriorating performance among the liquidity driven trades drive the changes in the performance of the aggregate mutual fund trades, we should observe a negative change in the performance of the trades of the funds with most volatile flows. The results do not offer support for this hypothesis. We find no statistically significant changes in the performance of the trades of funds with most volatile flows in quintile five, although we do find a statistically significant change in the performance of the trades of funds in quintile four. Moreover, the only funds with a statistically significant deterioration in purchases are the ones with the least volatile flows.

4.4.3 Reduction in Selective Access to Firm Information

The results in Section 4.4.2 indicate that the reversal in the performance of the trades of mutual funds is probably due to a decrease in their informational advantage rather than a deterioration in their liquidity driven trades. Pinning down a particular event that has directly decreased the private information fund managers use when making investment decisions can potentially better support the conjecture that the deteriorating returns to mutual fund trades are due to a decreasing information advantage. In particular, we investigate whether a major regulatory reform – Regulation Fair Disclosure (Reg FD) , has decreased the information content in the trades of fund managers.

The SEC promulgated Regulation Fair Disclosure (Reg FD) in August 2000. Prior to the institution of Reg FD, there were concerns that analysts and fund managers had unjustly benefited from selective access to firm information. The purpose of Reg FD was to limit the privileged access that institutions and analysts enjoyed and thus prevent parties with selective access to information from making profits at the expense of

Table 4.8. Fund Flow Volatility and Returns to Mutual Fund Trades.

At the end of quarter $t-1$ we sort funds in our sample in 5 buckets based on their monthly flow volatility during the preceding 12 months. For each stock owned by mutual funds in our sample we calculate the change in fund ownership between quarters t and $t-1$, separately for each bucket. We define BUYS (SALES) as stocks for which there is an increase (decrease) in the aggregate stock ownership between quarters t and $t-1$, separately for each bucket. We calculate benchmark-adjusted returns for the BUYS and SALES portfolios for quarter $t+1$, where we weight the stocks using the change in the number of shares owned by mutual funds times the per share price at the end of quarter $t-1$. TRADES are defined as the difference between BUYS and SALES. We report results separately for 1980-2000, 2001-2010 and for the differences between the 2001-2010 and the 1980-2000 periods. Results are expressed in percentage points per quarter. * denotes statistical significance on the 10% level, ** denotes statistical significance on the 5% level, and *** denotes statistical significance on the 1% level.

	Buys	Sales	Trades	Buys	Sales	Trades	Buys	Sales	Trades
	1980-2000			2001-2010			(2001-2010) - (1980-2000)		
1 (low)	0.53***	0.38	0.16	-0.21	0.05	-0.26	-0.74*	-0.33	-0.41
	(0.20)	(0.27)	(0.32)	(0.40)	(0.29)	(0.52)	(0.45)	(0.40)	(0.62)
2	0.21	0.08	0.13	-0.48	0.35	-0.83	-0.69	0.27	-0.96
	(0.24)	(0.20)	(0.32)	(0.63)	(0.31)	(0.68)	(0.67)	(0.37)	(0.75)
3	0.27	-0.08	0.36	0.05	0.14	-0.08	-0.22	0.22	-0.44
	(0.23)	(0.26)	(0.35)	(0.52)	(0.33)	(0.61)	(0.57)	(0.42)	(0.71)
4	0.42*	0.13	0.28	-0.21	0.82**	-1.03**	-0.63	0.69	-1.31**
	(0.24)	(0.35)	(0.42)	(0.42)	(0.36)	(0.44)	(0.48)	(0.50)	(0.61)
5 (high)	0.44	-0.61*	1.05***	0.48	0.05	0.43	0.04	0.67	-0.62
	(0.32)	(0.36)	(0.40)	(0.46)	(0.24)	(0.48)	(0.56)	(0.44)	(0.63)

those left in the dark. Reg FD has negatively affected the accuracy of analysts' forecasts and increased the dispersion in their forecasts, consistent with the notion that they had benefited from privileged access (see Bailey et al. (2003), Gintschel and Markov (2004), Groysberg et al. (2008)).

Bhojraj et al. (2012) argue that the privileged access to firm information was more pronounced for funds belonging to larger fund families. The reason is that funds belonging to larger fund families constitute a larger portion of the existing and potential investor base of the firm and could therefore command preferential treatment. Bhojraj et al. (2012) provide evidence consistent with their hypothesis that funds belonging to larger families experienced a larger decrease in performance following the implementation of Reg FD.

To test the reduction in privileged information hypothesis, we condition the analysis on fund family assets under management. We rank the funds in our sample in five buckets based on their fund family size in quarter $t-1$, identify the portfolios of BUYS, SALES, and TRADES separately for each bucket, based on quarterly holdings data from quarters t and $t-1$, and track their benchmark-adjusted performance in quarter $t+1$.

The results in Table 4.9 show that the purchases of funds belonging to the largest family size quintile have the highest decrease in performance between the two periods. The difference amounts to 1% per quarter and statistically different from zero. This evidence is consistent with the hypothesis that Reg FD is responsible for the aggregate results since the reversals in performance are strongest for group of funds that most likely benefited most from the privileged access to firm information. Moreover, the promulgation of Reg FD roughly coincides with the breakpoint in the cumulative performance of the trades portfolio, documented in Figure 4.1. Table 4.9 further points that there is a significantly positive change among the sales of funds belonging to the middle portfolio, indicating that there are probably additional dynamics that are not captured by Reg

Table 4.9. Fund Family Size and Returns to Mutual Fund Trades.

At the end of quarter $t-1$ we sort funds in our sample in 5 buckets based on the net assets under management of their family. For each stock owned by mutual funds in our sample we calculate the change in fund ownership between quarters t and $t-1$, separately for each bucket. We define BUYS (SALES) as stocks for which there is an increase (decrease) in the aggregate stock ownership between quarters t and $t-1$, separately for each bucket. We calculate benchmark-adjusted returns for the BUYS and SALES portfolios for quarter $t+1$, where we weight the stocks using the change in the number of shares owned by mutual funds times the per share price at the end of quarter $t-1$. TRADES are defined as the difference between BUYS and SALES. We report results separately for 1992-2000, 2001-2010 and for the differences between the 2001-2010 and the 1992-2000 periods. Results are expressed in percentage points per quarter. * denotes statistical significance on the 10% level, ** denotes statistical significance on the 5% level, and *** denotes statistical significance on the 1% level.

	Buys	Sales	Trades	Buys	Sales	Trades	Buys	Sales	Trades
	1980-2000			2001-2010			(2001-2010) - (1980-2000)		
1 (low)	0.06	0.32	-0.25	0.32	0.05	0.27	0.26	-0.26	0.52
	(0.35)	(0.29)	(0.36)	(0.38)	(0.26)	(0.35)	(0.52)	(0.39)	(0.50)
2	0.30	0.07	0.23	0.24	0.61**	-0.37	-0.07	0.53	-0.60
	(0.42)	(0.36)	(0.50)	(0.42)	(0.24)	(0.38)	(0.59)	(0.43)	(0.63)
3	0.27	-0.38	0.65**	-0.23	0.51***	-0.73**	-0.50	0.89**	-1.39***
	(0.23)	(0.32)	(0.29)	(0.39)	(0.20)	(0.35)	(0.46)	(0.37)	(0.46)
4	0.21	-0.17	0.38	0.08	0.25	-0.17	-0.13	0.42	-0.55
	(0.40)	(0.29)	(0.45)	(0.44)	(0.16)	(0.37)	(0.60)	(0.33)	(0.59)
5 (high)	0.54**	0.06	0.47	-0.47	0.22	-0.68*	-1.00**	0.16	-1.16**
	(0.27)	(0.40)	(0.40)	(0.38)	(0.25)	(0.37)	(0.47)	(0.47)	(0.55)

FD. Thus, our results suggest that although Reg FD may be responsible for the decrease in the performance of the aggregate purchases of the actively managed mutual funds, it may not fully explain the reversal in the trades portfolio.

4.5 Conclusion

This paper studies the performance of the aggregate trades of actively managed mutual funds in the USA. We find evidence for a deterioration in the performance of the trades of mutual fund managers. Prior to 2001 and consistent with Chen et al. (2000), stocks purchased by mutual funds have significantly higher returns than stocks they sell. However, after 2001, mutual funds buy stocks which have significantly lower returns than stocks the sell. The effects we document are economically large. Prior to 2001, the purchases of mutual funds have a significantly positive risk-adjusted performance of 0.44% per quarter. After 2001, we find an effect size of similar magnitude, but an opposite sign – -0.43%. The difference of 0.88% is marginally significant and economically substantial. We further report a reversal in the performance of the aggregate sales, although the magnitude is smaller and the effect is statistically not different from zero. As a result, the difference in the performance of the trades (buys minus sales) portfolio across the two periods amounts to 1.45% and is statistically different from zero. The effect is most pronounced among large and growth stocks and stocks with high institutional ownership and analyst coverage.

We differentiate two potential channels for the above results. On the one hand, funds might have lost their competitive edge and consequently decreased their ability to pick stocks. On the one hand, there may be an increase in the costs associated with liquidity driven trades. Following Alexander et al. (2007), we use fund flows to identify whether trades are liquidity or information driven. Our finds are consistent with a decreasing information advantage rather than a deterioration in the performance of the liquidity driven trades.

We further propose a particular regulatory reform which might be responsible for the reversal of the returns to the mutual fund trades. Prior to 2001, some institutional investors could command a privileged access to firm information and consequently trade on it. Regulation Fair Disclosure (Reg FD), effective 2001, aimed at limiting such selective access. Our results suggest that Reg FD is likely to contribute to the decrease in the informational advantage of fund managers. However, our results also point that Reg FD may not be the sole driving factor for our main results.

Further research is needed to unveil the rest of the contributing factors for the reversal in the trades. For instance, Chordia et al. (2008) show that liquidity is positively related to market efficiency which in turn may leave less scope for value-enhancing trades. The period after 2000 corresponds to a number of events, which have increased liquidity, such as the reduction in tick size in 2001 (see Bessembinder (2003)) and the rise in algorithmic trading (see Hendershott et al. (2011)). Consequently, improvements in market liquidity during the last decade are also likely to contribute to the decrease in the returns to trades. Dasgupta et al. (2011) show that persistently sold stock by institutions outperform stock that they persistently buy. Thus, another possibility is that due to the increase in the size of the mutual fund industry, persistent institutional trading might have increased and hence reduced the performance of the aggregate trades. However, this is less likely to be the case since our results are concentrated among the largest stocks while the results of Dasgupta et al. (2011) are driven by stocks in the bottom size tertile.

Appendix A: Database Construction and Sample Selection

We start by selecting all mutual funds from the Thomson Financial/CDA database with an investment objective code of either growth, aggressive growth, or growth and income between 1980 and 2010. We delete funds that have the strings 'INDEX', 'INDE', 'INDX', 'S&P", or 'MSCI' in their names. Next, from CRSP Mutual Fund Database we select all actively managed equity mutual funds between 1980 and 2010. To ensure that we cover the universe of domestic diversified equity funds, for which the holdings data is most reliable, we select in our sample only funds with one of the following objective codes, provided by Lipper, Wiesenberger, and Strategic Insight and available in the CRSP Mutual Fund Database:

- Lipper: 'EI', 'EIEI', 'EMN', 'FLX', 'G', 'GI', 'I', 'LCCE', 'LCGE', 'LCVE', 'LSE', 'MC', 'MCCE', 'MCGE', 'MCVE', 'MLCE', 'MLGE', 'MLVE', 'SCCE', 'SCGE', 'SCVE', 'SESE', 'SG'
- Wiesenberger:'SCG', 'AGG', 'G', 'G-S', 'S-G', 'GRO', 'LTG', 'I', 'I-S', 'IEQ', 'ING', 'GCI', 'G-I', 'G-I-S', 'G-S-I', 'I-G', 'I-G-S', 'I-S-G', 'S-G-I', 'S-I-G', 'GRI', 'MCG'
- Strategic Insight: 'SCG','GRO','AGG','ING','GRI','GMC'

We link the two mutual fund databases, using the MFLINKS database provided by WRDS. We select funds with two consecutive quarterly holdings data from Thomson Financial/CDA for which we have net asset and return data from CRSP. More information on how MFLINKS assigns a unique fund identifier to each fund in the two databases can be found in Wermers (2000). We manually check the MFLINKS databases for assigning reports from different Thomson Financial funds to the same fund in MFLINKS, and resolve such problems manually.

If a fund offers multiple share classes to investors, we aggregate fund information data across different share classes. For total net assets (TNA) under management, we sum the TNAs of individual shares. For funds's age, we select the age of the oldest share class. For the other fund attributes (net returns, expenses, turnovers, etc.), we take the weighted average of the attributes of the individual share classes, where the weights are the lagged TNAs of the individual share classes.

Chapter 5

Conclusion

This dissertation bundles three empirical studies on actively managed mutual funds. These studies provide new insights into the costs and benefits of portfolio disclosure and shed more light on the question whether mutual fund investors have an information advantage over other market participants.

Chapter 2 shows that a real-time trading strategy which front-runs the anticipated forced sales by mutual funds experiencing extreme capital outflows generates an alpha of 0.5% per month during the 1990-2010 period. The abnormal return stems from selling pressure among stocks that are below the NYSE mean size and cannot be attributed to the arrival of public information. While the largest stocks also exhibit downward price pressure, their prices revert before the front-running strategy can detect it. The duration of the anticipated selling pressure has decreased from about a month in the 1990s to about two weeks in the most recent decade. The results suggest that publicly available information of fund flows and holdings exposes mutual funds in distress to predatory trading.

Chapter 3 investigates the sensitivity of fund flows to a simple portfolio-based measure of managerial skill (the difference between the reported fund return and the hypothetical return of the fund's most recently disclosed portfolio holdings – the "return gap"). The chapter documents a number of empirical patterns consistent with the hypothesis that investors use the return gap as an information variable for inferring managerial skill. The sensitivity of fund flows to the return gap is: 1) strong and positive; 2) increasing with investor sophistication; 3) highly non-linear, potentially due to information acquisition costs; and 4) decreasing with the informativeness of past fund returns. The chapter further establishes that the response to the return gap helps investors enhance their performance. The results in this chapter suggest that there is a sophisticated mass of investors who can process publicly available information on fund holdings and identify funds likely to add value in the future.

Chapter 4 documents a strong reversal in the performance of the trades of actively managed mutual funds. Prior to 2001 and consistent with Chen et al. (2000), stocks purchased by funds significantly outperform stocks they sell. However, there is an opposite pattern after 2001 – stocks purchased by funds have lower returns than stocks they sell. The difference in the performance of the trades (buys minus sales) portfolio across the two periods amounts to 1.45% per quarter. This suggests that funds might have lost their information advantage after 2001. The effect is stronger for the largest funds, is present in both skilled and unskilled funds, is unlikely to be attributed to non-informational driven trades, and is concentrated among the most widely held stocks. The results further indicate that limiting selective access to firm information, following the implementation of Regulation Fair Disclosure, is likely to contribute to the decrease in the information advantage of fund managers.

There are a few important insights stemming from this dissertation:

1. Publicly available information on fund holdings exposes mutual funds in distress to predatory trading. Using a fairly simple front-running algorithm, sophisticated investors can anticipate the outflow-driven pressure among the common holdings of mutual funds in distress.

2. Mutual fund investors are probably more sophisticated than previously thought. We show that investors use portfolio holdings information in order to infer managerial skill and benefit from directing capital towards skilled fund managers.

3. The information advantage of actively managed mutual funds is likely to have reduced after 2001. An important although probably not sole reason for this effect is reduction in selective access to firm information following the implementation of Regulation Fair Disclosure in 2001.

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About the Author

Teodor Dyakov was born on January 28 1987 in Razgrad, Bulgaria. He spent his childhood in the city of Bourgas on the Black Sea coast, where he studied Mathematics and Computer Science at the Akademik Nikola Obreshkov High School of Mathematics and Natural Sciences (graduated with excellence in 2005). Then he continued his education in Bremen, Germany, where he obtained his BA degree in Integrated Social Sciences from Jacobs University in 2008. During his undergraduate studies, Teodor held numerous student, teaching, and research assistant positions and did summer internships at the Bulgarian Deposit Insurance Fund in Sofia, Bulgaria, and at Kema Consulting in Bonn, Germany. Between 2008 and 2010 Teodor did his Mphil studies in Finance at the Rotterdam School of Management and graduated with appellation *Cum Laude*. During this time Teodor did a summer internship at Cambridge Energy Research Associates in Paris, France. In October 2010 Teodor joined the department of Finance at RSM Erasmus University as a PhD Candidate. His PhD trajectory was supported by the Erasmus Research Institute of Management (ERIM). During his PhD studies, Teodor spent 4 months as a visiting PhD student at the National University of Singapore Business School between August and December 2012. Teodor presented his work at numerous conferences, including FMA Europe in Istanbul (2012) and Luxembourg (2013), Swiss Society for Financial Management Research in Zürich (2012), EFMA Asset Management Symposium in Hamburg (2012), and PBFEAM in Melbourne (2013). Teodor's job market paper is a winner of the *Best PhD Paper Award* at the 2013 FMA European Meeting in Luxembourg and the paper on which Chapter 2 of this dissertation is based has already been published in the *Journal of Banking and Finance*. He has supervised numerous bachelor and master student theses and has received excellent teaching evaluations (average score 4.4/5). Teodor's current research interests span institutional investors and asset pricing. In October 2013 Teodor joined the department of Finance at the Faculty of Economics and Business Administration at Vrije Universiteit Amsterdam as a tenure track Assistant Professor in Finance.

Summary

This dissertation bundles three empirical studies on actively managed mutual funds. These studies provide new insights into the costs and benefits of portfolio disclosure and shed more light into the question whether mutual fund investors have an information advantage over other market participants. Chapter 2 develops a simple trading strategy which front-runs the anticipated forced sales by mutual funds experiencing extreme capital outflows. The findings in this chapter suggest that publicly available information on fund holdings exposes mutual funds in distress to predatory trading. Chapter 3 studies investors sophistication and shows that mutual fund investors are probably more sophisticated than previously thought. The evidence in this chapter suggests that investors use portfolio holdings information in order to infer managerial skill and benefit from shifting capital towards skilled fund managers. Thus, while chapter 2 provides evidence for the potential costs of portfolio disclosure, chapter 3 quantifies the benefits from the actual use of portfolio holdings information by mutual fund investors. Chapter 4 uses disclosed fund holdings in order to study the information content of mutual funds' trades. The study documents that prior to 2001, stocks purchased by funds outperform stocks they sell. However, the opposite happens after 2001. The findings in this chapter suggest that mutual fund managers might have lost their information advantage over time. An important, although not sole reason for this effect is reduction in selective access to firm information following the implementation of Regulation Fair Disclosure in 2001.

Nederlandse Samenvatting (Summary in Dutch)

Dit proefschrift bevat drie empirische studies over actief-beheerde beleggingsfondsen. Ze bieden nieuwe inzichten in de kosten en baten van openheid met betrekking tot de samenstellinge van de beleggingsportefeuille, en onderzoekt of de beleggers in deze fondsen een informatievoorsprong hebben ten opzichte van andere marktpartijen. Hoofdstuk 2 analyseert een simpele handelsstrategie die bestaat uit het 'front-runnen' op voorspelde gedwongen verkopen van beleggingen door beleggingsfondsen die getroffen worden door een grote kapitaaluitstroom. De winstgevendheid van de strategie suggereert dat openbare informatie over fondsposities de beleggingsfondsen kwetsbaar maakt voor roofzuchtig handelen van andere partijen. Hoofdstuk 3 analyseert hoe geavanceerd de beleggers zijn die beleggen in beleggingsfondsen en toont aan dat zij waarschijnlijk beter zijn dan eerder gedacht. Beleggers lijken de informatie over handelsposities te gebruiken om de kwaliteit van de portefeuillebeheerder te beoordelen en profiteren door vooral te beleggen in de meest getalenteerde portefeuillebeheerders. Waar hoofdstuk 2 de kosten van openbaarheid voor het beleggingsfonds analyseert, laat hoofdstuk 3 zien hoe de informatie over handelsposities door beleggers wordt gebruikt. Hoofdstuk 4 gebruikt de openbaar gemaakte handelsposities van beleggingsfondsen om de informatie-inhoud van hun transacties te analyseren. Hierin wordt gevonden dat vóór 2001, gekochte aandelen beter presteren dan de aandelen die verkocht worden door beleggingsfondsen. Na 2001 is het omgekeerde effect zichtbaar. De resultaten suggereren dat portefeuillebeheerders hun informatievoordeel langzaam kwijt geraakt zijn. Een mogelijke oorzaak is het verliezen van de exclusieve toegang van beleggingsfondsen tot bedrijfsspecifieke informatie in 2001 door invoering van de "Regulation Fair Disclosure" van de Amerikaanse toezichthouder SEC in 2001.

Обобщение на български (Summary in Bulgarian)

Растежът на взаимните фондове през последните няколко десетилетия е впечатляващ. Към края на 2012 година размерът на активите управлявани от мениджърите на взаимни фондве достига 26.8 трилиона долара в световен мащаб. За това не е и изненадващо че са проведени множество академични изследвания които проучват работата на взаимните фондове и последствията им за ценообразуването на различни активи. Тази дисертация надгражда над тази линия от изследвания и включва три емпирични анализа които ни предоставят нови знания по темата. В тази част на моята дисертация предоставям кратко обобщение на работата ми през последните няколко години и скицирам основните заключения от моята работа като канидат за званието доктор. Преди това обаче ще предоставя кратко въведние към темата на моите изследвания.

Взаимните фондове могат най-общо да се дефинират като регистрирани инвестиционни компании които обединяват в общ фонд активите на множество инвеститори. Те са управлявани от мениджъри които инвестират набрания капитал в различни инструменти като акции, облигации, парични инструменти и други. Инвеститори могат да участват във взаимни фондове като закупуват дялове директно издадени от фондовете, или закупени през борса. Взаимните фондове обикновено се класифицират въз основа на инструментите в които инвестират, като например високодоходни облигации, нискокапитализирани компании, нарастващи акции, и т.н. Взаимните фондове допълнително се класифицират въз основа на това дали целта на мениджърите е да имитират пасивно поведението на индекс или активно да подбират подценени или надценени инструменти от пазара, ценовата им структура, и други характеристики.

Интересно е да се отбележи, че взаимните фондове съществуват вече доста дълго време и датират от втората половина на 18ти век. В действителност първият взаимен фонд в света е основан недалеч от мястото където са проведени по-голямата част от изследванията в тази дисертация – Амстердам. Мотивиран от финансовата криза между 1772 и 1773 г., холандецът Абрахам ван Кетуич основава през 1774 първият взаимен фонд под името Eendracht Maakt Magt (това е било мотото на тогавашната Холандска Република, което се превежда "Съединението Прави Силата"). Основната цел на фонда е била да предостави на инвеститори с ограничени ресурси възможността да инвестират в различни европейски страни както и в новите плантации в Америка.

Въпреки че са минали повече от две десетилетия от основаването на първия взаимен фонд, фундаменталните предимства на инвестирането във взаимни фондове остават непроменени. На първо място стои принципа на диверсификация на риска. Идеята на диверсификацията на риска е да минимизира риска който стои пред инвеститорите чрез инвестирането в портфейл от инструменти вместо единични инструменти: негативната възвращаемост на един инструмент може да се компенсира с позитивната възвращаемост на друг инструмент. От теоретична гледна точка, максимална диверсификация на риска може да се постигне чрез притежанието на дялове във всички търгувани инструменти на пазара. От практическа гледна точка обаче има доста пречки пред постигането на диверсификация. Първо, налага огромен инвестиционен бюджет за закупуването на достатъчно голям брой инструменти за постигането на приемливо ниво на диверсификация. Също така инвестиционния капитал на отделните инвеситори обикновено не е делим на много от инвестиционните инструменти което би възпрепятствало пълното му инвестиране по всяко възможно време. Друг проблем пред индивидуалните инвеститори е свързан с потенциално големи транзакционни разходи, тъй като тези разходи се състоят от фиксирана и промемнлива част. Затова и ползите от диверсификацията на отделните инвеститори е възможно да не надделяват над разходите. Общо взето всички от тези проблеми са свързани с ограничения капитал пред индивидуалните инвеститори. Обединяването на капитал (откъдето произлиза и термина "взаимен") до голяма степен разрешава тези проблеми. Заради големия размер на обединения капитал, взаимните фондове предоставят диверсивикация на отделните инвеститори на относително ниска цена.

Друга често давана причина за инвестиране във взаимни фондове е така нареченото "професионално управление на активи". Този термин се отнася до способността на професионалните мениджъри да увеличават доходността на техните портфейли като подбират доходоносни инвестиционни инструменти и като купуват и продават инвестиционни инструменти в подходящото време. Повечето индивидуални инвеститори нямат времето, когнитивните ресурси и подходящите умения да следят финансовите пазари. За повечето индивидуални инвеститори е по-евтино да делигират следенето на възвращемостта на техните инвестиции на професионалисти отколкото сами да следят отделни компании, трендове на пазара, и т.н.

От основна значимост за тази десертация е регулационният режим за оповестяване на портфейлите на взаимните фондове в САЩ. По-специално, Комисията за Борси и Ценни Книжа (КБЦ) в САЩ изисква от взаимните фондове да оповестяват композицията на техните портфейли веднъж на всеки три месеца. По този начин веднъж на всяко тримесичие всеки настоящ или потенциален инвеститор може да види колко и какви активи държи даден фонд. Благодарение на тази информация инвеститорите (както и КБЦ) може да осъществяват по-добър мониторинг над действията на фондовите мениджъри. Например, инвеститорите могат да следят дали състоянието на портфейла отговаря на това което мениджърите рекламират. Композицията на портфейлите също така може да бъде използвана от потенциални инвеститори за идентифицирането на умели мениджъри.

От друга страна, информацията за композицията на портфейлите може да предостави възможност на трети лица да се възползват безплатно от усилията на мениджърите да идентифицират подценени или надценени от пазара инструменти, което е в ущърб на фондовете и настоящите инвеститори в тях. Също така тази информация може да доведе до наличието на така наречените хищнически практики – търгуване в очакване на търгуването на фондовите мениджъри, което също може да доведе до вреди за фонда и неговите инвеститори. Заради тези потенциални проблеми произтичащи от оповестяването на композицията на портфейлите на взаимните фондове, КБЦ изисква мениджърите да оповестяват техните портфейли само по веднъж на три месеца.

В тази дисертация аз заедно с моите ръководители изследваме информацията произтичаща от оповестяването на композицията на портфейлите на взаимните фондове в САЩ. Научния принос се състои в документирането на потенциални ползи и вреди от оповестяването на тази информация. В Глава 2, която е базирана на публикация в Journal of Banking and Finance от Декември 2013, ние демонстрираме как оповестяването на композицията на портфейлите на мениджърите излага фондвете пред потенциални хищнически практики от трети лица. За да покажем това, ние съставяме не-сложна стратегия за търгуване която се базира на продажбата на акции преди очакваните продажби на фондове от които инвеститорите откупуват обратно масово своите дялове. Използвайки добре документирането взаимоотношение между инвестиционни потоци и предишно представяне, ние прогнозираме кои фондове ще изпитат огромен отлив от инвеститори. Когато отлива от инвеститори настъпи, мениджърите нямат друга алтернатива освен да продават акциите в своите портфейли на пожар. Въпреки, че ние не можем да видим конкретните действия на мениджърите, ние използваме информацията от оповестените веднъж на три месеца портфейли за да апроксимираме акциите които е най-вереоятно да изпитат натиск за продажба (което довежда и до тяхното поевтиняване). Така, ние използваме къси продажби на акциите които са държани най-много от мениджърите които ние очакваме да изпитат най-голям отлив от инвеститори. За да работи тази стратегия, ние не изключваме акциите с най-голяма капитализация. Причината за това е, че те са много ликвидни и всеки възможен натиск вътрху техните цени от масовите продажби на мениджърите се компенсира бързо от участниците на пазара. Нашата стратегия се представя много добре и генерира рисково претеглена възвращаемост от 0.5% на месец. Ние също така документираме и намаляване на продължителността на очаквания натиск върху цените от около месец през 90те до около две седмици през последното десетилетие. Така, резултатите в тази глава показват как публично наличната информация за композицията на портфейлите излага фондове в лошо състояние на потенциални хищнически практики.

Глава 3 използва оповестената композиция на портфейлите на мениджърите за да изследва рационалността на инвеститорите във взаимни фондове. Много изследвания от последните десетина години посочват, че инвестиращите във взаимни фондове взимат погрешни решения при избора на фондовете в които инвестират. Настоящето изследване в Глава 3 обаче показва, че информация произтичаща от оповестяването на композицията на портфейлите се използва от инвестиращите във взаимни фондове по начин който спомага за по-голямата възвращаемост на тяхните инвестиции. За да покажем това ние първо изчисляваме една лесна мярка за измерване на това колко умели са мениджърите – разликата между нетната възвращемост на фонда и хипотетичната възвращаемост на портфейла на мениджъра на Кацперцжик и др. (2007). Тази мярка е лесна за пресмятане и интерпретация, постоянна и може да прогнозира бъдещата фондова възвращаемост над други мерки за прогнозиране. Ние намираме няколко резултата съвместими с хипотезата, че инвеститорите във взаимни фондове използват тази мярка за идентифицирането на умели мениджъри. Ние показваме как инвеститорите базират своите решения използвайки тази мярка, като ефектът е по-силен за по-вещите инвеститори. Ние също така показваме как инвеститорите изпозлват мярката по не-линеен начин, тоест така както те използват и други мерки. Ние също така показваме как тогава, когато информацията от други критерии е по-малка за идентифицирането на умели мениджъри, инвеститорите прибягват по-често до мярката която ние изследваме. Последно, ние намираме че инвеститорите не просто изпозлват тази мярка, но и увеличават рисково претеглената възвращаемост на своите инвестиции. Така, Глава 3 допринася научно като показва реалните ползи на инвеститорите от използването на оповестената композиция на портфейлите на мениджърите.

Глава 4 спомага за разбирането ни относно един от най-важните въпроси по темата за взаимните фондове – умели ли са мениджърите или не? Ние изследваме този въпрос посредством рисково претеглената възвращемост на сделките на взаимните фондове. В унисон с изследването на Чен и др. (2000), ние намираме че преди 2001 акциите закупувани от мениджърите на взаимните фондове се представят по-добре от акциите които те продават. Но също така намираме, че след 2001 резултатите са напълно противоположни. Спадът в рисково претеглената възвращаемост на сделките (дефинирани като покупки минус продажби) възлиза на 1.45% за тримесечие. Ние допълнително показваме, че основната причина за това е загуба на информационното преимущество на мениджърите, а не потенциално покачване на разходите свързани с ликвидно мотивираните им транзакции. Ефектът е по-силен за по-големите фондове, присъстващ за умелите и неумелите мениджъри, и концентриран сред най-предпочитаните акции от фондовете. Последно, ние показваме как загубата на преференциален достъп до информация от страна на фондовете след важна регулаторна промяна през 2000 г. спомага за този ефект.

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EMPIRICAL STUDIES ON ACTIVELY MANAGED MUTUAL FUNDS

NEW INSIGHTS INTO THE COSTS AND BENEFITS OF PORTFOLIO DISCLOSURE

This dissertation bundles three empirical studies on actively managed mutual funds. These studies provide new insights into the costs and benefits of portfolio disclosure and shed more light into the question whether mutual fund investors have an informational advantage over other market participants. Chapter 2 develops a simple trading strategy which front-runs the anticipated forced sales by mutual funds experiencing extreme capital outflows. The findings in this chapter suggest that publicly available information on fund holdings exposes mutual funds in distress to predatory trading. Chapter 3 studies investors sophistication and shows that mutual fund investors are probably more sophisticated than previously thought. The evidence in this chapter suggests that investors use portfolio holdings information in order to infer managerial skill and benefit from shifting capital towards skilled fund managers. Thus, while chapter 2 provides evidence for the potential costs of portfolio disclosure, chapter 3 quantifies the benefits from the actual use of portfolio holdings information by mutual fund investors. Chapter 4 uses disclosed fund holdings in order to study the information content of mutual funds' trades. The study documents that prior to 2001, stocks purchased by funds outperform stocks they sell. However, the opposite happens after 2001. The findings in this chapter suggest that mutual fund managers might have lost their information advantage over time. The results further point that reduction in selective access to firm information following the implementation of Regulation Fair Disclosure in 2001 is an important contributor to this effect.

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