London School of Economics and Political Science

Essays on incentives and risk-taking in the fund industry

Gabriela Bertol Domingues

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Declaration

I certify that the thesis I have presented for examination for the PhD degree of the London School of Economics and Political Science is solely my own work other than where I have clearly indicated that it is the work of others (in which case the extent of any work carried out jointly by me and any other person is clearly identified in it).

Abstract

The first paper of this thesis uses a unique data set to assess the determinants of inflows and outflows in the fund industry. The higher frequency of the data allows to examine whether *recent* past performance affects the flow-performance relation. I find that the latter is concave for the worst-performing funds and convex for the best-performing funds. This is in stark contrast to previous studies in the literature that document a strict convex relationship. The disaggregation by inflows and outflows further indicates that the concavity is mainly due to outflows, which react much quicker to bad performance than previously assumed, whereas the convexity is driven by inflows. Finally, I also compare how the type of client affects the flow-performance relationship. I show that investors deemed less sophisticated care more about short-term performance than other investors, and more about raw returns than risk-adjusted returns.

The second paper investigates how funds shift risk as a function of past performance. In contrast to the literature, I manage to disentangle the implicit incentive generated by the flow-performance relationship from the direct incentive generated by the portfolio manager remuneration contract. Identification is only possible because I focus on funds that pay bonus every six months instead of every year. I show not only that contracts have an asymmetric effect on risk, but also that the tournament within the fund family is the main driver of risk shifting. This is consistent with families actively engaging in the tournament by transferring not only performance, as suggested by the literature, but also risk from their worst- to their best-performing

funds.

The last paper is joint with Pedro A. Saffi and uses a data set of Brazilian hedge funds holdings to examine the impact of long and short positions on performance. In particular, we test if changes in long/short positions and their risk can forecast future performance. While we find that funds with large increases in the risk of long-only positions risk relative to the previous 24 months underperform by about 3% per year on average, those that increase the risk of short-only positions overperform their peers by about 1% a year on average, net of fees. Neither monthly changes of long nor short positions can forecast next month's abnormal returns.

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Introduction

The original idea of this dissertation came from the discussion of Chevalier and Ellison (1997). It immediately struck me that, if the person responsible for running the fund, the trader, is also compensated in the beginning of the year based on the previous year's performance, how can they argue that the changes in risk that happen in the end of the year are a response only to the implicit incentive generated by the flow-performance relationship? Having previously worked in the banking industry in Brazil, I remembered that there, traders are compensated every six months instead of every year and that it could be possible, using Brazilian data, to try to disentangle these effects. This idea developed into the second chapter of this dissertation. There I show that not only the implicit (flow-performance relationship) and explicit incentives (bonus) have an asymmetric impact on risk, but that there exists another tournament within the fund family that is one of the main drivers of risk shifting. This extra layer of contracting (between the investor and the family, and between the family and the trader) gives rise to an agency problem that needs to be further investigated.

Before embarking on the analysis of the relation between past performance and risk-shifting, I had to take one step back and evaluate how the flow-performance relationship looked like for Brazilian data. As I use a data set that has seldom been used before, from an emerging market country whose financial market is not commonly studied, a few questions needed to be answered beforehand. To the surprise of most people I encounter, Brazilian fund data are much richer than their American counterpart. They span a shorter period of time (most data start from the mid-1990's), but it is usually easier to impose transparency in a new, developing market than trying to change a very mature one. The completeness of the database, allowed me to study the flow-performance relationship using data at a higher frequency (monthly instead of annually) and disaggregated in inflows and outflows instead of just looking at net flows as it is common in the literature. As a result, a study that should have been a section of a paper was transformed in a full paper, and is now the first chapter of this dissertation. In contrast to previous papers, I find that the flow-performance relationship, although convex for the best performing funds, is concave for the worst performing funds, not flat as most papers assume. This difference arises because outflows react much quicker to a bad performance than inflows. As a consequence, papers that rely on annual data, ignoring short-term fund performance, will most certainly fail to detect the concavity on the left tail of the distribution. Moreover it implies that investors tend to buy high at sell low, which may turn funds into a particularly bad investment.

The richness of the database allows one not only to study old issues from a different perspective, but also to make empirical studies that would have been impossible using American data. In the last paper, co-authored with Pedro A. Saffi, we use a data set of Brazilian hedge funds holdings to examine the impact of long and short positions on performance. In particular, we test if changes in long/short positions and their risk can forecast future performance. While we find that funds with large increases in the risk of long-only positions risk relative to the previous 24 months underperform by about 3% per year on average, those that increase the risk of short-only positions overperform their peers by about 1% a year on average, net of fees. Neither monthly changes of long nor short positions can forecast next month's abnormal returns. This paper is still a working paper and needs to be further expanded, especially in what concerns the time span. However, it gives an idea of the amount of information we have and how it can be further explored.

Chapter 1

Is the flow-performance relation really convex? New evidence using higher frequency data

1.1 Introduction

The behavior of mutual fund flows in the US is very well documented. Several studies find that the best performing funds receive disproportionately more resources relative to other funds, whereas investors fail to withdraw from poorly performing funds (see e.g. Chevalier and Ellison, 1997; Sirri and Tufano, 1998). In other words, managers appear to receive large rewards in the form of increased flows after large returns, but very little punishment for underperforming. These results always puzzled practitioners that tend to assert that investors buy at the peak and sell at the bottom, i.e., flocking to the best performing funds but redeeming their shares as soon as the fund's relative performance deteriorates.

In this paper, I use disaggregated inflows and outflows data to show that investors are actually much quicker in withdrawing funds from bad performing funds than the literature suggests. More specifically, I find that the flow-performance relationship is not strictly convex once one accounts for the funds' most recent performance (up to the previous month). It is in fact concave for the worst performing funds, becoming convex only as performance improves. I show that this results from the fact that outflows are much more sensitive to very recent performance than inflows. Previous studies are not able to capture this feature because they use aggregated net flow data at the yearly frequency, relating net inflows in a specific year with performance in the previous year. This not only disregards any differences between inflows and outflows, but it also implicitly assumes that either both inflows and outflows occur mostly in the beginning of the year or that investors ignore the funds' most recent information whenever they are rebalancing their portfolio. As a result, given that outflows respond quicker to recent performance than inflows, analyzing yearly data completely misses out the concave component of flow-performance relation.

This analysis is only possible because I examine a unique data set from the Brazilian fund industry that provides funds' returns, assets under management as well as both inflows and outflows at a *daily* frequency. The fund industry in Brazil is relatively big, with about \$1.1 trillion dollars under management,[1] and very transparent. The regulatory framework is the same for every investment fund in the country (non off-shore). This means that both mutual and hedge funds have to disclose exactly the same amount of information at the same frequency. This allows studying their behavior at a much higher frequency and assessing the determinant of inflows and outflows independently. In addition, the database is free of self-reporting bias and allows one to measure the flow-performance relationship controlling for any specific fund characteristic that might affect investment decisions, such as share restrictions and investor type.

Differentiating between fund type and controlling for fund characteristics and restrictions is key to determine the flow-performance relationship. Agarwal, Daniel and Naik (2004) find a convex flow-performance relationship for hedge funds, but their result is not consensual. For instance, Goetzmann, Ingersoll and Ross (2003) report a

[1] The Brazilian fund industry ranked sixth in the world in the second quarter of 2011 according to the ICI. Ireland with USD\$1.1 trillion appeared in the fifth and the UK, with USD\$0.9 trillion, in seventh position.

concave relation, whereas Baquero and Verbeek (2005) document a linear one. Ding, Getmansky, Liang and Wermers (2009) try to reconcile these results by arguing that these differences are due to specific restrictions that hedge funds managers impose on investors, e.g., statutory restrictions on the number of investors, minimum investment amounts, lockup and redemption periods, etc. They show that hedge funds with little or no flow restrictions are more similar to mutual funds, and hence exhibit a convex flow-performance relationship, whereas funds with flow restrictions display a concave relationship.

Hedge funds and mutual funds dwell however within very distinct institutional frameworks and cater to different types of investors. As a result, isolating the effect of a specific fund characteristic can produce results not applicable to other types of funds and/or countries. In addition, there are some serious limitations on the data available for empirical studies on both hedge funds and mutual funds that might affect the reliability of the results. Most hedge-fund data sets are based on self-reporting and hence very likely to carry serious sample selection bias. Furthermore, there is no actual data on flows. All the results are for net inflows calculated from net assets value and returns. Although it is possible to draw inferences for the response of net inflows to past performance, there is ample evidence that market participants behave differently according to whether they are investing or withdrawing money (see, among others, Chevalier and Ellison, 1997). This means that inflows and outflows are possibly driven by distinct factors, which are impossible to identify using the usual data sets in the empirical literature.

The outline for the remainder of this paper is as follows. Section 1.2 provides a primer on the Brazilian regulatory environment as well as describes the main features of the data set and of the sample. Section 1.2.5 then delineates the model, whereas Section 1.3 discusses the empirical findings and a number of robustness checks. Finally, Section 1.4 offers some concluding remarks.

1.2 Data description

1.2.1 Regulatory environment

Brazilian funds are regulated by both the Brazilian Securities and Exchange Commission (Comissao de Valores Mobiliarios, from now on CVM) and by a self-regulatory body, Anbima.[2] Although rules have been evolving over time, both agencies have a very strong bend towards transparency. Brazilian funds have to send daily reports with return, net assets, share value, and number of shareholders to CVM. Since January 2005, CVM has also started disclosing daily information on disaggregated inflows and outflows. In addition, CVM requests a monthly report with end-of-the-month information on their portfolio holdings since 2006. The daily information is made available to the public from the CVM website within, at most, two days. The delay in the portfolio holdings disclosure dropped in July 2009 from three months to just fifteen days, though funds may request CVM to delay the disclosure to the public for up to three months. Such requests are usually granted. In addition to the disclosing rules, funds are required to mark to market since 2002.

Investment funds in Brazil must have a fund administrator and a custodian, each must be completely independent of the portfolio manager. The fund administrator is the legal representative of the shareholders with the fund. Along with the custodian, they are responsible for keeping the books, calculating and posting the fund's share price daily. It is the administrator that actually does the reporting to the CVM and to the shareholders. Given the mark-to-market requirements, administrators are key players in that they are responsible for checking the prices of all securities a fund holds. As a rule, the same security held by different funds needs to have the same price on their books as long as they have the same administrator. Given that administrators

[2] See Varga and Wengert (2009) for a detailed description of the regulatory environment.

are audited every six months and that three companies work as custodians of about three quarters of the investment funds in Brazil, prices of illiquid assets are never too far apart.

In contrast to US regulations that distinguishes between mutual funds and hedge funds, every investment fund in Brazil falls under the same regulatory framework. Until March 2008, the classification of the funds was based mainly on the classes of assets they could invest in (e.g., multi-market without restrictions, equity, and fixed-income) and to what extent they could use derivatives and short selling. As from March 2008, the classification changed, becoming more dependent on the trading strategy chosen by the fund. Instead of using the usual classification of mutual funds and hedge funds, I will differentiate funds by their restrictions and the type of client they cater.

When starting a new fund, the manager must decide to which type of investor the fund will cater. There are six broad categories, though I restrict attention to funds on three specific categories - all investors, qualified investors and institutional investors - as the other four impose a strict restriction on the type of shareholders.[3] Qualified investors consist of financial institutions, pension funds, chartered financial analysts and any other investor with at least BRL$300,000 available for investment. Some types of funds (as hedge funds in the US) can cater only to qualified investors. The client restriction is usually linked to the type of financial instruments the fund is allowed to invest in: the riskier the fund, the more restrictions on the investor. Recently, the CVM has required some types of funds to only accept qualified investors that invest a minimum of BRL$1 million (super-qualified investors).

[3] The four excluded categories are: 'Exclusive' (one single shareholder), 'pension funds', 'restrict' (shareholders need to be linked somehow, e.g. family, business partners, organizations) and 'dedicated' (only employees within the same company).

1.2.2 Sample selection

As of June 2011, assets under management in the Brazilian fund industry tallied around USD$1.1 trillion according to the ICI. The daily data I employ come from the Quantum Axis database, which tracks virtually all funds based in Brazil. In addition to the CVM data, Quantum also provides all sorts of qualitative information about the fund: e.g., inception date, style, flow restrictions, fees, investment objectives, and the type of investors the fund caters to. The daily data can be very noisy and I aggregate the flow data to a monthly frequency. I nonetheless use the daily data to compute monthly risk measures for every fund.

I focus exclusively on multi-market and equity funds, dropping short-term, fixed-income, and pension funds. Among the funds within the multi-market and equity styles, I also eliminate balanced, money market, international, index funds, funds exclusive to one or very few specific clients (i.e., less than four), and funds of funds. I disregard the first year of life of every fund as this is usually associated with incubation stage, and very small funds. I define small as a fund that manages less than R$5 million (USD$2.87 million) for more than 75% of the sample period. The daily sample ranges from January 1997 to June 2009, apart from information on inflows/outflows and on the number of shareholders, which start only in January 2005. According to Anbima, as of December 2011, multi-market and equity funds comprised, respectively, 24.6% and 12.3% of total assets under management in Brazil and the sample selected represents around 60% of their total volume.

Table 1.1 presents summary statistics. The final sample includes 906 distinct funds with 42,579 valid fund-month observations (or 4,348 valid fund-year observations) of net-of-fees returns and total net assets. Out of these 906 funds, 327 funds did not survive past June 2009, with 128 incorporations and 199 liquidations. Although the Quantum database keeps record of defunct funds, the fact that no funds are liquidated between 1997 and 2000 indicates that there might be a backfill bias for the first years of the data set. Table 1.1 shows that the number of equity and multi-market funds increases steadily from 1997 to 2000, then stabilizes until 2003. The industry resumes growing in 2004, slowly at first, but then at a faster rate even during the recent global financial crisis. This is despite an increase in the number of funds that are either liquidated or incorporated by other funds. The average assets under management is stable from 1997 to 2002, at around USD$30 million but increases almost exponentially between 2003 and 2007.

1.2.3 Fees, flows and client restrictions

Table 1.2(a) shows that 20% of the funds in the sample impose some kind of flow restriction: e.g., lockup and advance notice periods (with or without early withdrawal fee). The lockup period is the initial amount of time investors have to keep their money in the fund before being able to redeem shares. Investors can only access their money once the lockup period is over. The advance notice period is the time of advance notice investors must give to the fund before cashing in shares of the fund. There are funds that significantly reduce their notice period in exchange for an early withdrawal fee. Finally, over 5% of the funds restrict inflows by closing to new investors.

Some funds also have restrictions on the type of investor they are allowed to cater to. This restrictions is defined at fund inception and is determined by the CVM based on the type of assets and financial instruments the fund chooses to trade. The majority of funds don't impose any restriction on the investor, but 42% can only cater to qualified investors (which includes institutional investors). Given this breakdown, it is possible to analyze whether different investors have distinct reactions to past performance.

Table 1.2(b) shows the distribution of restrictions and fees across funds. There are only 16 funds in the database that impose a lockup period. Although it varies from 2 days to 2 years, most funds require less than 3 months of lockup period. The number of funds with significant lockup period (over 3 months) is, however, too small to make any inference and I have excluded them from the sample. In contrast, just over half of the funds impose an advance notice period. The latter is on average about one month without any redemption fee, even if it ranges from 5 days to 3 months. The average number of days the investor has to wait to redeem her shares is 5 days (possibly in exchange for a redemption fee), though the majority of funds require only one day of advance notice. There are 114 funds that charge early withdrawal fees from 1% to 15% (typically around 5%). There are only 12 funds in which the advance notice period and withdrawal fee depend on the size of the withdrawal. As expected, the bigger the withdrawal, the longer the wait. Because of the very particular nature of this restriction and because the number of funds that impose it is too small, I have also excluded this group of funds from the sample. Section 1.3.3 discusses how restrictions might affect the slope of the flow-performance relationship.

Brazilian funds have, in general, the same fee structure as US funds: the typical management and performance fees are, if any, of 2% and 20%, respectively. There is not much variation in the former, whereas the latter vary more frequently from 10% to 100%. The performance fee is charged on whatever exceeds the hurdle rate and is typically 105% of the CDI, which can be defined as a Brazilian libor rate. Both fees are charged daily as fund expenses but the performance fee is only paid every six months (end of June and end of December) relative to the previous six months.

1.2.4 Flow data description

Table 1.3 reports some summary statistics for monthly flow data. The statistics for net(-of-returns) flows refer to the period from January 1997 to July 2009, whereas inflows and outflows figures are for January 2005 to July 2009. Ideally, I would have all data spanning the same time period, however the industry is relatively new and disregarding the first years of information is not a plausible option. Changes in regulation over the years mean that the availability of information has been increasing.

I define flows relative to the previous month's total net assets. For each month, I first calculate the total net flow, the inflow and the outflow, and then divide each by the previous month's total assets under management. Finally, I take the average of the monthly flows for each fund through time before reporting the cross-sectional characteristics of the data. The sample excludes incorporated and incorporating funds on the day of the event. However, it does not drop funds that are liquidated for any other reason. Instead, their net flows are set to -100% and their final outflow to 100%.

It is interesting to observe that despite the robust growth in the fund industry over the sample period, the typical net flow is close to zero, with a slightly positive mean and a marginally negative median. In addition, the average net flow becomes slightly negative if one weighs the net flows by assets under management. This happens because larger funds receive more net inflows than smaller funds not only in absolute values, but also relative to their assets under management.[4]

The breakdown between inflows and outflows is one of the unique features of this database. It is interesting to observe that their distributions are pretty similar, thereof indicating a significant monthly turnover within the industry. The mean, median and standard deviation of the inflows are about 10% higher than the corresponding values for the outflows. Weighing by assets under management reduces considerably

[4]Capital gain tax do not affect flows because Brazilian funds must account for them by decreasing the number of shares rather than the share value.

the difference in mean, though slightly increasing the discrepancy in the standard deviations. Notice that the sample period for net inflows and gross flows is not the same.

Table 1.4(a) describes the after-fee returns of an equally-weighted fund indices from January 1997 to July 2009. Although funds experience average monthly returns of over 1%, they seem to entail poor excess returns. For instance, the average monthly return on multi-market funds is of almost 1.2%, though the average excess return over the interbank loan rate (CDI), used as a benchmark across the market, is of -0.09%, translating into an annualized excess return of -1.2%. The same pattern arises for the equity funds. They entail an average monthly return of 1.28%, but with an average excess return of -0.95% per year. Further analysis reveals that both distributions are quite asymmetric, with skewness and kurtosis coefficients around -0.7 and 5.5, respectively.

A somewhat different story arises if one considers asset-weighted indices in Table 1.4(b). The overall index keeps yielding an average monthly return of about 1%, but with a significantly more negative excess return. The multi-market index returns on average the same 1.20% as before, but now with a marginally positive average excess return over the CDI. Finally, weighing by asset under management has a profound impact in the performance of the equity segment. The asset-weighted index of equity funds displays a relatively lower monthly return of 0.33% and a very negative excess return of -0.83% per month. Moreover, the standard deviation shoots up to almost twofold the corresponding equal-weighted value.

1.2.5 Measuring the flow-performance relation

To estimate the flow-performance relationship, I use a piecewise linear relationship between current fund flows and past returns. The objective is to capture the nonlinearity of the flow-performance relationship using a simple parametric model. I divide the funds in quintiles of performance and calculate a different slope for each quintile. In particular, I split funds into groups according to their performance ranking as in Sirri and Tufano (1998). Their methodology guarantees different slopes for each quintile but also that the final flow-performance relationship is continuous. The first step is to calculate the fractional rank $\mathrm{FR}_{f,t} \in [0,1]$ at time t for all funds within a category (i.e., either equity or multi-market) based on their returns over a specific time period. Next, I transform the fractional ranking within each performance quintile as follows:

$$\mathrm{QR}^{(1)}_{f,t} = \min\left\{0.2, \mathrm{FR}_{f,t}\right\}$$
$$\mathrm{QR}^{(q)}_{f,t} = \min\left\{0.2, \mathrm{FR}_{f,t} - \sum_{j=1}^{q-1} \mathrm{QR}^{(j)}_{f,t}\right\}, \qquad \text{for } q = 2, \ldots, 5.$$

As for the performance horizon, I calculate rankings for the previous month, previous six months and previous twelve months using the cumulated total returns over the period. For the main analysis, I sort funds on the basis of risk-unadjusted returns because this is the main information investors have access to. For robustness check, I also generate a ranking based on the cumulated return over the past twenty-four months. Some funds report their Sharpe ratio, hence I also calculate a ranking based on it.

As monthly flows are very volatile, I winsorize inflows, both gross and net, at the 99.5 percentile.[5] Funds that are liquidated have their outflow set at 100%, and their net inflows set at -100%. Funds that are incorporated and those that incorporate other funds are dropped from the sample for that particular date. Since information on inflow and outflow is only available since January 2005, I back out earlier monthly

[5] Monthly inflows and outflows are calculated from daily information. In rare occasions, funds with a very big turnover can have outflows of over 100%. I set the maximum monthly outflow to be equal to 100%.

net flows from assets under management (AUM) and returns data as follows:

$$\mathrm{NF}_{f,t} = \mathrm{AUM}_{f,t} - \mathrm{AUM}_{f,t-1}(1 + R_{f,t}), \tag{1.1}$$

where $R_{f,t}$ is the return on the fund f on month t. I then investigate the determinants of fund flows by regressing the ratio of fund flow to total net assets on the different performance quintiles plus controls. More specifically, the ratio is given by either net flow (NF), inflow (IF) or outflow (OF) divided by the fund's total net assets in the previous month. On top of time and fund fixed effects, the set of additional regressors includes the volatility of the fund in the previous 1, 6 and 12 months. As suggested by Merton (1980) and French, Schwert and Stambaugh (1987), I measure volatility by the square root of the annualized realized variance based on daily squared returns over the specified period. I also control for the size of the fund and the growth of the category to which the fund belongs (either multi-market or equity), both at the end of the previous month. I gauge them respectively by the logarithm of the total net assets under management and by the relative net flows to the broad category/style. The latter first aggregates the monthly net flows of every fund within a particular style and then divide it by the total net assets under management within that style in the previous month.

Given that the fund custodian (and not the portfolio manager) is responsible for pricing the securities and for keeping record of the fund's trades, there is little room for performance smoothing (Getmansky, Lo and Makarov, 2004). In addition, due to the marking-to-market practice and to the reliance on the fund custodian/administrator to price the assets, exposure to illiquid assets should play a minor role as well.

1.3 Flows and past performance

1.3.1 Net inflows

I estimate a panel data regression with fund and time fixed effects. As I use monthly data, it is possible to analyze the impact of the recent history on flows. In order to better assess the impact of past performance, I generate the ranking of funds' returns in the previous month, in the previous six months and in the previous twelve months. I refer to them as short-, medium- and long-run past performances, respectively. The shape of the flow-performance relationship varies with the time horizon and, what is in general neglected by the literature, flows are quite responsive to short-run past performance.

Table 1.5(a) shows the coefficient estimates as well as their standard errors clustered by fund. A double cluster procedure (by fund and time) as suggested by Petersen (2009) has also been used but doesn't affect the results. The dependent variable is the percentage monthly net inflows with respect to total net assets in the end of the previous month. The regressors of interest are the ranking position of the fund split into quintiles for three different time horizons (one, six and twelve months). Models (2) to (4) display the impact of the three measures of past performance individually. The short-run and long-run measures have a similar pattern. The flow-performance relationship is concave for the poor performing funds, but then becomes convex once funds start performing better. The medium-run measure of performance is clearly convex.

Including all measures of past performance in the same regression improves the goodness of fit significantly, though their individual impact becomes smaller. There is no qualitative change in the shape of the flow-performance relationship and in the precision of the estimates of the coefficients, though. In general, investors seem to classify funds in three groups: big losers, average funds and top performers. Net inflows increase with performance but at different growth rates. Moreover the responses to short-, medium- and long-run performances also vary considerably. Funds performing poorly in the short run and/or in the long run receive proportionally much less net inflows than all other funds. Investors however do not seem to punish funds that perform badly only in the medium-run. As for the best funds, investors give more weight to medium- and long-run performances, whereas short-run performance has little impact on net inflows. Figure 1.1 plots the flow-performance relationship for the 3 measures of past performance.

Although the concavity of the bottom part of the distribution seems to conflict with previous findings in the literature, the differences are likely due to the sampling frequency. Apart from a few exceptions (e.g., Elton, Gruber, Blake, Krasny and Ozelge, 2010), the literature uses end-of-year information only, relating net inflows in a particular year with performance in the previous year. The aggregation of net inflows within a year prevents the analysis of the impact of recent past performance on flows. In contrast, there is no loss of information due to aggregation here, because of the monthly frequency of the data. The results are in fact consistent with the conclusion of Elton et al. (2010) that the use of more frequent data may change, or even reverse, previous findings about investment manager behavior.

As net inflows are just the difference between inflows and outflows, negative net inflows indicate the fund has more outflows than inflows. As the focus here is to relate past performance to flows, it is natural to expect that better performing funds will have more inflows than outflows, i.e. positive net inflows, and that the worst performing funds will have negative net inflows. For instance, the bottom quintile aggregates the worst performing funds, and hence its coefficient is most likely driven by outflows. In the next section, I look into gross inflows and outflows to better understand their individual reactions to past performance.

1.3.2 Gross inflows and outflows

In general, the information necessary for calculating net inflows are readily available as opposed to disaggregated data on gross flows. As a result, most studies in the literature focus on the determinants of net inflows. Bergstresser and Poterba (2002) is the one exception up to my knowledge that examines gross inflows and outflows, although in a different context. Inflows- and outflows-performance relationship may have diverse patterns if the decision of investing and redeeming shares respond to different time horizons of past performance. Tables 1.5(b) and 1.5(c) report that inflows are mostly driven by medium- and long-term performance, whereas outflows react mainly to short- and medium-term performance.

For gross inflows, the magnitude of the coefficients is larger the longer the time horizon, especially for the top and bottom quintiles. Short-term performance has almost no impact, if any, on inflows. Better performing funds in the long run are the clear winners and long-run worst-performing funds, the losers. There is still a clear convex inflow-performance relationship for medium-run performance.

The results for outflows are in line with the findings for net inflows, with a stronger impact of short and medium-term performance relative to long-term performance. Outflow data are however a bit misleading because it may take several days from the date the investor notifies the fund of the withdrawal until they can actually redeem the shares. As Table 1.2(b) shows, around half of the funds in the sample has some sort of redemption restriction and it may take up to ninety days for an investor to actually cash in her shares. With daily outflows, it is possible to correct outflows by the length of the redemption restriction. If high-frequency data were not available, the solution would be to aggregate within a longer period of time.

Tables 1.5(d) and 1.5(e) show the impact of past performance on two measures of gross outflows. The first measure is adjusted for the minimum redemption period an investor needs to wait (usually implies the payment of a fee). The second is adjusted for the maximum redemption period (in general free of charge). Short-run performance is relatively more important for investors that are willing to pay to redeem their shares as soon as possible, whereas investors that are inclined to wait care more about long-term performance. A particularly bad short-term performance thus induces investors to withdraw funds as soon as possible, corroborating the conjecture that aggregation wastes valuable information.

1.3.3 Robustness Checks

Performance terciles

Table 1.6 shows the result for performance terciles instead of quintiles. The above patterns are even more pronounced now. For net inflows, there is a clear convexity in the medium run, and, to some extend, also on the long-run. However, as before, investors seem to act very quickly to punish a really bad performance. Inflows respond mainly to medium and long-term performances. The long-run inflow-performance relationship is clearly convex, whereas the response of outflows to long-run past performance is flat for the bottom quintile and then decreases linearly with performance. This difference generates a slight convexity in the net response.

Risk-adjusted returns

All the previous results were based on returns not adjusted for risk. This specification is key if one wants to further investigate the implicit incentive that the flow-performance relationship entails for fund managers. However if investors care about risk-adjusted returns, the previous results would only be concealing the true relation between flows and returns. Although several measures of risk-adjusted returns could be calculated, I will concentrate on Sharpe ratio for the simple reason that this measure is, in general, available to investors. Several funds print on their monthly reports not only their volatility but also their Sharpe ratio which can be used by investors to compare funds. Table 1.7(a) shows that although the main results are still valid, the relation between flows and performance is less clear than previously stated. Net inflows are still convex in the medium-run and there's still evidence that outflows react to short-term performance as opposed to inflows. Investors however seem to only differentiate the bad funds and the very good funds.

Table 1.7(b) used terciles of past performance and the results are more neat. Net inflows reaction to long-run performance is slightly convex, almost linear, and the medium-run flow-performance relationship is convex. Investors tend to chase funds with the best performance in the medium and long run and leave funds that have a poor performance in the short and medium run.

1.3.4 Type of investor

One of the main problems when comparing mutual and hedge funds is that the type of clients these funds cater to is very different. In general, only qualified investors can invest in hedge funds because they are deemed to be more sophisticated, with a better understanding of financial markets. This restriction also protects smaller investors from taking excessive risk and investing in products they might not fully understand. In this section, I divide funds in three sub-samples depending on the type of clients the funds caters: no restriction, qualified investors and institutional investors. If qualified investors are indeed more skilled, they should choose funds not based on total returns, but on risk-adjusted returns. Qualified investors should be even less responsive to raw returns as evidence shows that they react mainly to the fund's tracking error (see, among others, Del Guercio and Tkac, 2002).

Tables 1.8 and 1.9 show how different investors react to past performance by splitting funds in terciles. I employ terciles because the number of funds drop considerably as the sample gets more restricted. The results show that the type of client has indeed a very strong impact on the flow-performance relationship which might explain some of the differences between the flow-performance relationship on hedge funds and mutual funds in the US.

Table 1.8 relates net inflow to raw past performance and shows that the convexity on the top part of the distribution is even more accentuated in the group of funds that impose no restrictions on the type of client compared to the average. Non-qualified investors are more eager to favoring overall winners than other investors. They are also more unforgiving with a short-term bad performance. Comparing the second column in tables 1.8 and 1.9, although non-qualified investors chase good performance, they also care about Sharpe ratio, but not enough to punish a fund with low Sharpe ratio. In the battle between raw returns and risk-adjusted returns, general investors care more about the former even though they still pay some attention to risk.

Another important result is that qualified and institutional investor care relatively more about long-run performance than other investors. This is not surprising as these investors are usually bigger clients that cannot move funds around so quickly. Moreover they possibly have a different investment horizon. What is more curious is that institutional investors seem to display a strictly convex flow-performance relationship in response to long-term raw returns and to medium-term risk-adjusted returns which can be linked to the rebalancing frequency. The results also seem to indicate that institutional investors are driving all the results of qualified investors, as the data for qualified investors include institutional investors. Unfortunately there is not enough data points to generate a subsample based on non-institutional qualified investors only.

Further analysis using the subsample for which I have inflows and outflows show similar pattern, however due to the small number of observations they are not conclusive and are not reported.

1.4 Conclusion and Further Research

For years both academics and practitioners have been puzzled by the previous findings that investors react very slowly to bad performances. Investors seemed not to be fleeing from the worst performing funds, even though chasing the best performing funds. Although many would have claimed that investors tend to have bad timing by buying high and selling low, the empirical evidence suggested that the second part was not happening. This paper sheds some light in this discussion by claiming that investors do indeed withdraw funds after a short spell of bad performance. I claim that previous papers failed to find this relationship because they use data sampled at a yearly frequency, relating aggregated net inflows in a specific year with performance in the previous year. Although this is usually a restriction imposed by the availability of data, it ends up ignoring the impact of short-term performance on flows. By examining the data at the monthly frequency, I am able to account for the impact of short-performance and recent information on flows. I find that the flow-performance relationship starts concave, but, as performance improves, it becomes convex, rather than the strictly convex relationship previously described. This pattern is only apparent because of the sampling frequency. In particular, outflows respond more quickly to recent performance and hence analyzing yearly data misses out the concave component of flow-performance relation.

This paper also goes one step further and investigates how the type of investor the fund caters affect the flow-performance relationship. Studies based on US mutual funds tend to ignore the type of client the fund caters. However there is evidence that different clients indeed have different reactions to past performance (e.g pension funds, or mutual funds versus hedge funds). In this paper I show that investors deemed less sophisticated react more to raw returns than to risk-adjusted returns and that they have a shorter term horizon than more sophisticated clients.

Several questions are still worth investigating. First, if non-sophisticated investors have bad timing (buying high and selling low) they would receive a return on their investments that is lower than the fund return. Using daily information on inflows and outflows, if the series is long enough, it is possible to calculate the client money return by making a few assumptions and compare it with the actual fund return. Second, the type of investor seems to be a main determinant of the flow-performance relationship and it is important to investigate this relation by further the types of clients. Last, it is important to analyze funds' restrictions and their impact on the investors' decisions.

Table 1.1: Assets Under Management (in Thousands of US Dollars)

The table shows the end of the year assets under management in thousands of US Dollars for all multi-market and equity funds included in the sample in the end of each year. This excludes (from the set of multi-market and equity funds) fund-of-funds; funds that have one single exclusive client ("exclusive" funds); pension funds; funds whose shareholders need to have some kind of link as being business partners, or belonging to the same family or organization ("restrict"); and funds that are exclusive to employees within the same company ("dedicated"). The total number of funds across the sample is 906. All values are in US Dollars calculated at the exchange rate USD$1 = BRL$1.7412 (as of December 2009)

	Number of Funds	Mean	Median	Standard Deviation	Defunct Funds
1997	102	28,337	10,851	48,181	0
1998	162	22,100	5,677	42,481	0
1999	215	21,079	7,143	39,314	0
2000	253	31,448	12,056	55,100	0
2001	287	29,046	10,483	61,360	19
2002	278	27,384	8,789	70,911	44
2003	266	35,655	10,911	88,866	52
2004	293	52,884	16,261	119,764	33
2005	328	54,844	16,197	141,232	29
2006	367	70,703	20,912	176,155	36
2007	434	114,989	45,038	259,057	22
2008	532	92,789	33,869	226,968	53
2009	589	68,023	23,339	186,631	39

Table 1.2: Funds Characteristics

(a) Investor and Share Restrictions

The table shows the proportion of all funds in the sample that have either a share restriction, an investor restriction or both. The last column also shows the proportion of funds that charge performance fee. Funds that charge performance fee and only accept qualified investors are the hedge fund equivalent (7.17% of the sample).

	All Funds	With Flows Restrictions	With Performance Fee
All Funds	100%	19.7%	59.3%
No Investor Restriction	58.0%	12.3%	42.3%
Qualified Investors	42.0%	7.4%	17.0%
Institutional Investors	25.0%	1.2%	6.2%

(b) Share Restrictions and Fee Structure

Advance notice period 1 is the minimum number of days an investor need to wait after requesting his money to be withdrawn. Sometimes, receiving funds in this shorter period of time can only happen in exchange for a redemption fee. Advance notice period 2 is the maximum number of days an investor needs to wait after requesting her money to be withdrawn, usually free of charge.

	Number of Funds	Mean	Median	Standard Deviation	Minimum	Maximum
Lockup Period (in months)	16	7.99	2.50	8.99	0.07	24.00
Advanced Notice Period 1 *(in days, may be charged)*	470	5.54	1.00	14.39	1.00	90.00
Advanced Notice Period 2 *(in days, not charged)*	111	32.29	30.00	19.66	5.00	90.00
Early withdrawal fee (%)	114	6.06	5.00	2.47	1.00	15.00
Performance Fee (%)	534	20.21	20.00	5.51	0.10	100.00
Administration Fee (%)	819	1.77	2.00	1.07	0.00	8.00

Table 1.3: Summary Statistics of Funds Monthly Flows

The sample excludes the first year of the fund and runs from January 1998 to June 2008 for net inflows; and from January 2005 for inflows and outflows. The first five columns show statistics for equally-weighted flows whereas the last two column display information for asset-weighted flows.

	Equally Weighted (%)					Asset Weighted (%)	
	Mean	Median	Std. Dev.	25%	75%	Mean	Std. Dev.
Net Inflows	0.30	-0.06	4.25	-2.13	1.97	-0.25	3.50
Inflows	6.12	5.46	2.23	4.54	7.67	5.95	2.31
Outflows	5.59	5.17	2.04	4.19	6.73	5.73	2.02

Table 1.4: Summary Statistics of Funds Monthly Returns

(a) Equally-weighted returns

Summary statistics of funds' monthly returns between January 1997 and December 2008.

		Gross Returns (%)			Excess Returns (%)		
	Number of Funds	Mean	Median	Standard Deviation	Mean	Median	Standard Deviation
All Funds	819	1.23	1.43	4.22	-0.07	0.20	4.09
Multi-market	510	1.19	1.38	4.09	-0.09	0.20	3.98
Equity	309	1.28	1.43	4.38	-0.05	0.21	4.24

(b) Asset-weighted returns

Summary statistics of funds' asset-weighted monthly returns between January 1997 and December 2008.

		Gross Returns (%)		Excess Returns (%)	
	Number of Funds	Mean	Standard Deviation	Mean	Standard Deviation
All Funds	726	0.94	5.34	-0.23	5.26
Multi-market	447	1.21	2.82	0.02	2.77
Equity	279	0.33	8.71	-0.83	8.59

Table 1.5: Flow-Performance Relationship Regressions

(a) Net inflows to all funds

Panels a to c report the OLS estimates of a monthly fixed effect panel data with net inflows, inflows and outflows as a dependent variable, respectively, for all funds in the database. Panels d and e have outflows adjusted for the redemption period as dependent variables. Flows are calculated as a percentage of the fund's previous month's net assets. The independent variables are five quintiles of performance in the previous month, in the previous six months and in the previous twelve months; the realized volatility of daily returns in the previous month, previous six months and previous twelve months; the ratio of the fund volatility and stock market volatility in the previous month, previous six months and previous twelve months; the natural logarithm of the fund assets in the previous month; style effect, measured as the percentage net inflow to a particular category at time t relative to the previous month. Regressions include both year and month time dummies.

Net Inflows	(1)	se	(2)	se	(3)	se	(4)	se
Previous month								
1st Quintile	0.092***	(0.035)	0.122***	(0.034)				
2nd Quintile	0.060***	(0.022)	0.092***	(0.021)				
3rd Quintile	0.018	(0.021)	0.042**	(0.020)				
4th Quintile	0.048**	(0.021)	0.084***	(0.020)				
5th Quintile	0.041	(0.032)	0.112***	(0.032)				
Previous 6 months								
1st Quintile	-0.037	(0.036)			0.039	(0.036)		
2nd Quintile	0.049*	(0.025)			0.109***	(0.024)		
3rd Quintile	0.055**	(0.022)			0.107***	(0.021)		
4th Quintile	0.077***	(0.024)			0.129***	(0.023)		
5th Quintile	0.110***	(0.038)			0.238***	(0.038)		
Previous 12 months								
1st Quintile	0.107**	(0.043)					0.142***	(0.045)
2nd Quintile	0.060**	(0.025)					0.098***	(0.025)
3rd Quintile	0.073***	(0.022)					0.119***	(0.023)
4th Quintile	0.067***	(0.024)					0.119***	(0.024)
5th Quintile	0.122***	(0.040)					0.228***	(0.041)
Fund Volatility$_{t-1}$	-0.034	(0.032)	-0.098***	(0.034)				
Fund Volatility$^{6m}_{t-1}$	-0.036	(0.023)			-0.024	(0.016)		
Fund Volatility$^{12m}_{t-1}$	0.052*	(0.030)					0.012	(0.020)
Closed to investment	-0.119***	(0.036)	-0.133***	(0.048)	-0.132***	(0.040)	-0.122***	(0.037)
Ln(Assets)$_{t-1}$	-0.024***	(0.002)	-0.020***	(0.002)	-0.022***	(0.002)	-0.026***	(0.002)
Style Effect$_{t-1}$	1.063***	(0.048)	0.610***	(0.043)	0.988***	(0.045)	1.049***	(0.049)
Constant	0.327***	(0.035)	0.345***	(0.030)	0.352***	(0.030)	0.380***	(0.035)
Observations	37,110		43,337		41,160		37,110	
Number of Funds	886		942		938		886	
Adjusted R^2	10.58%		6.96%		9.24%		9.31%	

Robust standard deviations are in parentheses. ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.

(b) Gross Inflows to all funds

Inflows	(1)	se	(2)	se	(3)	se	(4)	se
Previous month								
1st Quintile	-0.030	(0.035)	-0.029	(0.038)				
2nd Quintile	0.054**	(0.021)	0.082***	(0.023)				
3rd Quintile	0.007	(0.021)	0.031	(0.022)				
4th Quintile	0.023	(0.025)	0.038	(0.025)				
5th Quintile	0.019	(0.036)	0.078**	(0.036)				
Previous 6 months								
1st Quintile	-0.071*	(0.039)			0.003	(0.040)		
2nd Quintile	0.024	(0.022)			0.062***	(0.023)		
3rd Quintile	0.040*	(0.023)			0.083***	(0.023)		
4th Quintile	0.048*	(0.027)			0.077***	(0.026)		
5th Quintile	0.127**	(0.049)			0.230***	(0.051)		
Previous 12 months								
1st Quintile	0.133***	(0.049)					0.131***	(0.050)
2nd Quintile	-0.006	(0.026)					0.017	(0.027)
3rd Quintile	0.084***	(0.025)					0.115***	(0.025)
4th Quintile	0.022	(0.028)					0.057**	(0.028)
5th Quintile	0.185***	(0.052)					0.275***	(0.055)
Fund Volatility$_{t-1}$	-0.072*	(0.038)	-0.041	(0.064)				
Fund Volatility$_{t-1}^{6m}$	-0.014	(0.026)			0.005	(0.030)		
Fund Volatility$_{t-1}^{12m}$	0.067	(0.056)					0.036	(0.045)
Ln(Assets)$_{t-1}$	-0.029***	(0.003)	-0.026***	(0.003)	-0.027***	(0.003)	-0.031***	(0.003)
Style Effect$_t$	0.505***	(0.060)	0.480***	(0.061)	0.490***	(0.058)	0.470***	(0.058)
Constant	0.531***	(0.061)	0.535***	(0.060)	0.521***	(0.059)	0.566***	(0.060)
Observations	20,345		21,478		21,401		20,345	
Number of Funds	706		746		746		706	
Adjusted R-squared	8.98%		6.23%		8.06%		8.31%	

Excludes funds closed to new investors

Robust standard deviations are in parentheses. ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.

(c) Gross Outflows from all funds

Outflows	(1)	se	(2)	se	(3)	se	(4)	se
Previous month								
1st Quintile	-0.048	(0.032)	-0.078**	(0.033)				
2nd Quintile	-0.041**	(0.018)	-0.048***	(0.018)				
3rd Quintile	0.031*	(0.017)	0.023	(0.016)				
4th Quintile	-0.048***	(0.017)	-0.063***	(0.017)				
5th Quintile	0.014	(0.024)	0.022	(0.024)				
Previous 6 months								
1st Quintile	-0.039	(0.033)			-0.071**	(0.036)		
2nd Quintile	-0.056**	(0.022)			-0.080***	(0.023)		
3rd Quintile	0.012	(0.019)			-0.008	(0.019)		
4th Quintile	-0.050***	(0.017)			-0.073***	(0.018)		
5th Quintile	0.115***	(0.033)			0.084**	(0.035)		
Previous 12 months								
1st Quintile	-0.006	(0.053)					-0.055	(0.054)
2nd Quintile	-0.043*	(0.026)					-0.066**	(0.027)
3rd Quintile	-0.019	(0.022)					-0.031	(0.023)
4th Quintile	-0.050***	(0.018)					-0.068***	(0.018)
5th Quintile	0.007	(0.034)					0.031	(0.037)
Fund Volatility$_{m-1}$	-0.089***	(0.029)	-0.063	(0.052)				
Fund Volatility$^{6m}_{m-1}$	0.024	(0.024)			-0.012	(0.024)		
Fund Volatility$^{12m}_{m-1}$	-0.029	(0.052)					-0.024	(0.039)
Closed to New Investors	0.009	(0.014)	0.009	(0.017)	0.009	(0.015)	0.010	(0.013)
Ln(Assets)$_{m-1}$	0.002	(0.003)	-0.000	(0.003)	0.001	(0.003)	0.002	(0.003)
Style Effect$_m$	-0.536***	(0.046)	-0.527***	(0.047)	-0.542***	(0.046)	-0.542***	(0.046)
Constant	0.088	(0.060)	0.092*	(0.054)	0.085	(0.055)	0.061	(0.060)
Observations	21,085		21,732		21,646		21,085	
Number of Funds	732		751		751		732	
Adjusted R-squared	5.48%		4.33%		4.83%		4.91%	

Robust standard deviations are in parentheses. ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.

(d) Adjusted Gross Outflows from all funds - Minimum redemption period

Adjusted Outflows	(1)	se	(2)	se	(3)	se	(4)	se
Previous month								
1^{st} Quintile	-0.053*	(0.031)	-0.082***	(0.031)				
2^{nd} Quintile	-0.031*	(0.018)	-0.037**	(0.017)				
3^{rd} Quintile	0.019	(0.016)	0.011	(0.015)				
4^{th} Quintile	-0.036**	(0.016)	-0.050***	(0.016)				
5^{th} Quintile	0.009	(0.024)	0.018	(0.023)				
Previous 6 months								
1^{st} Quintile	-0.048	(0.032)			-0.067*	(0.034)		
2^{nd} Quintile	-0.049**	(0.021)			-0.072***	(0.021)		
3^{rd} Quintile	0.006	(0.018)			-0.012	(0.018)		
4^{th} Quintile	-0.043**	(0.017)			-0.063***	(0.017)		
5^{th} Quintile	0.118***	(0.032)			0.082**	(0.033)		
Previous 12 months								
1^{st} Quintile	0.009	(0.051)					-0.041	(0.051)
2^{nd} Quintile	-0.037	(0.025)					-0.058**	(0.026)
3^{rd} Quintile	-0.024	(0.022)					-0.035	(0.022)
4^{th} Quintile	-0.045**	(0.018)					-0.060***	(0.018)
5^{th} Quintile	0.009	(0.033)					0.036	(0.037)
Fund Volatility$_{t-1}$	-0.069**	(0.029)	-0.050	(0.048)				
Fund Volatility$^{6m}_{t-1}$	0.020	(0.023)			-0.011	(0.023)		
Fund Volatility$^{12m}_{t-1}$	-0.026	(0.049)					-0.020	(0.038)
Closed to new investors	0.011	(0.014)	0.011	(0.017)	0.010	(0.015)	0.012	(0.013)
Ln(Assets)$_{t-1}$	0.003	(0.003)	0.001	(0.003)	0.002	(0.003)	0.003	(0.003)
Style Effect$_t$	-0.502***	(0.044)	-0.488***	(0.044)	-0.499***	(0.043)	-0.505***	(0.044)
Constant	0.068	(0.058)	0.077	(0.051)	0.071	(0.052)	0.043	(0.058)
Observations	21,329		22,514		22,427		21,329	
Number of Funds	743		786		786		743	
Adjusted R-squared	5.04%		4.00%		4.43%		4.50%	

Robust standard deviations are in parentheses. ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.

(e) Adjusted Outflow from all funds - Maximum redemption period

Adjusted Outflows (2)	(1)	se	(2)	se	(3)	se	(4)	se
Previous month								
1^{st} Quintile	-0.060**	(0.030)	-0.079**	(0.032)				
2^{nd} Quintile	-0.028	(0.017)	-0.034**	(0.017)				
3^{rd} Quintile	0.020	(0.016)	0.014	(0.015)				
4^{th} Quintile	-0.042***	(0.016)	-0.055***	(0.016)				
5^{th} Quintile	0.015	(0.024)	0.030	(0.024)				
Previous 6 months								
1^{st} Quintile	-0.027	(0.031)			-0.051	(0.034)		
2^{nd} Quintile	-0.060***	(0.021)			-0.081***	(0.022)		
3^{rd} Quintile	0.015	(0.017)			-0.000	(0.018)		
4^{th} Quintile	-0.044**	(0.017)			-0.065***	(0.018)		
5^{th} Quintile	0.122***	(0.031)			0.100***	(0.033)		
Previous 12 months								
1^{st} Quintile	0.025	(0.049)					-0.017	(0.049)
2^{nd} Quintile	-0.055**	(0.024)					-0.077***	(0.025)
3^{rd} Quintile	0.001	(0.022)					-0.008	(0.022)
4^{th} Quintile	-0.053***	(0.018)					-0.068***	(0.018)
5^{th} Quintile	0.019	(0.031)					0.050	(0.035)
Fund Volatility$_{m-1}$	-0.065**	(0.029)	-0.033	(0.049)				
Fund Volatility$^{6m}_{m-1}$	0.022	(0.023)			-0.002	(0.023)		
Fund Volatility$^{12m}_{m-1}$	-0.018	(0.049)					-0.009	(0.037)
Closed to New Investors	0.013	(0.014)	0.013	(0.017)	0.013	(0.015)	0.014	(0.013)
Ln(Assets)$_{m-1}$	0.004	(0.003)	0.003	(0.003)	0.003	(0.003)	0.004	(0.003)
Style Effect$_m$	-0.449***	(0.042)	-0.440***	(0.043)	-0.449***	(0.042)	-0.452***	(0.042)
Constant	0.040	(0.056)	0.046	(0.050)	0.037	(0.051)	0.016	(0.056)
Observations	21,086		21,735		21,649		21,086	
Number of Funds	732		751		751		732	
Adjusted R-squared	4.60%		3.66%		4.05%		4.05%	

Robust standard deviations are in parentheses. ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 1.6: Flow-Performance Relationship - Terciles

This table reports the OLS estimates of a monthly panel data with funds' and time fixed effects. The dependent variable is the net inflows as a percentage of the previous month assets under management. The independent variables are three terciles of performance in the previous month, in the previous six months and in the previous twelve months. Past performance is measure as non-risk adjusted after fees returns. Other controls are the realized volatility of daily returns in the previous month, previous six months and previous twelve months; a dummy variable for funds that are closed to new investments; the natural logarithm of the fund assets in the previous month; and style effect, measured as the percentage net inflow to a particular category (either equity or multi-market) at time *t-1* relative to month *t-2*.

VARIABLES	Net Inflows	p-val	Inflows	p-val	Outflows	p-val
Previous month						
1^{st} Tercile	0.089***	(0.000)	0.014	(0.408)	-0.040***	(0.002)
2^{nd} Tercile	0.028**	(0.019)	0.023**	(0.047)	-0.004	(0.607)
3^{rd} Tercile	0.043***	(0.004)	0.018	(0.256)	-0.014	(0.207)
Previous six months						
1^{st} Tercile	0.045**	(0.035)	-0.014	(0.567)	-0.064***	(0.001)
2^{nd} Tercile	0.070***	(0.000)	0.039***	(0.004)	-0.025**	(0.017)
3^{rd} Tercile	0.097***	(0.000)	0.093***	(0.000)	0.012	(0.344)
Previous twelve months						
1^{st} Tercile	0.072***	(0.006)	0.039	(0.182)	-0.034	(0.269)
2^{nd} Tercile	0.090***	(0.000)	0.071***	(0.000)	-0.037**	(0.011)
3^{rd} Tercile	0.097***	(0.000)	0.086***	(0.000)	-0.038***	(0.002)
Fund Volatility$_{m-1}$	0.156***	(0.005)	0.070	(0.146)	-0.171***	(0.000)
Fund Volatility$^{6m}_{m-1}$	0.007	(0.845)	0.016	(0.535)	0.038	(0.129)
Fund Volatility$^{12m}_{m-1}$	0.015	(0.721)	0.031	(0.525)	-0.072**	(0.014)
Closed to New Investors	-0.109***	(0.003)			0.005	(0.667)
Ln(Assets)$_{m-1}$	-0.024***	(0.000)	-0.037***	(0.000)	0.001	(0.760)
Style Effect$_{m-1}$	0.944***	(0.000)	0.398***	(0.000)	-0.619***	(0.000)
Constant	0.315***	(0.000)	0.667***	(0.000)	0.120**	(0.037)
Time fixed effects	YES		YES		YES	
Funds' fixed effects	YES		YES		YES	
Observations	28,548		16,293		17,245	
Number of Funds	674		551		586	
Adjusted R-squared	13.3%		11.8%		8.9%	

Robust standard deviations are in parentheses. ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.

Figure 1.1: Flow-performance Relationship - Net Inflow

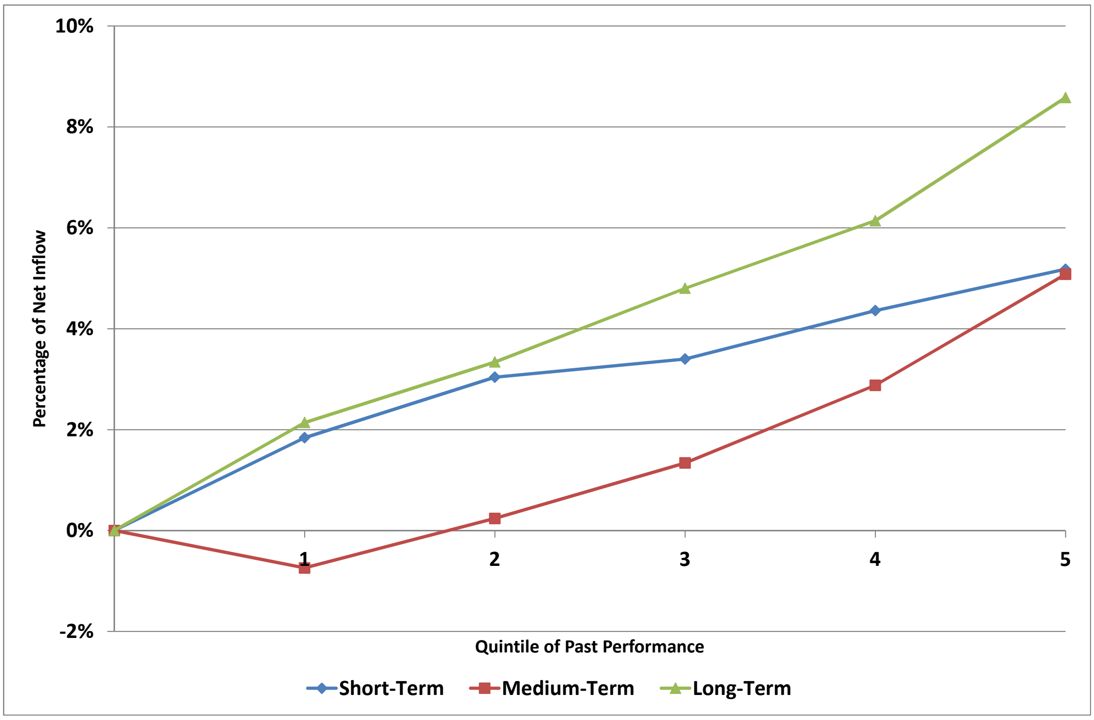


Table 1.7: Flow-Performance Relationship: Sharpe Ratio Ranking

(a) Quantiles

VARIABLES	(1) Net Inflows	(1) p-val	(2) Gross Inflows	(2) p-val	(3) Gross Outflows	(3) p-val
Sharpe ratio ranking, previous month						
1st Quantile	0.044	(0.293)	-0.033	(0.370)	-0.059*	(0.089)
2nd Quantile	0.030	(0.222)	0.021	(0.397)	-0.028	(0.174)
3rd Quantile	0.035*	(0.097)	0.023	(0.276)	-0.000	(0.997)
4th Quantile	0.040*	(0.068)	0.016	(0.478)	-0.020	(0.149)
5th Quantile	-0.005	(0.896)	0.041	(0.246)	-0.002	(0.935)
Sharpe ratio ranking, previous six months						
1st Quantile	0.026	(0.589)	-0.024	(0.616)	-0.125***	(0.003)
2nd Quantile	0.043	(0.120)	0.024	(0.287)	0.009	(0.662)
3rd Quantile	0.061**	(0.013)	0.041*	(0.088)	-0.025	(0.187)
4th Quantile	0.072***	(0.005)	0.025	(0.351)	-0.022	(0.226)
5th Quantile	0.093**	(0.020)	0.117***	(0.009)	-0.009	(0.710)
Sharpe ratio ranking, previous twelve months						
1st Quantile	-0.053	(0.355)	-0.010	(0.853)	0.072	(0.155)
2nd Quantile	0.135***	(0.000)	0.025	(0.396)	-0.058**	(0.020)
3rd Quantile	0.013	(0.597)	0.064**	(0.010)	-0.007	(0.726)
4th Quantile	0.095***	(0.000)	0.085***	(0.001)	-0.012	(0.476)
5th Quantile	0.038	(0.320)	0.088*	(0.055)	0.001	(0.977)
Closed to New Investors	-0.110**	(0.013)			0.008	(0.573)
Ln(Assets)$_{m-1}$	-0.026***	(0.000)	-0.039***	(0.000)	0.003	(0.369)
Style Effect$_{m-1}$	0.992***	(0.000)	0.429***	(0.000)	-0.705***	(0.000)
Constant	0.417***	(0.000)	0.750***	(0.000)	0.063	(0.285)
Time fixed effects	YES		YES		YES	
Funds' fixed effects	YES		YES		YES	
Observations	28,020		16,192		17,135	
Number of Funds	659		540		572	
Adjusted R-squared	11.6%		11.4%		8.2%	

Robust standard deviations are in parentheses. ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 1.7: Flow-Performance Relationship: Sharpe Ratio Ranking (Cont.)

(b) Terciles

VARIABLES	(1) Net Inflows	(1) p-val	(2) Gross Inflows	(2) p-val	(3) Gross Outflows	(3) p-val
Sharpe ratio ranking, previous month						
1^{st} Tercile	0.031	(0.115)	-0.011	(0.535)	-0.052***	(0.001)
2^{nd} Tercile	0.044***	(0.000)	0.025**	(0.021)	-0.009	(0.308)
3^{rd} Tercile	0.020	(0.179)	0.030*	(0.058)	-0.015	(0.114)
Sharpe ratio ranking, previous six months						
1^{st} Tercile	0.033	(0.178)	0.008	(0.725)	-0.059***	(0.005)
2^{nd} Tercile	0.069***	(0.000)	0.032**	(0.013)	-0.015	(0.142)
3^{rd} Tercile	0.087***	(0.000)	0.075***	(0.001)	-0.018	(0.115)
Sharpe ratio ranking, previous twelve months						
1^{st} Tercile	0.059**	(0.030)	-0.006	(0.843)	-0.012	(0.653)
2^{nd} Tercile	0.070***	(0.000)	0.071***	(0.000)	-0.023**	(0.044)
3^{rd} Tercile	0.068***	(0.000)	0.092***	(0.000)	-0.002	(0.887)
Closed to New Investors	-0.112**	(0.012)			0.007	(0.625)
Ln(Assets)$_{m-1}$	-0.026***	(0.000)	-0.038***	(0.000)	0.002	(0.630)
Style Effect$_{m-1}$	0.995***	(0.000)	0.429***	(0.000)	-0.703***	(0.000)
Constant	0.392***	(0.000)	0.733***	(0.000)	0.086	(0.153)
Time fixed effects	YES		YES		YES	
Funds' fixed effects	YES		YES		YES	
Observations	28,077		16,224		17,170	
Number of Funds	662		542		575	
Adjusted R-squared	11.5%		11.4%		7.9%	

Robust standard deviations are in parentheses. ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 1.8: Flows by Type of Investor and Terciles of Performance

Panels a to c report the OLS estimates of a panel data for net inflows, inflows and outflows as a dependent variable, respectively. Model (1) includes all funds in the sample; in model (2)-(4) funds are divided in sub-samples according to the type of investor the funds cater to. Panel (b), gross inflows, excludes funds closed to new investment. Regressions include both time and fund fixed effects.

VARIABLES	(1) All Funds	(1) p-val	(2) No Restriction	(2) p-val	(3) Qualified Investors	(3) p-val	(4) Institutional Investors	(4) p-val
Previous month								
1^{st} Tercile	0.089***	(0.000)	0.099***	(0.000)	0.054*	(0.070)	0.062	(0.198)
2^{nd} Tercile	0.028**	(0.019)	0.026*	(0.056)	0.020	(0.314)	-0.018	(0.545)
3^{rd} Tercile	0.043***	(0.004)	0.052***	(0.003)	0.018	(0.477)	0.071*	(0.077)
Previous six months								
1^{st} Tercile	0.045**	(0.035)	0.048*	(0.055)	0.049	(0.184)	0.049	(0.400)
2^{nd} Tercile	0.070***	(0.000)	0.075***	(0.000)	0.063***	(0.002)	0.075**	(0.016)
3^{rd} Tercile	0.097***	(0.000)	0.114***	(0.000)	0.043	(0.125)	0.075	(0.110)
Previous twelve months								
1^{st} Tercile	0.072***	(0.006)	0.080***	(0.007)	0.035	(0.405)	0.093	(0.120)
2^{nd} Tercile	0.090***	(0.000)	0.099***	(0.000)	0.080***	(0.001)	0.077**	(0.027)
3^{rd} Tercile	0.097***	(0.000)	0.113***	(0.000)	0.067**	(0.012)	0.101***	(0.009)
Fund Volatility$_{t-1}$	0.156***	(0.005)	0.139*	(0.052)	0.210***	(0.002)	0.193	(0.130)
Fund Volatility$^{6m}_{t-1}$	0.007	(0.845)	-0.005	(0.915)	0.017	(0.652)	-0.047	(0.420)
Fund Volatility$^{12m}_{t-1}$	0.015	(0.721)	0.022	(0.695)	0.018	(0.677)	0.068	(0.363)
Closed to New Investors	-0.109***	(0.003)	-0.151***	(0.000)	0.023	(0.393)		
Ln(Assets)$_{m-1}$	-0.024***	(0.000)	-0.025***	(0.000)	-0.025***	(0.000)	-0.034***	(0.000)
Style Effect$_{m-1}$	0.944***	(0.000)	0.982***	(0.000)	0.836***	(0.000)	0.953***	(0.000)
Constant	0.315***	(0.000)	0.321***	(0.000)	0.370***	(0.000)	0.529***	(0.000)
Time fixed effects	YES		YES		YES		YES	
Funds' fixed effects	YES		YES		YES		YES	
Observations	28,548		20,683		11,149		6,183	
Number of Funds	674		496		282		163	
Adjusted R-squared	13.3%		15.6%		8.7%		9.8%	

Robust p-values in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 1.9: Flows by Type of Investor and Terciles of Performance Ranked using Sharpe Ratio

Panels a to c report the OLS estimates of a panel data for net inflows, inflows and outflows as a dependent variable, respectively and the Sharpe ratio ranking as main independent variable. Model (1) includes all funds in the sample; in model (2)-(4) funds are divided in sub-samples according to the type of investor the funds cater to. Panel (b), gross inflows, excludes funds closed to new investment. Regressions include both time and fund fixed effects.

	(1)	(1)	(2)	(2)	(3)	(3)	(4)	(4)
					Qualified		Institutional	
VARIABLES	All Funds	p-val	No Restriction	p-val	Investors	p-val	Investors	p-val
Sharpe ratio ranking, previous month								
1^{st} Tercile	0.031	(0.115)	0.033	(0.174)	0.031	(0.365)	0.032	(0.602)
2^{nd} Tercile	0.044***	(0.000)	0.057***	(0.000)	0.008	(0.706)	0.000	(0.994)
3^{rd} Tercile	0.020	(0.179)	0.019	(0.277)	0.012	(0.638)	-0.022	(0.531)
Sharpe ratio ranking, previous six months								
1^{st} Tercile	0.033	(0.178)	0.023	(0.418)	0.040	(0.343)	0.033	(0.599)
2^{nd} Tercile	0.069***	(0.000)	0.073***	(0.000)	0.063***	(0.005)	0.071**	(0.043)
3^{rd} Tercile	0.087***	(0.000)	0.098***	(0.000)	0.071**	(0.014)	0.117***	(0.009)
Sharpe ratio ranking, previous twelve months								
1^{st} Tercile	0.059**	(0.030)	0.059*	(0.068)	0.083*	(0.050)	0.128**	(0.026)
2^{nd} Tercile	0.070***	(0.000)	0.088***	(0.000)	0.047**	(0.045)	0.071**	(0.040)
3^{rd} Tercile	0.068***	(0.000)	0.080***	(0.000)	0.034	(0.196)	0.037	(0.376)
Closed to New Investors	-0.112**	(0.012)	-0.165***	(0.000)	0.033	(0.108)		
Ln(Assets)_{m-1}	-0.026***	(0.000)	-0.027***	(0.000)	-0.027***	(0.000)	-0.037***	(0.000)
$\text{Style Effect}_{m-1}$	0.995***	(0.000)	1.037***	(0.000)	0.871***	(0.000)	0.925***	(0.000)
Constant	0.392***	(0.000)	0.408***	(0.000)	0.444***	(0.000)	0.652***	(0.000)
Time fixed effects	YES		YES		YES		YES	
Funds' fixed effects	YES		YES		YES		YES	
Observations	28,077		20,330		10,965		6,080	
Number of Funds	662		486		275		157	
Adjusted R-squared	11.5%		13.4%		8.1%		9.1%	

Robust p-values in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Chapter 2

Contract-implied and flow-induced incentives in the asset management industry

2.1 Introduction

Agency problems due to delegated portfolio management have been extensively discussed in the literature. In principle, if fund managers are compensated based on their performance, they should exert higher effort and generate higher (risk-adjusted) returns. However such contracts may have a perverse effect as well, namely, inducing managers to take excess risk. This could well exacerbate the agency problem instead of offering a correction (Palomino and Prat, 2003). This problem may arise even in the absence of any explicit contract. The tournament feature of the money management industry, in which the best performing funds reap most of the funds flowing to the industry, generates an implicit incentive for the fund manager to beat the competition over the year. Funds that are lagging relative to their peers during mid-year would then have an incentive to shift risk towards the end of the year, regardless of the shareholders' preferences (Brown, Harlow and Starks, 1996).

This paper contributes to the literature on incentives and risk taking behavior of fund managers by disentangling the effect due to the implicit contract generated by the tournament feature within the industry, from the explicit remuneration contract offered by the asset management company to the fund managers. In particular, I restrict attention to funds that pay bonus to their managers every six months (viz., July and January) instead of every end of year. As portfolio managers face the same contract-implied incentive every six months and the incentive generated by the flow-performance is stronger in the end of the year, differences in risk-taking between the second and the fourth quarters are due to the tournament effect. The results suggest that funds engage in a tournament, but not in the way the literature suggest: fund families behave strategically, not only transferring gains to the best performing funds as Nanda, Wang and Zheng (2004), Gaspar, Massa and Matos (2006) and others suggest, but moving risk from the best funds to the worst. In addition, the relative position of a fund relative to the other funds in the same family is much more important to determine risk-shifting than its position relative to other funds in the industry.

The empirical literature in this field usually treats funds as stand-alone entities with no strategic behavior at the fund level. In most cases, however, a fund is part of a family of funds. The family collects all the fees paid by the investors and pays all the costs that do not arise from the trading activities of the funds such as rent, salaries, IT etc. Whatever is left is then redistributed to the fund managers at specific times of the year.[1] This is the variable component of the fund manager's remuneration (the bonus) and I will assume that it is, at least partly, linked to the fund manager's past performance.

There are thus two layers of contracting: one between the investors and the family, and another between the family and the traders. As fees are proportional to assets under management, the goal of the top management is to maximize assets under management, i.e., net inflows. As for the traders, they just want to maximize their

[1] In this chapter, I will use fund managers, portfolio managers and traders indistinguishably. The same goes for company, top management company or family.

own payoff. In general, the literature on fund tournament theory assumes that funds engage in an yearly tournament for flows against other funds in the industry: funds that are lagging relative to the market have an incentive to shift risk towards the end of the year in order to climb a few positions on the ranking. However, fund managers also engage in an internal tournament against other managers in the same family for a share of the profits. As in general traders receive their bonus every January relative to their performance in the previous year, they also have an incentive to shift risk towards the end of the year. As a result, there are two types of tournament affecting the risk taking behaviour of a fund towards the end of the year. Most empirical papers in this area fail to recognize this feature.

The results in this paper relate to the literature on incentives and delegated portfolio management and more precisely to the few papers that analyze family fund structure and strategic competition at the family level. Massa (1998) show that having a star fund generates a positive spillover for all the funds belonging to the same family. Nanda et al. (2004) investigate the consequences of such spillover and argue that it may induce some families to pursue a star-creating strategy, by increasing the cross-return variance or the number of funds in the family. Guedj and Papastaikoudi (2004) demonstrate that there is performance persistence for funds belonging to the same family which increases with the number of funds a family manages. This is consistent with families allocating resources in proportion to fund performance. Gaspar et al. (2006) show that families engage in cross-subsidization of returns, transferring performance across funds to favor those more likely to increase overall family profits, hurting the individual investor.

The previous papers focus on the decision of the top management of a family and study whether they affect the performance of the funds they manage. Nonetheless, they still assume that funds belonging to the same family are coordinated entities, with no strategic interaction between them. Kempf and Ruenzi (2008) analyze the behavior of funds within a family and show that they engage in an internal tournament against each other. Kempf and Ruenzi (2008) find that the effects are particularly pronounced 'among manager of funds with high expense ratios, which are managed by a single manager and which belong to large families'.

The literature on tournament is, by contrast, vast. Brown et al. (1996) test the tournament theory and find evidence that mid-year losers do indeed increase the risk of their portfolio in the second half of the year. Koski and Pontiff (1999) find similar results after calculating several measures of riskiness, including the total volatility, market beta and idiosyncratic risk of the funds' returns. Busse (2001) and Goriaev, Nijman and Werker (2005) point out however that the above difference-in-risk tests are not robust to cross-sectional correlation. This is in contrast with the panel framework I employ, which explicitly controls for the covariance between the funds' returns. It also does not affect studies based on portfolio holdings, whose results corroborate mine. For instance, Chevalier and Ellison (1997) find that fund managers lagging behind have an incentive to gamble by taking more unsystematic risk, whereas winning funds would lock-in their gains by indexing more.

Chen and Pennacchi (2009) develop a model where they show that tournament competition induces losers to deviate from the benchmark, increasing the tracking error of the fund, rather than the volatility of total returns. Their results suggest that losers tend to decrease their total volatility in the second half of the year whilst increasing at the same time their tracking error. As before, this is well in line with the findings in this paper.

Reed and Wu (2005) show that mutual fund managers respond much more to year-to-date performance relative to the market index than relative to each other. Fund managers reduce risk after beating the S&P500, but not after beating the median return of the competitors. This is not surprising in that fund managers are compensated based on their performance relative to a benchmark. Similarly, Basak, Pavlova and

Shapiro (2007) also use returns data to examine whether beating a benchmark implies risk shifting. They develop a model in which implicit incentives induce a risk-averse manager to take more or less risk depending on her degree of risk aversion.

Changing risk as a response to past performance should not depend on the time of the year. If one assumes that a fund's level of risk also relates to performance calculated over calendar years as some papers show (see, among others, Koski and Pontiff (1999), Chevalier and Ellison (1997)), then the flow-performance relationship will generate an implicit incentive that can affect the risk taking behavior of a fund specifically towards the end of the year.

In most countries, bonus payments occur at the beginning of the year relative to the performance in the previous year, and hence it is impossible to empirically distinguish risk shifting due to the compensation contract from the one due to incentive structure implied by the flow-performance relationship. Given the bi-annual compensation scheme in Brazil, contract-induced changes in risk may happen not only towards the end of the year, but also on the second quarter of the year. Of course, there is always a subjective component in the bonus determination. Accordingly, fund/portfolio managers could endogenize this feature, facing in practice a different incentive in the second half of the year. This means that differences in the risk-taking behavior between the second and the fourth quarter of the year are due to the incentives implicit in the flow-performance relation.

The paper is organized as follows. Section 2.2 describes different measures of risk shifting and the main variables used in the empirical model. Section 2.3 describes the data and the institutional framework. Section 2.4 discusses the empirical results. Section 2.5 concludes.

2.2 Measuring risk shifting

There are two general ways to measure the riskiness of a fund. The first employs returns data only, whereas the second also requires portfolio holdings data. The data set I employ allows me to calculate risk shifting in both ways and hence to compare their results. The three main question are then (1) who changes risk, (2) how they change risk, and (3) in response to what. The rest of this section examine these issues in more detail.

2.2.1 How do funds change their risk?

Funds can increase their total risk by either taking more systematic risk, i.e. tilting towards assets with higher beta, or by taking more idiosyncratic risk, i.e. decreasing the level of diversification in their portfolio. However, if funds measure their performance against a specific benchmark, as Chen and Pennacchi (2009) and Basak et al. (2007) point out, the way to increase their performance relative to this benchmark is not to increase total risk, but to increase the tracking error. The argument is similar to Brown et al.'s (1996) reasoning. Mid-year losers that want to improve their performance relative to their peers need not only to take more risk, but also to take more risk than mid-year winners. This would mean that total fund volatility is not necessarily the appropriate measure of risk to use when analyzing risk shifting. Increasing tracking error indeed does not necessarily translates into a rise in the total volatility.

To answer the question on how funds shift risk, I employ both total volatility and tracking error as dependent variables and then check if the regression results differ or not. If there is a change in tracking error and/or total volatility, the signs of the changes will give a hint of what funds are actually doing. If total volatility increases, it can either mean that the fund's diversification has decreased or that the fund is taking more systematic risk. If, on the other hand, the tracking error increases, it will then mean that the market beta of the fund is moving further away from one, i.e., the active beta is increasing in magnitude. The less tracking error, the more benchmarking, but, all else being equal, the fund can be decreasing or increasing total volatility depending on whether the original beta was above or below one, respectively.

Alternatively, one can also investigate risk shifting from funds' portfolio holdings by looking at the market betas of the individual assets that compose the portfolio. Huang, Sialm and Zhang (2011) suggest a measure of active risk-shifting calculated from portfolio holdings that captures when a fund migrates to assets with lower or higher beta. Although I have access to the holdings of the funds in the database, the sample is much shorter than the one used for most of the analysis. I will, however, use this measure in section 2.4.4 as a further test.

2.2.2 Risk shifting and past performance

The main objective of this paper is to disentangle the effect of the direct compensation contract from the implicit incentive generated by the flow-performance relationship. As both flows and the bonus respond to past performance, I need at least two distinct measures of past performance to test whether they induce a different risk-taking behaviour.

The choice of the dependent variables reflects the time span over which the fund manager and the management company are evaluated. The management company is evaluated by the shareholders and other outside investors and its payoff is expressed by an increase or decrease in net inflows. Fund managers are evaluated by the company and their payoff is just the bonus they get on top of any fixed salary they might already receive. Note that, in this setting, the asset management company first collects the fees, pays all the company's costs and, only then, redistribute whatever is left to the portfolio managers. The key aspect is that the contract does not specify the exact percentage fund/portfolio managers will receive of total fees which means that fund managers and top management incentives are not necessarily aligned.

Fund managers receive their bonus every January and July relative to the previous six months. Unfortunately, I have no information on the contracts the top management offers to fund managers, but, if the top management wants incentives to be aligned, bonus will be linked to the fund manager's performance relative to the market as this is the main determinant of net inflows. Moreover, acknowledging a competition between fund managers within the same family, I will introduce a second measure of performance that captures an internal competition for bonus.

In order to account for the features previously described, I first calculate the fund return over the January-to-date period for the first half of the year and over July-to-date period for the second half of the year and then generate two different rankings: one for the company and another for the industry. For the first ranking, for each month and company, I separate funds into terciles; $T1^{(JTD)}$ being the worst and $T3^{(JTD)}$ the best performing. JTD stands for either January-to-date or July-to-date depending on whether month t belongs to the first or second half of the year. Ideally, one should use returns before fees to rank the funds, but this is unfortunately not available in the database. Accordingly, I use net-of-fees returns instead. For the second ranking, for each month, funds are split into quintiles; $Q1^{(JTD)}$ aggregates the worst performing, whereas $Q5^{(JTD)}$ the best within their segment (i.e., equity or multi-market) according to their net-of-fee returns. It would have been preferable to use the same number of quantiles for both measures, but some families are just not big enough to divided in five groups. For the sake of robustness, I look into different quantiles without any major change in the results.

The choice of a performance dependent variable that captures the incentive faced by the asset management company is not as straightforward. Chevalier and Ellison (1997) and Brown et al. (1996) among others claim that, if official rankings are only released annually, funds should be mostly concerned with their performance within a specific year. This means that returns since January (year-to-date) would probably be the most appropriate measure. However, using exactly the same sample as in this paper, Bertol-Domingues (2011) finds that the past 12-month performance explains most of the net inflows to a fund. This measure has also the advantage of providing an incentive every month that, in theory, does not depend on the time of the year. As before, I divide funds into quintiles according to their 12-month performance. The worst performing funds are in $Q1^{(12m)}$, whereas $Q5^{(12m)}$ consists of the best performing funds. Note that I differentiate the notation for the performance quintiles by superscripts. As previously mentioned, JTD stands for either January-to-date or July-to-date, whereas $12m$ refers to the longer horizon of 12 months.

2.2.3 Funds' characteristics and other controls

As funds in the same family compete against each other for a share of the total fees, the structure and some characteristics of the asset management can affect the competition and the risk-taking behavior of the fund managers. Huang, Wei and Yan (2007) report that funds in smaller families usually have a more convex flow-performance relationship.

The number of funds within a family also plays a role. Kempf and Ruenzi (2008) show that funds that belong to a large family, i.e., with more funds, don't behave as funds that belong to a small family. More specifically, mid-year winners in a big family tend to increase risk less than mid-year losers, whereas, in small families, the exact opposite occurs. They, however, also notice that adjustments in risk are bigger in bigger families. This is consistent with Huang et al.'s (2011) evidence that the bigger the fund family, as measured by total net assets, the more the fund shifts risk.

2.3 Data description

2.3.1 Sample selection

I use a database of Brazilian funds provided by Quantum that comprises daily information on share value, total net assets, number of shareholders, inflows and outflows, as well as monthly portfolio holdings for both mutual and hedge funds.[2] The data set contains information on both long and short positions on every security in the portfolio, including derivatives. It also has important information on the fund such as style/segment, age, fees, minimum investment amount and the type of client the fund caters to. For the last two and a half years of data, there is also information on the exact number of shares each fund bought and sold over any given month from which I can back out the exact turnover of the fund.[3]

The database is extremely rich and has many advantages compared to the usual data in the extant literature. First, it includes monthly portfolio holdings rather than quarterly. As pointed out by Elton et al. (2010), the sampling frequency of the data has a significant impact on the results. Quarterly data misses all the intra-quarter trades, and adding more information might change, or even reverse, the previous findings. Moreover, portfolio holdings information includes all positions rather than restricting attention to long positions in equity. Second, since 2007, Brazilian funds have been required to report not only the net position at the end of each month but also how much they bought and sold of each security within that month. Although we still do not know when the trades happened within the month, it gives us a more much precise measure of turnover and indicates how active the funds are. Last, but not least, the database includes hedge funds. In general, hedge funds are required to provide very little information on their activities. Under the Brazilian regulation,

[2] According to ICI, in the last quarter of 2010, Brazil ranked sixth in the ranking of mutual funds behind USA, Luxembourg, France, Australia, and Ireland.

[3] For more information on Brazilian fund data, see Bertol-Domingues (2011). See also Varga and Wengert (2009) for a thorough discussion of the Brazilian fund industry and its legislation.

they are required to disclose similar information as mutual funds. They are, however, still free to trade in all markets and to take short positions. As a consequence, it is possible to evaluate under the same regulatory framework the risk-shifting behavior of hedge funds relative to mutual funds conditional on the funds' characteristics. One main difference between Brazilian hedge funds and their counterpart elsewhere is that funds domiciliated in Brazil cannot borrow cash in order to increase leverage. This can significantly decrease their level of risk, but also limit their ability to arbitrage.

For the purpose of this paper, the main advantage of this database is that Brazilian funds normally pay bonus every six months instead of every year: in July (relative to period between January and June) and in January (relative to the period between July and December). This is a crucial feature because it allows disentangling the incentives faced by the fund management company from the short-term incentive faced by the fund/portfolio manager. Assuming the compensation contract does not change considerably over time, the fund manager will face the same contract-induced incentive every six months. Whereas, in theory, fund management companies will have a constant incentive every month given by the flow-performance relationship (see Bertol-Domingues, 2011). If we take into account the fact that funds are also evaluated based on their annual performance, there is a tournament to be played and won every year (see, among others, Brown et al., 1996; Chevalier and Ellison, 1997). As the end of the year approaches, both the fund manager and the company could have an incentive to alter the risk of the portfolio.

I focus the analysis on actively managed domestic funds, which consist of equity and multi-market funds, excluding fund-of-funds. As determined by the CVM (i.e., the Brazilian SEC), multi-market funds can trade in any market with no restriction, whereas equity funds are required to invest 80% of their assets in equity. From this sample, I then further exclude balanced, bond, international and index funds as well as funds that manage less than $5 million or with up to three shareholders for over

50% of the sample.

2.3.2 Descriptive statistics

The final sample includes 925 distinct funds and 42,460 valid fund-month observations from December 1996 to June 2009. The number of funds ranges from 140 in December 1997 to 667 in June 2009. The database has no survivorship bias, though there is some evidence of backfill bias from 1997 to 2000 (Bertol-Domingues, 2011). Daily information on returns, share value and assets under management are available since December 1996. Daily information on the number of shareholders, gross inflows and gross outflows per fund start in January 2005. Monthly information on portfolio holdings start in January 2005 and information on the monthly turnover is available from January 2007.

Table 2.1 reports summary statistics for several fund's characteristics. The median fund is just under five years old, manages around R$114 million, with just under 2,000 shareholders, and yields 1.8% a month with an average volatility of 4.9% and tracking error of 7.1%. It receives a typical inflow of 9.1% over a month and suffers an outflow of 5.5% of the total net assets. As and when a fund is liquidated, both the net flow and the outflow are set to -100%. Both inflows and outflows are very volatile. I thus winsorize them at the 99.5% quantile.

2.4 Panel-regression analysis of risk shifting

Tables 2.2 and 2.3 illustrate how past performance and funds' characteristics affect the general risk-taking behavior of a fund as measured by the total volatility, their beta and their idiosyncratic volatility, respectively. The fund's beta and idiosyncratic volatility are monthly, calculated from daily return. The fund's monthly volatility is calculated by summing squared daily returns as suggested in Merton (1980) and French et al. (1987):

$$\sigma_{f,m} = \sqrt{21 \frac{\sum_{t=1}^{N_m} r_{f,t}^2}{N_m - 1}}$$

Note that dividing the realized variance by the number of trading days within the month yields a measure that does not depend on the length of the month (otherwise, volatility in March would on average exceed that in February, say).

Fund managers that decide to lock in their gains can do three things: decrease the absolute value of the beta of their portfolio; increase its level of diversification; and/or decrease the proportion of risky assets relative to cash or cash equivalents. These three options are, of course, not mutually exclusive. If fund managers are however competing against the other fund managers in the industry, the best option might not be to lock their absolute return, but their relative return. In this case, instead of decreasing the absolute value of the beta of their portfolio, $|\beta|$, they will track the benchmark index more closely, i.e. they will decrease $|\beta - 1|$. As funds have $0 < \beta < 1$ in over 80% of the time, increasing β is then equivalent to benchmarking more.

The main objective of this paper is to link changes in volatility over the year to past performance, especially at close-to-bonus-payment times. Thus, I develop a panel data model with both fund and time-fixed effects and measures of past performance that reflect either the contract generated incentive or the implicit incentive produced by the fund flows along with other controls. I then compare the results for total volatility and tracking error so as to pin down exactly how fund managers change the riskiness of their portfolio.

There are three main sets of regressors in the baseline model: $T1^{(JTD)}, \ldots, T3^{(JTD)}$ denote the fund ranking within the family of funds over the January/July-to-date period, $Q1^{(JTD)}, \ldots, Q5^{(JTD)}$ refer to the fund ranking in the whole industry over the same time period, and $Q1^{(12m)}, \ldots, Q5^{(12m)}$ describe the fund ranking in the whole industry over the previous twelve months. The JTD window reflects the fact that fund managers receive their bonus every six months and hence the related performance measures aim to capture the contract-induced risk-taking behavior of the fund/portfolio manager due to the internal and external competitions. The 12-month performance quintile attempts to account for the incentive implied by the flow-performance relationship. To avoid obvious endogeneity issues, all regressors are lagged.

If funds indeed strategically alter their risk in response to incentives, I should observe a change in the level of risk in the second and in the last quarter of the year. Changes in the second quarter are mainly bonus-driven, whereas changes in the fourth quarter will also depend on the flow-performance incentive. In order to identify these changes I have created two dummy variables that are interacted with the explanatory variables: one for the contract, which is equal to one for quarters 2 and 4, and another for the flow-performance relationship that is equal to one only in the fourth quarter. In particular, I expect variables that directly affect the flow-performance relationship, i.e. segment rankings, to be relatively more important on the last quarter of the year.

In what follows, I will discuss the results for each of the three main explanatory variables. Note that within the JTD window, the performance terciles are about internal competition within the asset management company, whereas the performance quintiles refer to external competition within the segment of the fund industry. But, despite the distinction between internal and external competition, they are both essentially about the contract-generated incentives faced by the portfolio manager.

2.4.1 Contract-generated incentive

Internal competition

In general, contracts induce a general increase in idiosyncratic risk, whereas the implicit flow-related incentive lead to a general decrease in total risk and idiosyncratic risk. Results are however not symmetric for the top and bottom funds.

One of the most important results from Table 2.2 is that the family internal competition matters. The competition within the fund family ($T^{(JTD)}$) bears no contamination from the flow-generated incentive and hence any difference in risk between the second and fourth quarters is presumably due to an end-of-year effect. Although there is no reason to believe that investors keep track of what happens in June, final year numbers will show up in any fund report. Nanda et al. (2004), Guedj and Papastaikoudi (2004) and Gaspar et al. (2006), for example, show that families engage in cross-fund subsidization, shifting performance between their funds in order to generate a star effect. Following this reasoning, families would use the second half of the year to achieve any objectives they might have. The second quarter effect is exclusively due to the bonus payment proximity, whereas changes in the last quarter are also driven by the top management strategy. The riskiness of the portfolio and its determinants change quite actively in response to the fund ranking within its family. In order to properly analyze the results, I will use Table 2.3 instead of Table 2.2 which does not impose any constraint on the level of risk on the first and third quarters.

In the second quarter of the year, both bottom and top quintile funds increase the β of their portfolio by a similar amount, but the worst funds also show a 4% decrease in the level of idiosyncratic risk. The latter indicates that, close to bonus time, funds that are performing poorly relative to other funds in the family benchmark more. This is in line with Basak et al. (2007). In their paper, they argue that a less risk averse manager will take on more systematic risk and bet on improving their performance when the benchmark increases. If the benchmark falls, they will just be losing with all the others.

The results for the second half of the year are more striking. The worst funds increase both β and total volatility, in such way that tracking error decreases. Total volatility decreases by around 3% every quarter and tracking error by 5.6% and 4%

in the third and fourth quarters, respectively. The best performing funds do the exact opposite. They have total volatility 6% lower in the second half od the year, with tracking error 7% higher. As before, the bottom tercile is benchmarking more, increasing total volatility, whereas the top funds are locking in their gains tilting their portfolio towards assets with lower β.

This mirror-image pattern between top and bottom performers may indicate that families have a target level of risk for their funds as suggested by Daniel and Wermers (2001). This is a possibility that needs to be further investigated.

External competition

Table 2.2 shows that the worst performing funds in their segment on the JTD window take on average 3.3% more idiosyncratic risk than their peers, boosting it even more in the last quarter of the year (9% increase on average). Top performing funds decrease both β and idiosyncratic risk (the latter by -4.9%) in anticipation of the bonus, but they do the opposite close to the end of the year with idiosyncratic risk increasing by 8.1% on average relative to the second quarter of the year. All in all, performance-linked contracts induce top and bottom funds to decrease β with top funds also decreasing idiosyncratic risk.

The $Q^{(JTD)}$ variable covers the period over which bonus is decided, while it also captures a competition between funds that affects the flow-performance relationship: even if one assumes that investor are interested in the fund's return year-to-date or that they continuously evaluate funds, there is no reason to suppose that they keep track of the return up to June or July-to-date. One of the arguments of this paper is that bonus will have a component that reflects the performance relative to the industry and this is what this variable is capturing. Is it interesting to observe that the implicit incentive generated by the flow-performance relationship induce the top funds in the JTD window to increase the total volatility of their portfolio by almost 5% (by means of increases in both β and idiosyncratic risk). Funds in the top quintile of the July-to-date ranking have been doing very well recently. When fund managers (and the top management) realize the success of their trading strategy, they might have an extra incentive to boost their positions in the end of the year to gain even more ground relative to the other funds. This, however, only explains the increase in idiosyncratic risk, but not necessarily the change in β in the last quarter of the year. Interestingly, changing the model to include, in the second half of the year, both year-to-date and July-to-date returns (excluding past 12 months) does not affect the coefficients of JTD ranking.[4] This further indicates that, even if the tournament within the industry happens on an yearly basis, fund managers compensation is indeed more closely linked to the performance in the half-year.

Overall, there is a strong evidence that the worst performing funds gamble for survival, with a 9% increase in idiosyncratic risk in the last quarter of the year, and that the best performing funds do engage in a tournament against other funds in the industry.

2.4.2 Flow-generated incentive

Next, I turn the attention to shifts in risk due to the flow-performance relationship. These changes are about the drive for long-run performance that asset management firms attempt to instill in their fund/portfolio managers so as to attract more inflows to their funds.

The first thing to notice from Table 2.2 is that the better the performance of the fund in the past 12 months, the smaller the fund's β, the larger its idiosyncratic risk and its tracking error without affecting overall risk. The increase in tracking error is only significant for the top funds, though. If funds were just locking in their absolute gains, one would observe a decrease in β and subsequent increase in tracking

[4] These results are available upon request.

error, but not an increase in idiosyncratic risk. This pattern is consistent with the reasoning behind Cohen, Polk and Silli (2010): funds whose best ideas are proving particularly good can improve their performance with a more concentrated portfolio. As best performing ideas are most effective in illiquid and unpopular stocks, the more concentrated portfolio not only would have higher idiosyncratic volatility but also a lower β.

The impact of past 12 months performance on risk-taking behavior over the year is weak. Table 2.3 shows some evidence that poor performing funds increase idiosyncratic volatility in the last quarter and that the best funds, decrease it. All things considered, despite the time frame of the tournament among all funds, the timing of the bonus payment is dominant. Two major conclusions arise from the previous analysis: (1) The tournament within the family is more important for fund managers than the competition with other funds in the industry and (2) the convexity of the flow-performance relationship does not necessarily induce funds to gamble, but it does induce families to behave strategically, cross-subsidizing funds not only in return, but also in risk.

2.4.3 Monthly data

Table 2.4 and Figures 2.1 to 2.4 show similar results with monthly dummies instead of quarter dummies. As the most important periods relate to the second and fourth quarters, I have expanded these quarters into months keeping quarter dummies for the first (constant) and the third quarters. Results are similar to the ones obtained before: the family ranking displays the most significant variables with the worst performing funds in the family increasing both total risk and the β of their portfolio towards the end of the year while the best funds do the exact opposite.

One curious result worth mentioning is that funds do not change abruptly their level of risk on the last month of the year. Actually, if I expand the model to include all month dummies (results not reported), I notice that managers of top (bottom) performing funds start decreasing (increasing) the level of risk of their portfolio from as early as August (September). Top performers accelerate the rate of change from September onwards. This is further evidence that changes in risk in the second half of the year are not just due to a tournament effect where funds compete in return, but due to a more elaborate strategy defined for the whole family of funds.

2.4.4 Risk-shifting and portfolio holdings

The previous analysis was all based on realized volatility and information extracted from returns data. Following Huang et al. (2011), I will now employ a portfolio-based measure of risk-shifting, $RS_{f,t}$, to analyze whether I can extract further information about changes in risk. Unfortunately, portfolio holdings have only been disclosed since 2006 and as the measure suggested Huang et al. (2011) requires at least 2 years of data to be calculated, the time spanned by this measure is significantly shorter than the one used in the previous sections.[5] The risk shifting measure is calculated as below:

$$RS_{f,t} = \sigma^H_{f,t} - \sigma^R_{f,t}. \tag{2.1}$$

The realized volatility $\sigma^R_{f,t}$ is a backward-looking measure of the total risk of the fund over the previous 24 months.[6] On the other hand, the portfolio-holdings-based volatility $\sigma^H_{f,t}$ is forward looking in that it captures the target volatility of the fund. It is computed as the sample standard deviation of the return of a hypothetical portfolio that holds the most recently disclosed fund positions over the previous 24 months. Alternatively, one can compute it by the square root of the variance of a portfolio

[5]The next chapter includes a detailed explanation of the drawbacks of this measure.

[6] Huang et al. (2011) use the past 36 months to evaluate the intended risk level of the fund. The data employed in this paper spans a shorter period of time and hence the shorter window.

with the weights $\omega_{f,t}$ given by the fund's holdings positions:

$$\sigma^H_{f,t} = \sqrt{Var(\omega'_{f,t}R_t)} = \sqrt{\omega'_{f,t}Var(R_t)\omega_{f,t}} = \sqrt{\omega'_{f,t}\Sigma_t\omega_{f,t}} \tag{2.2}$$

where Σ_t is the realized variance-covariance matrix of the assets returns.

The key aspect of this methodology is that, as it uses overlapping time periods, it only measures active risk shifting. For instance, if a fund does not change the portfolio composition over time, the risk-shifting measure will be zero even if the risk of the individual assets is time varying. This means that $RS_{f,t}$ does not vary with changes in the market conditions. Huang et al. (2011) point out that funds that decrease their total risk on average increase non-equity holdings, and decrease market beta and idiosyncratic volatility. Funds that increase total risk operate in the exact opposite direction.

Table 2.5 displays how the risk-measure reacts to past performance. The explanatory variables are the same as in the previous models as in Table 2.2 with a dummy variable for the second and fourth quarter and another for the fourth quarter only. Unfortunately, the results are not very elucidating. Nevertheless, family rankings are still the most significant variables: funds in the top tercile slightly decrease the level of risk in the second quarter and increase it on the fourth. The changes are, however, not economically significant.

It is also possible to use portfolio holdings to evaluate how funds actually change their risk by looking at changes in portfolio composition. I split assets in equity (long and short positions), derivatives, and cash and bonds. Probably due to the short sample, I could not find any result and coefficients are not reported.

2.5 Conclusion

In this paper I claim that fund managers and families may have different objective functions and that they behave strategically in order to increase their payoffs. Funds compete for bonus against other funds not just in the industry, but more importantly, in their own family. Moreover, the tournament funds engage in with other funds in the industry is not just played by them, but also by their families top management.

In the US, bonus is paid every year. As the tournament effect gets stronger as December approaches, both funds and families have an incentive to shift risk in the end of the year which makes these two incentives hard to disentangle.

In this paper I use a unique dataset with funds that pay bonus every six months instead of every year. I can, thus, separate the effect of bonus payment from the tournament effect. I show that the main determinant of changes in risk is not the fund's position relative to the market, but its position relative to the other funds in its family. There is no particular pattern for the first half of the year, close to mid-year bonus payment, but results for the second half of the year are consistent with families actively managing funds, transferring risk from the best performing funds to the worst. The previous literature had already shown that families engage in a cross-subsidization of returns in order to favor the best performer. Here, I show that families not only want to generate a start fund in terms of returns, but also in terms of risk. These results are striking as they add a new dimension in the tournament played by funds. They need to be further investigated and the analysis of the funds' portfolio holdings might shed some light in this issue.

Table 2.1: Summary Statistics

This table includes summary statistics for the funds included in the sample. In order to calculate total net assets, I took the average on the cross-section for every fund in the sample every are end of year and then took the average over the time-series. Monthly volatility is calculated from daily returns. Average number of funds per family is calculated first taking the average per family and then the average over all families.

	Mean	Median	St. Dev.
Total net assets (in million)	126.8	113.9	40.4
Investor return (%)	1.4	1.8	3.4
Monthly volatility (%)	3.8	3.2	2.0
Tracking error (%)	7.1	7.0	4.3
CAPM Beta	0.31	0.10	0.33
Number of shareholders	1778	1965	790
Age (years)	4.8	4.9	0.3
Outflows (%)	5.3	5.5	2.5
Inflows (%)	9.9	9.1	5.8
Net inflows (%)	5.6	4.5	5.2
Average number of funds per family	4.5	2.2	8.5
Number of valid funds	1003		
Number of fund families	219		
Number of valid observations	65,374		

Table 2.2: Risk-Shifting and Past Performance

This table depicts the result of a panel data regression of log of total fund monthly volatility, beta, log of idiosyncratic volatility and of tracking error volatility on dummies of past performance, quarter dummies, their interactions, and other control variables. Regressions include the first lag of the dependent variable and time dummies only for specific crisis periods. Monthly volatility is calculated from daily returns. For each dummy variable, **i**.*variable* = 1 when *variable* = **i**. The interaction variables **i**.*variable1*****j**.*variable2* = 1 when *variable1* = **i** and *variable2* = **j**. Funds are ranked within their management company by their performance January-to-date in the first half of the year, and July-to-date in the second half of the year, and divided in terciles of performance ($T^{(JTD)}$). Funds are also ranked by style and return relative to all the other funds in the industry over the same period of time and divided into quintiles ($Q^{(JTD)}$). Finally, funds are ranked by style and return relative to all the other funds in the industry for their performance over the past twelve months and also divided into quintiles ($Q^{(12m)}$). The latter variable captures the flow-generated incentive whereas the other two reflect the direct contract-generated incentive.

VARIABLES	Total Volatility	p-value	Beta	p-value	Idiosync. Volatility	p-value	Tracking Error	p-value
Dependent Var.$_{t-1}$	0.590***	(0.000)	0.548***	(0.000)	0.602***	(0.000)	0.446***	(0.000)
Quarter=2 or 4	0.008	(0.558)	0.005	(0.211)	0.073***	(0.003)	-0.064***	(0.000)
Quarter=4	-0.049***	(0.002)	-0.002	(0.701)	-0.100***	(0.000)	-0.030**	(0.024)
1.T^{JTD}	0.028***	(0.000)	0.006***	(0.005)	0.030**	(0.025)	-0.033***	(0.000)
3.T^{JTD}	-0.016*	(0.064)	-0.000	(0.977)	-0.000	(0.973)	0.026***	(0.000)
1.T^{JTD}*Quarter=2 or 4	-0.037**	(0.016)	-0.003	(0.416)	-0.042*	(0.079)	0.030***	(0.003)
3.T^{JTD}*Quarter=2 or 4	0.042***	(0.000)	0.017***	(0.000)	-0.023	(0.289)	-0.050***	(0.000)
1.T^{JTD}*Quarter=4	0.084***	(0.000)	0.008*	(0.062)	0.017	(0.484)	-0.041***	(0.001)
3.T^{JTD}*Quarter=4	-0.070***	(0.000)	-0.020***	(0.000)	0.031	(0.176)	0.082***	(0.000)
1.Q^{JTD}	0.011	(0.323)	0.000	(0.911)	0.033*	(0.063)	0.020**	(0.011)
2.Q^{JTD}	-0.011	(0.272)	-0.003	(0.330)	-0.002	(0.901)	0.005	(0.496)
4.Q^{JTD}	-0.017*	(0.066)	-0.001	(0.735)	-0.018	(0.228)	-0.011	(0.137)
5.Q^{JTD}	-0.030***	(0.005)	-0.005	(0.170)	0.002	(0.927)	-0.006	(0.436)
1.Q^{JTD}*Quarter=2 or 4	-0.008	(0.668)	-0.010*	(0.087)	-0.024	(0.403)	0.002	(0.907)
2.Q^{JTD}*Quarter=2 or 4	-0.004	(0.809)	-0.004	(0.422)	-0.016	(0.558)	0.020	(0.112)
4.Q^{JTD}*Quarter=2 or 4	-0.007	(0.675)	-0.001	(0.884)	-0.024	(0.364)	0.005	(0.698)
5.Q^{JTD}*Quarter=2 or 4	-0.023	(0.185)	-0.011*	(0.064)	-0.049*	(0.093)	0.015	(0.292)
1.Q^{JTD}*Quarter=4	0.031	(0.198)	0.008	(0.246)	0.090***	(0.008)	0.028*	(0.090)
2.Q^{JTD}*Quarter=4	0.013	(0.452)	0.008	(0.106)	0.046	(0.115)	-0.011	(0.435)
4.Q^{JTD}*Quarter=4	0.014	(0.395)	0.004	(0.462)	0.030	(0.271)	0.011	(0.422)
5.Q^{JTD}*Quarter=4	0.049**	(0.027)	0.015**	(0.014)	0.081***	(0.005)	-0.000	(0.983)
Observations	31,445		31,447		31,447		31,449	
Number of Funds	737		737		737		737	
Adjusted R-squared	0.4032		0.2731		0.3658		0.5049	

Robust standard errors, clustered by fund, in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 2.2: Risk-Shifting and Past Performance (Cont.)

Continuation from the previous page. LN(AUM_{t-1}) is the natural log of total net assets of a fund. LN(No. funds in $family_{t-1}$) in the log of the number of funds each asset management company manages included in the sample. LN(Total AUM $family_{t-1}$) is the total assets under management of the family for the funds in the sample (excludes fixed income funds).

VARIABLES	Total Volatility	p-value	Beta	p-value	Idiosync. Volatility	p-value	Tracking Error	p-value
1.Q^{12m}	0.027	(0.109)	-0.005	(0.221)	0.030	(0.216)	0.002	(0.807)
2.Q^{12m}	0.008	(0.397)	-0.005*	(0.097)	0.026*	(0.097)	0.005	(0.566)
4.Q^{12m}	0.002	(0.853)	-0.006**	(0.028)	0.032**	(0.019)	0.008	(0.323)
5.Q^{12m}	0.003	(0.808)	-0.015***	(0.000)	0.056***	(0.000)	0.025***	(0.001)
1.Q^{12m}*Quarter=2 or 4	-0.023	(0.392)	0.016***	(0.003)	-0.036	(0.292)	-0.003	(0.853)
2.Q^{12m}*Quarter=2 or 4	-0.007	(0.660)	0.009*	(0.054)	-0.016	(0.521)	-0.027**	(0.028)
4.Q^{12m}*Quarter=2 or 4	-0.010	(0.469)	0.001	(0.890)	-0.053**	(0.021)	0.006	(0.606)
5.Q^{12m}*Quarter=2 or 4	-0.004	(0.819)	0.009*	(0.095)	-0.040*	(0.085)	-0.001	(0.931)
1.Q^{12m}*Quarter=4	0.006	(0.804)	-0.012*	(0.050)	0.074**	(0.034)	0.010	(0.521)
2.Q^{12m}*Quarter=4	-0.022	(0.200)	-0.003	(0.551)	-0.006	(0.848)	0.022	(0.136)
4.Q^{12m}*Quarter=4	0.016	(0.340)	0.004	(0.436)	0.050*	(0.086)	-0.013	(0.368)
5.Q^{12m}*Quarter=4	-0.008	(0.658)	-0.002	(0.692)	-0.005	(0.870)	-0.017	(0.213)
AUM_{t-1}	0.012**	(0.029)	0.009***	(0.000)	-0.009	(0.279)	-0.010***	(0.001)
LN(No. funds in $family_{t-1}$)	-0.001	(0.969)	0.014**	(0.042)	-0.096***	(0.001)	-0.020	(0.159)
LN(Total family AUM_{t-1})	-0.017*	(0.063)	0.006*	(0.051)	-0.012	(0.363)	-0.013**	(0.016)
Constant	-1.813***	(0.000)	-0.151***	(0.001)	-1.518***	(0.000)	-0.779***	(0.000)
Observations	31,445		31,447		31,447		31,449	
Number of Funds	737		737		737		737	
Adjusted R-squared	0.4032		0.2731		0.3658		0.5049	

Table 2.3: Risk-Shifting and Past Performance

This table depicts the result of a panel data regression of log of fund monthly volatility, beta, log of idiosyncratic volatility and of tracking error volatility on dummies of past performance, quarter dummies, their interactions, and other control variables. Regressions include the first lag of the dependent variable and time dummies only for specific crisis periods. Monthly volatility is calculated from daily returns. For each dummy variable, **i**.*variable* = 1 when *variable* = **i**. The interaction variables **i**.*variable1****j**.*variable2* = 1 when *variable1* = **i** and *variable2* = **j**. Funds are ranked within their management company by their performance January-to-date in the first half of the year, and July-to-date in the second half of the year, and divided in terciles of performance ($T^{(JTD)}$). Funds are also ranked by style and return relative to all the other funds in the industry over the same period of time and divided into quintiles ($Q^{(JTD)}$). Finally, funds are ranked by style and return relative to all the other funds in the industry for their performance over the past twelve months and also divided into quintiles ($Q^{(12m)}$). The latter variable captures the flow-generated incentive whereas the other two reflect the direct contract-generated incentive.

VARIABLES	Total Volatility	p-value	Beta	p-value	Idiosync. Volatility	p-value	Tracking Error	p-value
Dependent Var.$_{t-1}$	0.592***	(0.000)	0.547***	(0.000)	0.604***	(0.000)	0.438***	(0.000)
2.quarter	-0.011	(0.479)	0.015***	(0.001)	0.037	(0.173)	-0.140***	(0.000)
3.quarter	-0.045***	(0.006)	0.022***	(0.000)	-0.083***	(0.002)	-0.170***	(0.000)
4.quarter	-0.060***	(0.000)	0.013***	(0.003)	-0.063**	(0.016)	-0.170***	(0.000)
1.T^{JTD}	0.016	(0.124)	-0.005	(0.144)	0.044***	(0.010)	-0.006	(0.406)
3.T^{JTD}	0.012	(0.222)	0.009***	(0.009)	-0.019	(0.243)	-0.010	(0.197)
1.T^{JTD}*2.quarter	-0.025	(0.176)	0.008**	(0.043)	-0.056**	(0.032)	0.003	(0.798)
1.T^{JTD}*3.quarter	0.028*	(0.070)	0.023***	(0.000)	-0.028	(0.233)	-0.056***	(0.000)
1.T^{JTD}*4.quarter	0.060***	(0.000)	0.017***	(0.000)	-0.039	(0.110)	-0.040***	(0.001)
3.T^{JTD}*2.quarter	0.013	(0.310)	0.008*	(0.053)	-0.005	(0.847)	-0.015	(0.157)
3.T^{JTD}*3.quarter	-0.063***	(0.000)	-0.020***	(0.000)	0.040*	(0.060)	0.073***	(0.000)
3.T^{JTD}*4.quarter	-0.057***	(0.000)	-0.013***	(0.003)	0.026	(0.233)	0.068***	(0.000)
1.Q^{JTD}	-0.012	(0.448)	-0.004	(0.442)	0.011	(0.651)	0.014	(0.166)
2.Q^{JTD}	-0.012	(0.299)	-0.003	(0.470)	0.002	(0.908)	0.011	(0.271)
4.Q^{JTD}	-0.022*	(0.094)	-0.005	(0.160)	-0.017	(0.421)	0.003	(0.801)
5.Q^{JTD}	-0.034**	(0.012)	-0.003	(0.542)	0.005	(0.823)	0.013	(0.184)
1.Q^{JTD}*2.quarter	0.013	(0.588)	-0.005	(0.472)	-0.003	(0.923)	0.009	(0.561)
1.Q^{JTD}*3.quarter	0.049*	(0.086)	0.011	(0.294)	0.047	(0.227)	0.017	(0.265)
1.Q^{JTD}*4.quarter	0.045**	(0.036)	0.003	(0.700)	0.086**	(0.011)	0.037**	(0.020)
2.Q^{JTD}*2.quarter	-0.002	(0.893)	-0.004	(0.542)	-0.020	(0.501)	0.014	(0.323)
2.Q^{JTD}*3.quarter	0.008	(0.692)	0.000	(0.943)	-0.005	(0.878)	-0.007	(0.627)
2.Q^{JTD}*4.quarter	0.011	(0.471)	0.005	(0.382)	0.025	(0.372)	0.003	(0.806)
4.Q^{JTD}*2.quarter	-0.002	(0.921)	0.004	(0.456)	-0.025	(0.393)	-0.009	(0.535)
4.Q^{JTD}*3.quarter	0.014	(0.453)	0.007	(0.201)	0.006	(0.829)	-0.015	(0.298)
4.Q^{JTD}*4.quarter	0.013	(0.437)	0.007	(0.131)	0.004	(0.881)	0.003	(0.835)
5.Q^{JTD}*2.quarter	-0.019	(0.334)	-0.013*	(0.057)	-0.053	(0.113)	-0.005	(0.738)
5.Q^{JTD}*3.quarter	0.012	(0.565)	-0.006	(0.418)	0.001	(0.962)	-0.029**	(0.034)
5.Q^{JTD}*4.quarter	0.030	(0.124)	0.003	(0.679)	0.029	(0.359)	-0.005	(0.763)
Observations	31,445		31,447		31,447		31,449	
Number of funds	737		737		737		737	
Adjusted R-squared	0.4061		0.2775		0.3674		0.5242	

Robust standard errors, clustered by fund, in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 2.3: Risk-Shifting and past performance (Cont.)

Continuation from the previous page. LN(AUM$_{t-1}$) is the natural log of total net assets of a fund. LN(No. funds in family$_{t-1}$) in the log of the number of funds each asset management company manages included in the sample. LN(Total AUM family$_{t-1}$) is the total assets under management of the family for the funds in the sample (excludes fixed income funds).

VARIABLES	Total Volatility	p-value	Beta	p-value	Idiosync. Volatility	p-value	Tracking Error	p-value
1.Q^{12m}	0.042**	(0.017)	0.001	(0.901)	0.011	(0.702)	-0.017	(0.114)
2.Q^{12m}	0.019	(0.111)	-0.000	(0.965)	0.008	(0.720)	-0.014	(0.215)
4.Q^{12m}	0.016	(0.119)	-0.003	(0.476)	0.050**	(0.011)	0.002	(0.884)
5.Q^{12m}	0.016	(0.256)	-0.014***	(0.004)	0.077***	(0.001)	0.027***	(0.003)
1.Q^{12m}*2.quarter	-0.039	(0.155)	0.011*	(0.087)	-0.018	(0.637)	0.016	(0.292)
1.Q^{12m}*3.quarter	-0.036	(0.112)	-0.010	(0.243)	0.037	(0.255)	0.032**	(0.027)
1.Q^{12m}*4.quarter	-0.034	(0.109)	-0.001	(0.848)	0.056*	(0.099)	0.026	(0.108)
2.Q^{12m}*2.quarter	-0.017	(0.302)	0.004	(0.474)	0.002	(0.930)	-0.009	(0.556)
2.Q^{12m}*3.quarter	-0.021	(0.236)	-0.011*	(0.065)	0.039	(0.214)	0.040***	(0.009)
2.Q^{12m}*4.quarter	-0.040**	(0.012)	0.001	(0.915)	-0.004	(0.891)	0.013	(0.381)
4.Q^{12m}*2.quarter	-0.024	(0.105)	-0.003	(0.619)	-0.070***	(0.007)	0.013	(0.368)
4.Q^{12m}*3.quarter	-0.035**	(0.035)	-0.005	(0.361)	-0.044	(0.128)	0.003	(0.834)
4.Q^{12m}*4.quarter	-0.009	(0.573)	0.001	(0.811)	-0.022	(0.421)	-0.001	(0.965)
5.Q^{12m}*2.quarter	-0.016	(0.313)	0.008	(0.176)	-0.060**	(0.021)	-0.003	(0.834)
5.Q^{12m}*3.quarter	-0.029	(0.157)	0.000	(0.980)	-0.051	(0.106)	-0.015	(0.260)
5.Q^{12m}*4.quarter	-0.025	(0.139)	0.006	(0.334)	-0.066**	(0.016)	-0.021	(0.109)
AUM$_{t-1}$	0.012**	(0.041)	0.009***	(0.000)	-0.010	(0.255)	-0.011***	(0.000)
LN(No. funds in family$_{t-1}$)	-0.002	(0.913)	0.014**	(0.044)	-0.096***	(0.001)	-0.020	(0.152)
LN(Total family AUM$_{t-1}$)	-0.015*	(0.084)	0.006*	(0.052)	-0.011	(0.393)	-0.012**	(0.024)
Constant	-1.799***	(0.000)	-0.160***	(0.001)	-1.482***	(0.000)	-0.718***	(0.000)
Observations	31,445		31,447		31,447		31,449	
Number of funds	737		737		737		737	
Adjusted R-squared	0.4061		0.2775		0.3674		0.5242	

Robust standard errors, clustered by fund, in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 2.4: Risk-Shifting and Past Performance by Month

This table depicts the result of a panel data regression of log of fund monthly volatility, beta, log of idiosyncratic volatility and of tracking error volatility on dummies of past performance, month and quarter dummies, their interactions, and other control variables. Dependent variables are as previously defined.

VARIABLES	Total Volatility	p-value	Beta	p-value	Idiosync. Volatility	p-value	Tracking Error	p-value
Dependent Variable$_{t-1}$	0.597***	(0.000)	0.548***	(0.000)	0.608***	(0.000)	0.467***	(0.000)
3.quarter	-0.055***	(0.000)	0.020***	(0.000)	-0.086***	(0.000)	-0.167***	(0.000)
4.month	-0.070***	(0.000)	0.022***	(0.000)	-0.025	(0.328)	-0.214***	(0.000)
5.month	0.092***	(0.000)	0.019***	(0.000)	0.123***	(0.000)	-0.046***	(0.000)
6.month	-0.116***	(0.000)	0.001	(0.760)	-0.133***	(0.000)	-0.168***	(0.000)
10.month	0.003	(0.841)	0.010**	(0.019)	0.034	(0.178)	0.003	(0.814)
11.month	-0.076***	(0.000)	0.036***	(0.000)	-0.068***	(0.001)	-0.245***	(0.000)
12.month	-0.113***	(0.000)	0.009*	(0.061)	-0.132***	(0.000)	-0.235***	(0.000)
1.T^{JTD}*3.quarter	0.036***	(0.010)	0.025***	(0.000)	-0.008	(0.703)	-0.042***	(0.000)
3.T^{JTD}*3.quarter	-0.066***	(0.000)	-0.021***	(0.000)	0.026	(0.188)	0.059***	(0.000)
1.T^{JTD}	0.013	(0.185)	-0.005	(0.105)	0.036**	(0.028)	-0.011	(0.147)
3.T^{JTD}	0.012	(0.197)	0.010***	(0.006)	-0.015	(0.337)	-0.006	(0.401)
1.T^{JTD}*4.month	-0.015	(0.486)	0.004	(0.442)	-0.055*	(0.065)	0.011	(0.502)
1.T^{JTD}*5.month	-0.036*	(0.089)	0.010*	(0.100)	-0.028	(0.433)	0.028*	(0.086)
1.T^{JTD}*6.month	-0.013	(0.579)	0.012**	(0.032)	-0.058	(0.101)	-0.005	(0.700)
1.T^{JTD}*10.month	0.040*	(0.099)	0.013**	(0.020)	-0.057*	(0.099)	-0.033**	(0.023)
1.T^{JTD}*11.month	0.098***	(0.000)	0.027***	(0.000)	0.022	(0.484)	-0.024	(0.141)
1.T^{JTD}*12.month	0.051***	(0.008)	0.011	(0.102)	-0.044	(0.182)	-0.035**	(0.038)
3.T^{JTD}*4.month	-0.027	(0.195)	0.003	(0.607)	-0.050	(0.153)	-0.016	(0.353)
3.T^{JTD}*5.month	0.021	(0.266)	0.006	(0.379)	0.031	(0.347)	-0.014	(0.336)
3.T^{JTD}*6.month	0.038**	(0.025)	0.016***	(0.004)	-0.020	(0.480)	-0.034**	(0.032)
3.T^{JTD}*10.month	-0.048**	(0.017)	-0.015***	(0.009)	0.024	(0.455)	0.070***	(0.000)
3.T^{JTD}*11.month	-0.055***	(0.004)	-0.016***	(0.003)	0.045	(0.114)	0.054***	(0.001)
3.T^{JTD}*12.month	-0.066***	(0.001)	-0.009	(0.147)	-0.013	(0.664)	0.056***	(0.000)
1.Q^{JTD}	0.019*	(0.056)	0.002	(0.589)	0.036**	(0.028)	0.018***	(0.008)
5.Q^{JTD}	-0.019**	(0.026)	-0.005	(0.139)	0.012	(0.378)	-0.000	(0.972)
1.Q^{JTD}*4.month	-0.006	(0.811)	-0.006	(0.401)	-0.013	(0.698)	-0.008	(0.681)
1.Q^{JTD}*5.month	-0.017	(0.505)	-0.003	(0.719)	-0.062	(0.149)	-0.014	(0.421)
1.Q^{JTD}*6.month	0.011	(0.715)	-0.013*	(0.073)	0.052	(0.180)	-0.005	(0.796)
1.Q^{JTD}*10.month	0.026	(0.367)	-0.014	(0.112)	0.084**	(0.048)	0.010	(0.537)
1.Q^{JTD}*11.month	0.025	(0.387)	-0.008	(0.526)	0.035	(0.342)	0.034*	(0.087)
1.Q^{JTD}*12.month	-0.017	(0.617)	0.011	(0.314)	0.023	(0.607)	0.015	(0.416)
5.Q^{JTD}*4.month	0.035*	(0.083)	-0.010	(0.114)	0.021	(0.502)	0.037**	(0.029)
5.Q^{JTD}*5.month	-0.058***	(0.003)	-0.015*	(0.066)	-0.083***	(0.010)	-0.010	(0.567)
5.Q^{JTD}*6.month	-0.034	(0.152)	-0.003	(0.688)	-0.062*	(0.068)	0.006	(0.769)
5.Q^{JTD}*10.month	0.029	(0.180)	0.011*	(0.092)	0.059*	(0.063)	-0.003	(0.848)
5.Q^{JTD}*11.month	0.034	(0.112)	0.003	(0.641)	0.003	(0.929)	0.004	(0.786)
5.Q^{JTD}*12.month	0.002	(0.916)	-0.006	(0.429)	0.009	(0.780)	0.011	(0.503)

Robust standard errors, clustered by fund, in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 2.4: Risk-Shifting and Past Performance by Month (Cont.)

VARIABLES	Total Volatility	p-value	Beta	p-value	Idiosync. Volatility	p-value	Tracking Error	p-value
1.Q^{12m}	0.022	(0.144)	-0.000	(0.916)	0.009	(0.710)	-0.004	(0.527)
5.Q^{12m}	-0.002	(0.853)	-0.011***	(0.000)	0.032***	(0.008)	0.015***	(0.009)
1.Q^{12m}*4.month	0.019	(0.580)	0.017**	(0.016)	0.039	(0.366)	0.030	(0.125)
1.Q^{12m}*5.month	-0.019	(0.464)	0.006	(0.454)	-0.011	(0.823)	0.007	(0.667)
1.Q^{12m}*6.month	-0.048	(0.187)	0.014*	(0.057)	-0.057	(0.193)	-0.010	(0.564)
1.Q^{12m}*10.month	0.001	(0.980)	-0.007	(0.424)	0.081**	(0.044)	0.004	(0.839)
1.Q^{12m}*11.month	-0.032	(0.274)	0.005	(0.548)	0.030	(0.475)	0.022	(0.222)
1.Q^{12m}*12.month	0.010	(0.729)	0.001	(0.952)	0.046	(0.305)	0.025	(0.180)
5.Q^{12m}*4.month	0.001	(0.967)	-0.001	(0.933)	-0.019	(0.462)	-0.017	(0.247)
5.Q^{12m}*5.month	0.004	(0.843)	0.014**	(0.037)	-0.035	(0.207)	0.021	(0.126)
5.Q^{12m}*6.month	0.002	(0.924)	0.005	(0.488)	0.015	(0.659)	0.007	(0.638)
5.Q^{12m}*10.month	-0.006	(0.772)	0.014**	(0.047)	-0.037	(0.193)	-0.001	(0.966)
5.Q^{12m}*11.month	-0.013	(0.537)	-0.009	(0.310)	-0.029	(0.322)	-0.011	(0.497)
5.Q^{12m}*12.month	-0.001	(0.948)	0.005	(0.487)	-0.047	(0.162)	-0.021	(0.128)
AUM_{t-1}	0.011**	(0.039)	0.009***	(0.000)	-0.009	(0.266)	-0.011***	(0.001)
LN(No. funds in family_{t-1})	-0.001	(0.938)	0.015**	(0.038)	-0.095***	(0.001)	-0.021	(0.126)
LN(Total family AUM_{t-1})	-0.013	(0.136)	0.006**	(0.047)	-0.008	(0.536)	-0.010*	(0.067)
Constant	-1.818***	(0.000)	-0.166***	(0.000)	-1.523***	(0.000)	-0.730***	(0.000)
Observations	31,445		31,447		31,447		31,449	
Number of Funds	737		737		737		737	
Adjusted R-squared	0.4159		0.2799		0.3751		0.5476	

Robust standard errors, clustered by fund, in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 2.5: Risk-Shifting and Portfolio Holdings

This table depicts the result of a panel data regression of risk shifting measure, $RS_{f,t}$, on dummies of past performance, quarter dummies, their interactions, and other control variables as previously described

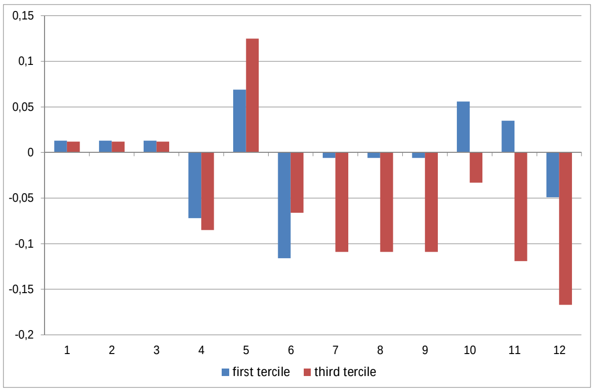
VARIABLES	$RS_{f,t}$ Long Position	p-value	$RS_{f,t}$	p-value
Dependent Variable$_{t-1}$	0.486***	(0.000)	0.363***	(0.000)
Quarter=2 or 4	0.000	(0.315)	0.000	(0.570)
Quarter=4	-0.002***	(0.002)	-0.002***	(0.005)
1.T^{JTD}	-0.000	(0.808)	0.000	(0.672)
3.T^{JTD}	0.001*	(0.091)	0.000	(0.357)
1.T^{JTD}*Quarter=2 or 4	0.000	(0.369)	-0.000	(0.986)
3.T^{JTD}*Quarter=2 or 4	-0.001**	(0.021)	-0.001	(0.251)
1.T^{JTD}*Quarter=4	-0.001	(0.336)	-0.000	(0.548)
3.T^{JTD}*Quarter=4	0.002***	(0.006)	0.002***	(0.009)
1.Q^{JTD}	0.001*	(0.069)	0.000	(0.508)
2.Q^{JTD}	0.000	(0.266)	0.000	(0.593)
4.Q^{JTD}	0.000	(0.236)	0.001	(0.154)
5.Q^{JTD}	0.001	(0.112)	0.001	(0.109)
1.Q^{JTD}*Quarter=2 or 4	-0.001	(0.220)	-0.001	(0.429)
2.Q^{JTD}*Quarter=2 or 4	-0.001	(0.133)	-0.001	(0.202)
4.Q^{JTD}*Quarter=2 or 4	-0.001*	(0.086)	-0.001*	(0.070)
5.Q^{JTD}*Quarter=2 or 4	0.000	(0.686)	0.000	(0.894)
1.Q^{JTD}*Quarter=4	0.002*	(0.074)	0.001	(0.154)
2.Q^{JTD}*Quarter=4	0.001*	(0.065)	0.001*	(0.096)
4.Q^{JTD}*Quarter=4	0.001*	(0.089)	0.002**	(0.044)
5.Q^{JTD}*Quarter=4	-0.001	(0.340)	-0.001	(0.320)
AUM$_{t-1}$	-0.000	(0.627)	-0.000	(0.508)
LN(No. funds in family$_{t-1}$)	-0.002***	(0.005)	-0.004**	(0.044)
LN(Total family AUM$_{t-1}$)	0.000	(0.876)	0.001	(0.319)
Constant	0.006	(0.270)	0.001	(0.862)
Observations	10,112		10,114	
Number of Funds	387		387	
Adjusted R-squared	0.4216		0.2723	

Table 2.5: Risk-Shifting and Portfolio Holdings (Cont.)

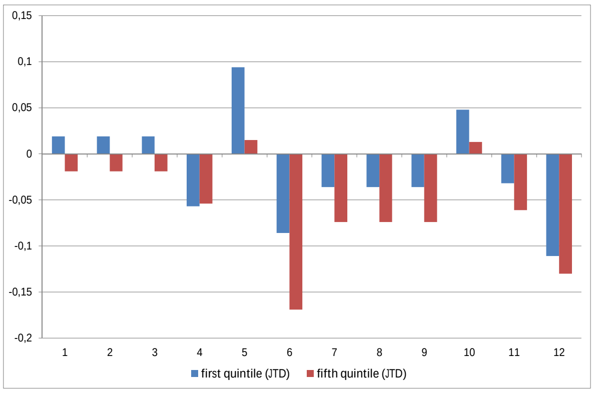
Continuation from the previous page. LN(AUM_{t-1}) is the natural log of total net assets of a fund. LN(No. funds in $family_{t-1}$) in the log of the number of funds each asset management company manages included in the sample. LN(Total AUM $family_{t-1}$) is the total assets under management of the family for the funds in the sample (excludes fixed income funds).

VARIABLES	$\sigma^H_{f,t}$ Long Position	p-value	$\sigma^H_{f,t}$	p-value
1.Q^{12m}	-0.001	(0.157)	-0.001	(0.344)
2.Q^{12m}	-0.000	(0.379)	-0.000	(0.321)
4.Q^{12m}	-0.000	(0.650)	-0.000	(0.348)
5.Q^{12m}	-0.000	(0.354)	-0.000	(0.615)
1.Q^{12m}*Quarter=2 or 4	0.001	(0.103)	0.001	(0.136)
2.Q^{12m}*Quarter=2 or 4	0.001**	(0.020)	0.001**	(0.021)
4.Q^{12m}*Quarter=2 or 4	0.000	(0.990)	0.000	(0.516)
5.Q^{12m}*Quarter=2 or 4	0.001	(0.113)	0.001*	(0.089)
1.Q^{12m}*Quarter=4	-0.001	(0.537)	-0.001	(0.258)
2.Q^{12m}*Quarter=4	-0.000	(0.491)	-0.000	(0.454)
4.Q^{12m}*Quarter=4	0.001	(0.178)	0.000	(0.772)
5.Q^{12m}*Quarter=4	-0.001	(0.395)	-0.001	(0.406)
Observations	10,112		10,114	
Number of Funds	387		387	
Adjusted R-squared	0.4216		0.2723	

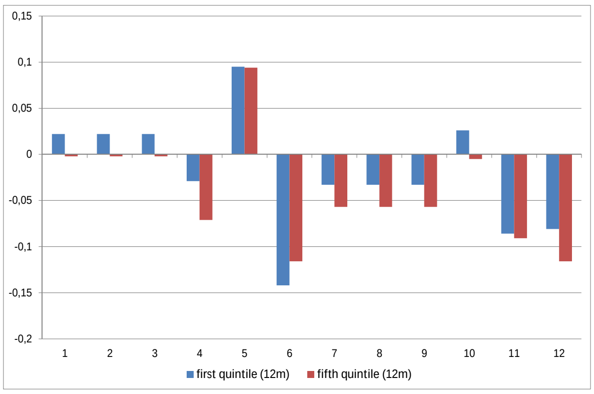
Figure 2.1: Monthly Variation in Total Volatility



(a) JTD company ranking

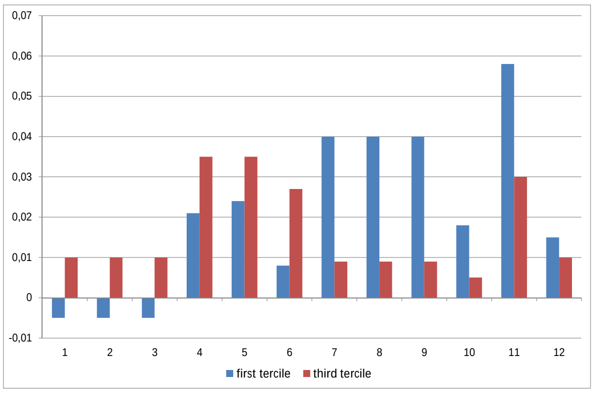


(b) JTD industry ranking

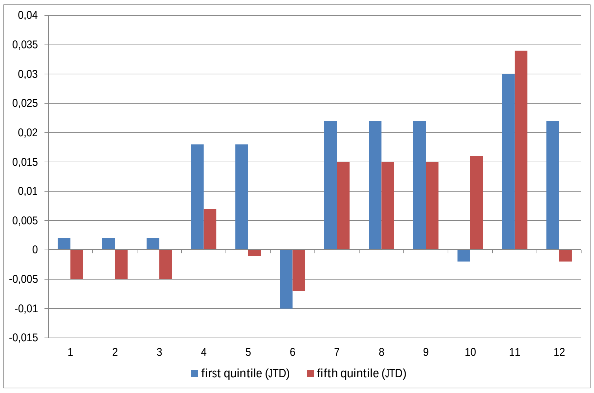


(c) 12-month industry ranking

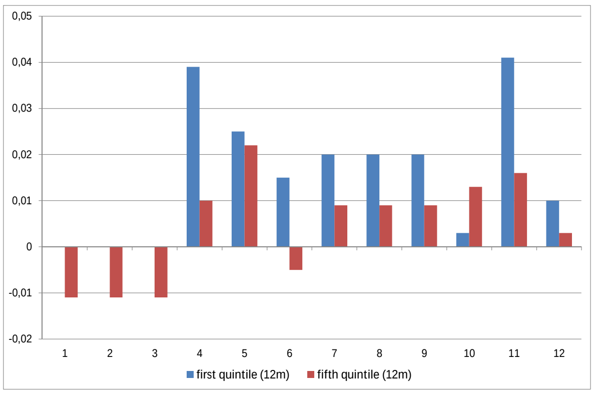
Figure 2.2: Monthly Variation in Beta by Month



(a) JTD company ranking

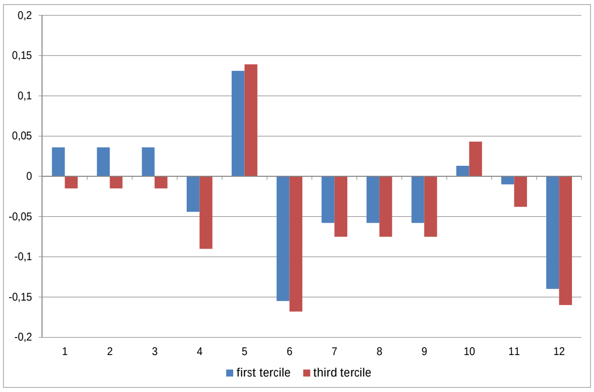


(b) JTD industry ranking

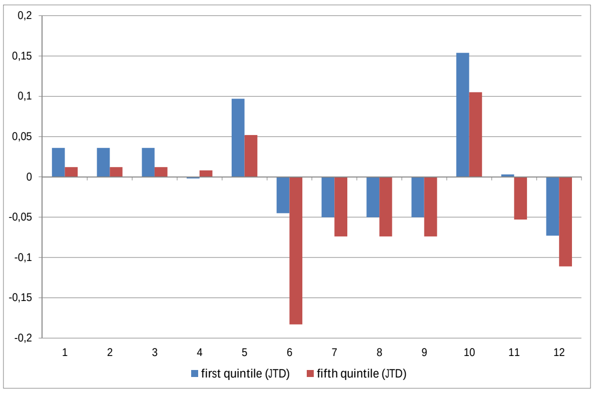


(c) 12-month industry ranking

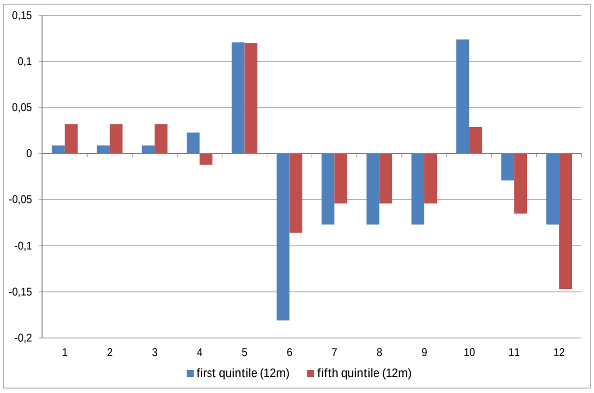
Figure 2.3: Monthly Variation in Idiosyncratic Volatility



(a) JTD company ranking

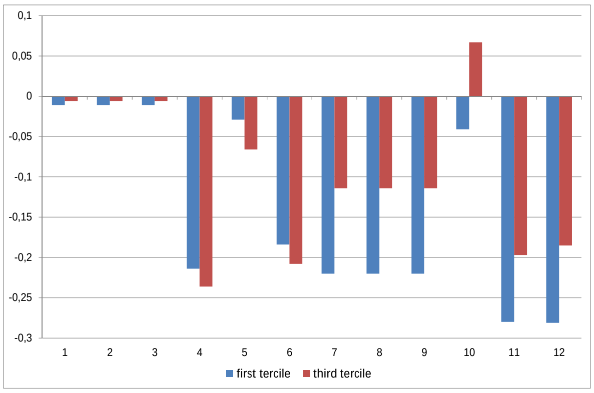


(b) JTD industry ranking

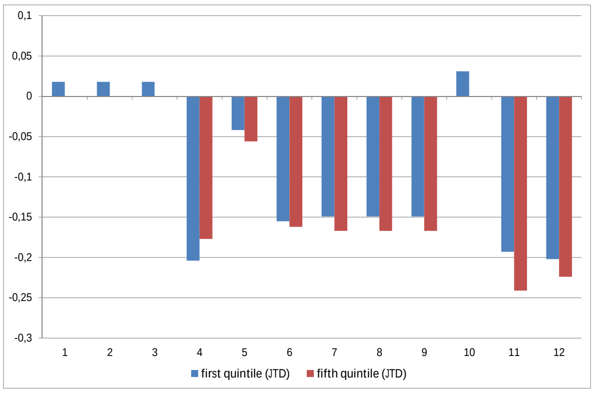


(c) 12-month industry ranking

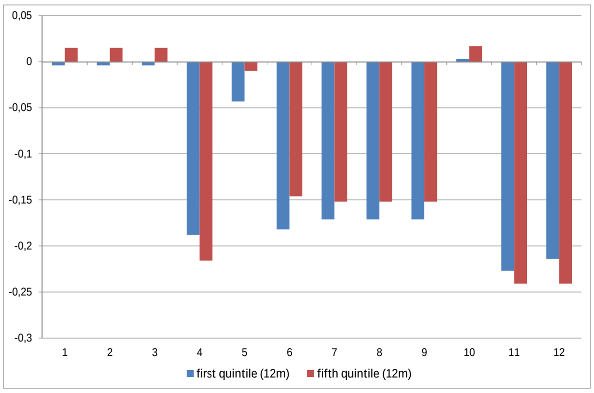
Figure 2.4: Monthly Variation in Tracking Error



(a) JTD company ranking



(b) JTD industry ranking



(c) 12-month industry ranking

Chapter 3

The Impact of Short Positions on Fund Performance

Co-authored with Pedro A. Saffi

Introduction

The analysis of the performance of investment funds and the ability of fund managers to generate value to investors are two of the most researched topics in Finance (see Ferson (2010) for an excellent review). Starting with the seminal paper by Grinblatt and Titman (1989), a large literature on portfolio holdings has developed, looking at their characteristics and their consequences on performance.

The majority of papers uses holdings information reported by mutual funds to the SEC (e.g. the Thompson-Reuters). These data only include *long* positions held by funds but lack information on the short positions. While this is likely not to be problematic for the analysis of equity mutual funds, it imposes an obvious constraint to the analysis of hedge fund performance. These funds use short selling as a key component of their trading strategies, often starting and exiting trades that are offset by long positions.

We use a unique dataset of Brazilian hedge funds holdings to examine the impact of long and short positions on performance. In particular, we test if changes in long/short positions and their risk can forecast future performance. While we find that funds with large increases in the risk of long-only positions risk relative to the previous 24 months underperform by about 3% per year on average, those that increase the risk of short-only positions overperform their peers by about 1% a year on average, net of fees. Neither monthly changes of long nor short positions can forecast next month's abnormal returns.

The Brazilian asset management industry is the sixth largest in the world, with assets under management around \$1.1 trillion USD (larger than the UK's) and with the average fund managing \$74.6 million USD.[1] The regulators requires that all registered funds disclose their investment positions every month, regardless of the direction of the position (i.e. long or short) or the asset class (e.g. equity, bonds, cash and derivatives), in effect providing a monthly snapshot of a fund's balance sheet. Regulators also ask that funds report, for each security, the total amount bought and sold within a particular month.

Using data from an emerging market like Brazil always comes with questions on the reliability of the data and the extension of any results to more developed markets like those found in the United States. The main disadvantages of our dataset relative to the ones used in the United States are the shorter time period (our data goes from January 2006 to June 2009) and the smaller size of Brazilian securities and funds, which restricts the calculation of abnormal return measures. However, we are confident the advantages of our data more than compensate for these drawbacks, enabling us to investigate the role played by short positions on portfolio performance unlike any other previous article in the literature.

The paper is organized as follows. Section 3.1 places our work in the context of the existing literature on short sales and ownership structure. Section 3.2 describes the Brazilian investment funds' data. Section 3.3 presents our results. Finally, Section

[1]For a more detailed description of the Brazilian fund industry see Varga and Wengert (2009) and Bertol-Domingues (2011).

3.4 concludes.

3.1 Literature Review

Portfolio holdings are first used in the paper by Grinblatt and Titman (1989), who use portfolio holdings to analyze managerial skill. Grinblatt and Titman (1993) and Wermers (1997) find that managers have stock picking abilities, particularly for growth funds. Wermers (2000) find that, on average, US mutual funds hold stocks that beat the CRSP value-weighted index by 1.3% a year before fees but underperform the market net of fees. All these papers look at the characteristics of the stocks in a fund's portfolio, analyzing, in particular, the ones held by skilled managers.

There are also other advantages in using holdings-based measures. As Jiang, Yao and Yu (2007) point out, these measures are a weighted average of a large number of stock prices, which provide a more accurate measure and with better statistical power even when fund holdings are observed less frequently than fund returns.

Another strand looks at how how managers might change risk levels due to agency issues. Brown et al. (1996), Chevalier and Ellison (1997), Busse (2001) analyze how a convex payoff function given by the flow-performance relationship may induce fund managers to take excess risk towards the end of the year. Palomino and Prat (2003) show under which conditions a risk neutral manager takes excess risk. Basak et al. (2007) show how a risk-averse manager behaves given an implicit incentive to outperform a benchmark.

Investors are not necessarily hurt by increasing risk levels. Managers with superior skill may select stocks with higher risk or actively choose to increase risk to time the market. Ultimately, the impact of risk shifting on performance is an empirical one.

Huang et al. (2011) are the first to look at the issue. They measure the future performance of funds that actively manipulate their level of risk and find that these funds tend to significantly underperform those that do not. They propose a holdings-based measure of risk-shifting, using only long positions, that controls for exogenous changes in the market conditions and allows one to capture the change in intended volatility without bias generated by subsequent trading or exogenous shocks. The underperformance comes mainly from funds that increase idiosyncratic risk and those that concentrate holdings on a few positions.

There is an extensive literature that looks at how aggregate measures of short selling affect stock returns (e.g. Jones and Lamont (2002), Asquith, Pathak and Ritter (2004), Cohen, Diether and Malloy (2007), and Nagel (2005)). The main finding is that stocks with abnormally high levels of short sales have lower abnormal returns in the future. However, there is no paper with an extensive analysis of the short positions held by funds and what securities are actually shorted by managers and which characteristics they have.

3.2 Data Description

3.2.1 Risk-Shifting Measures

Funds can actively change the level of risk of their portfolio by either changing their load on systematic risk or by changing the level of diversification of their portfolio. In order to capture the risk-shifting behaviour of funds, we employ the methodology proposed by Huang et al. (2011) and compare a fund's past realized volatility, $\sigma^R_{i,t}$, with the volatility implied by the fund's most recent disclosed positions, $\sigma^H_{i,t}$:

$$RS_{i,t} = \sigma^H_{i,t} - \sigma^R_{i,t} \tag{3.1}$$

The realized volatility, $\sigma^R_{i,t}$, is a backward-looking measure of the total risk of the fund and is calculated from daily fund returns over the previous 24 months.[2] The volatility calculated from the most recent portfolio holdings, $\sigma^H_{i,t}$, is, on the other

[2]Huang et al. (2011) use the past 36 months to evaluate the intended risk level of the fund. Our data spans a shorter period of time and doesn't allow us to use such a long period.

hand, a forward-looking measure that captures the intended volatility of the fund. It can be computed as the sample standard deviation of the return of a hypothetical portfolio that has held the most recently disclosed fund positions over the previous 24 months. This measure can alternatively be calculated as the square root of the variance of a fund with portfolio weights given by the fund's holdings positions, $\omega_{i,t}$ and the realized variance-covariance matrix of the assets returns, Σ_t:

$$\sigma^H_{i,t} = \sqrt{Var(\omega'_{i,t}R_t)} = \sqrt{\omega'_{i,t}Var(R_t)\omega_{i,t}} = \sqrt{\omega'_{i,t}\Sigma_t\omega_{i,t}} \tag{3.2}$$

The key aspect of this methodology is that, as it uses overlapping time periods, it only measures active risk-shifting. For instance, if a fund doesn't change its portfolio composition over time but the risk of the assets has changed, the risk-shifting measure will be zero. $RS_{i,t}$ will, hence, be unaffected by changes in market condition. Huang et al. (2011) also notice that this measure can potentially capture the impact of unobserved actions as window dressing or interim trades. Although other measures of risk-shifting are analyzed, these issues are not as problematic for us as our sample has monthly instead of quarterly portfolio holdings.

With the portfolio weights and the variance-covariance matrix of assets returns, we can then calculate the risk-shifting measure as per equations 3.1 and 3.2 every month. We perform these calculations for the whole fund (using all securities with return data available in the previous 24 months), only for long positions, and only for the short positions of a fund.

3.2.2 Excess Returns

We employ several measures of returns in an attempt to control for exposure to systematic factors. Many funds use the CDI as their benchmark, so the first measure of excess returns is the difference between the fund return and the risk free rate $R_i - R_f$. The second measure, $R_i - R_{CAPM}$, uses daily return data and is based on the CAPM model with betas estimated from all daily returns within a month.

The third measure, $R_i - R_{CAPM}^{Holdings}$, uses betas computed for each security held by the fund based on their previous 24 months of returns and then value-weighted to obtain the holdings-based portfolio beta. This measure allows for dynamic risk adjustments since betas change every month according to the securities held by a fund.

Our fourth measure is a characteristics-adjusted return computed by matching a fund to others with similar AUM and returns in the previous month. First, we rank all funds by lagged AUM and divide them in terciles. Then, within each tercile, we rank funds by lagged returns and further split then in terciles, creating 3x3 portfolios. Each fund is matched to one of these nine portfolios and we define $R_i - R_{Charac.}$ as the difference between the fund's return and its corresponding matched-portfolios average return.

3.2.3 Sample Selection

We use a database of Brazilian funds provided by Quantum, a Brazilian consulting company, that comprises monthly portfolio holdings for both mutual and hedge funds. This database is extremely detailed and has many features that enables a richer analysis of portfolio holdings. The data are collected from mandatory reports sent to the CVM (the Brazilian SEC) and directly by Quantum from asset management companies. It includes daily information on returns, assets under management, inflows and outflows, and the number of shareholders. It has monthly observations of **complete** portfolio holdings, i.e., long and short positions on several asset classes, including equity as well as bonds, derivatives and any other assets the fund might invest in. Quantum also provides qualitative information on the fund as style, fees structure, type of client and restrictions.

The holdings data is sampled at a higher frequency (monthly instead of quarterly) which, as pointed out by Elton et al. (2010), can have a significant impact on the results. As quarterly data misses the intra-quarter trades, adding more information can change or even reverse previous findings. Furthermore, since 2008 Brazilian funds are required to report not only the net position at the end of each month but also how much they bought and sold of each security within that month. Although we do not have access to the exact timing of trades within a month, it still allows a more precise measure of turnover and indicates how active funds are. Often, the lack of data only allows researchers to estimate turnover from net positions at the end of the period. This can be misleading if a fund is very active but keeps similar net positions at the end of each evaluation period.

Under CVM regulations, all funds are required to disclose similar information and there is no legal difference between a hedge fund and a mutual fund as all funds fall under the same regulatory framework. Rather than being divided in two distinct fund types as in the US, Brazilian funds differentiate themselves mainly by (1) the type of assets they are allowed to trade, (2) the maximum percentage they can hold of each type of asset, (3) the type of client they cater to, and (4) whether they engage in short-selling. Funds also decide on the fees structure and on the flow restriction they can impose on clients. The CVM imposes few restrictions on the funds ex-ante, being up to the fund manager to decide what specific type of fund she will run. All these decision are binding and occur before a fund's inception date. Any posterior change has to be approved by the shareholders and the CVM. The main advantage of this unified regulatory framework is that it allows any empirical study to control for the impact of each specific characteristic. In particular, conclusions drawn from studies based on US mutual (hedge) funds cannot be applied to hedge (mutual) funds because these two types of funds differ in too many levels. The database employed in this paper controls for each different characteristic and, as a consequence, the conclusions are more general.

We focus our analysis on actively managed domestic funds, following the classification determined by ANBIMA, the industry's self-regulatory body. They comprise of equity and multi-market funds, excluding balanced, bond, international, index funds and funds-of-funds. Multi-market funds can trade in any market with no restriction on holdings whereas equity funds are required to invest at least 67% of their assets in equity. We also excluded funds that manage less than $5 million and funds that have less than four shareholders for over 50% of the sample period.[3] These restrictions leaves us with around 700 funds. From these funds, we will concentrate on a subsample that engage in short-selling, leaving us with 427 funds and 7,689 valid fund-month observations. The number of funds with short-selling positions ranges from 67 in January 2007 to 305 in June 2009. Public data on portfolio holdings positions becomes available from 2006.

Table 3.1 reports summary statistics of the funds' total net assets under management (AUM), age, net-of-fees investor monthly returns and holdings returns. It also includes a description of the portfolio composition, the intended volatility, the realized volatility and the risk-shifting index. The average AUM_t is USD$116.2 million with a standard deviation of USD$287.1 million. The average age is 4 years with a standard deviation of 3.9 years. The investor return equals to 0.84% per month on average with a 4.75% volatility. Flows are defined as the total net inflow over total net assets in the previous period and are calculated as:

$$Flow_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1}(1 + r_{i,t})}{AUM_{t-1}} \tag{3.3}$$

where $r_{i,t}$ if the return of fund f in period t. The funds in our sample have a percentage net flow of 3% with a standard deviation of 24%.

In order to calculate the risk-shifting measure we need to evaluate, for each portfolio holding observation, the volatility of this position in the previous 24 months (holding's realized volatility). Each holding position will gives us portfolio weights that need to be matched to a variance-covariance matrix of past returns (see equation

[3]Funds that are not exclusive to one single client need to have at least three shareholders.

3.2). For equity, we collect returns from Datastream and only include firms stocks at least 24 months of previous data. For cash and fixed-income holdings we use the Brazilian interbank lending rate, the CDI, as a proxy for returns. Derivatives positions are, however, more problematic and have been excluded from our calculations. Although we know the underlying asset of a derivative position, these instruments are often short-lived and more difficult to price. Our measures of risk-shifting are hence only based on equity and fixed-income holdings. Every month, we match an average of 76.2% of AUM with an standard deviation of 20.8%; (matched) equities are, on average, 22.4% of AUM and (matched) cash or fixed income assets respond for 53.7% of assets. Although the latter might seem high, it possibly only reflects the fact that many funds that engage in short-selling have a long-short self-financing strategy which leaves them with a considerable proportion of their assets available to invest on the risk-free asset. Long positions (all asset classes as defined in Huang et al. (2011)) comprise 84.1% of matched assets and equity short positions are 7.5%.

In Figure 3.1, we plot the percentage of assets under management invested in short positions (top panel), the average number of shorted stocks and the total number of stocks held by a fund (bottom panel) for all funds in the sample. We can see a large increase in shorting from around March 2007 until July 2008, going from around 10% to 25% of AUM. While the average total number of stocks invested by a fund is generally stable around 25 stocks, the number of stocks held short follow the pattern seen for AUM. In March 2007, the number of shorted stocks held by funds increased from 2 and reached almost 10 stocks in July 2007.

The previous figures included all funds in the sample. If we constrain the sample to only include funds that have engaged in short-selling, we observe that they hold 27 different stocks on average with a standard deviation of 19 stocks. Funds short an average of 9 stocks with a standard deviation of over 11 stocks. They also have relatively low levels of systemic risk, with an average β of 0.25. This happens because many funds have significant investments in bonds or follow long/short strategies with low exposure to market risk. The equity positions, however, have a much higher β, around 0.8. All βs are calculated using a single factor model from weekly returns over a two-year window.

In Figure 3.2, the top panel displays the holdings-based volatility and the realized volatility for long-only positions while the lower panel shows the difference between these two variables. Similar to results found by Huang et al. (2011) for US mutual funds, there is a sharp reduction in risk in September 2008, the month that Lehman Brother's went bankrupt and the financial crisis reached its peak. In Figure 3.3, we observe a similar pattern for short-only positions. There is an increase in risk in early 2007 followed by a large decrease in the months around October 2008. This is evidence of a withdraw from all types of risky positions, both long and short ones, given the uncertainties brought by the financial crisis.

3.3 Empirical Results

Our multivariate tests look at how the returns of fund i in month $t+1$ are affected by changes in characteristics of its long and short positions at time t. Our baseline specification is:

$$R_{i,t+1} = \alpha + \beta' * \Delta(Positions)_{i,t} + \theta' * Risk\ Shifting_{i,t} + \gamma' \star Controls_{i,t} + \epsilon_{i,t+1} \quad (3.4)$$

where $R_{i,t+1}$ is one of our return measures at $t+1$. $\Delta(Positions)_{i,t}$ denote the change from $t-1$ to t of holdings classified according to investment type. We include positions held in long-only and short-only equity, derivatives, and in fixed income securities. These variables are meant to capture whether fund managers can successfully select securities that yield higher returns in the following month.

We also use four variables that capture risk-shifting. We compute the risk shifting measure shown in Equation 3.1 for long-only (RS Long) and short-only positions (RS

Short). Given the asymmetric impact of risk shifting measures found by Huang et al. (2011), we divide each risk shifting measure in terms of whether they are positive or negative.

We use several controls to make sure that our results are not driven by spurious correlation with previous factors used in the literature. We include the the six-month realized return volatility, fund age, AUM, fund-family AUM, previous month's return, and fund flow.

Our main results are presented in Table 3.2. We don't find any explanatory power for changes in holdings regardless of the excess return measures we use. In Columns (2) and (5) we find that funds that shift the risk of their long-only position, either decreasing or increasing it relative to its realized risk in the previous 24 months, tend to underperform in the next month by a large amount. For instance, the annualized underperformance for funds that increase their long-only risk by one standard deviation (1.39%) is equal to about 4.2% using CAPM-adjusted excess returns. Unlike Huang et al. (2011), we also find evidence that funds that decrease their risk also underperform by a similar amount. These results are in line with the reasoning that managers do not possess stock selection or market timing skills, instead having inferior ability or reacting to contractual incentives.

When we examine the impact of short-only positions in columns (3) and (6) we find the opposite effect. Funds that increase their short-only risk by one standard deviation actually outperform their peers by around 3.5% a year. We do not find evidence that decreases of short-only risk affect future performance. Managers who choose to increase the risk of their short-only positions seem to correctly time the market, yielding better returns in the following month.

In Table 3.3 we repeat these tests for two alternative measures of excess returns. In Columns (1) to (3) we use CAPM excess returns as our dependent variable. Each month we estimate betas of individual holdings using 24 months of past returns relative to the Brazilian stock market index, which are then aggregated using the fraction of each security in our matched holdings data to compute the portfolio holdings beta. In Columns (4) to (6) we compute fund characteristics-matched excess returns, assigning each fund to one of 3x3 portfolios sorted on lagged AUM and returns. Under both measures, our main result with the overperformance of increases in short-only risk remain significant.

In Table 3.4 we investigate the long-term performance of the results by looking at predictability of returns using explanatory variables measured up to four months before. Long-only results persist up to four months for funds that increase their risk, but not for those reducing the risk of their long positions not being statistically significant for variables measured more than two months before. When we examine short-only positions the results are much less persistent.

3.4 Conclusion

There are several advantages in using portfolio holdings data to analyze fund performance. Unfortunately, most funds database only report long-only positions and are disclosed, at most, on a quarterly basis. Moreover, hedge funds, that make extensive use of short selling and financial instruments, are not required to report their holdings and, in general, studies on these funds need to rely on, biased, self-reporting databases.

We use a unique data set of Brazilian hedge funds holdings to test whether changes in long or short positions can forecast future returns. The Brazilian asset management industry os the sixth largest in the world and all registered funds are required to disclosed *complete* holdings positions on a *monthly* basis.

Our main results indicate that funds with large increases in the risk of long-only positions underperform their peers by about 3% per year on average. Funds that increase the risk of short-only positions overperform their peers by about 1% on average. These results are robust for several measure of performance.

Results for the long positions are in line with previous findings in the literature and are consistent with changes in risk due to agency problems. Funds that actively change the risk of their short positions seem to correctly time the market, yielding better returns. Although the results are promising, the sample period the data covers is still short. Our next step will be to expand the data and further test for changes in portfolio composition.

Figure 3.1: Short Positions of Investment Funds - 2006 to 2009

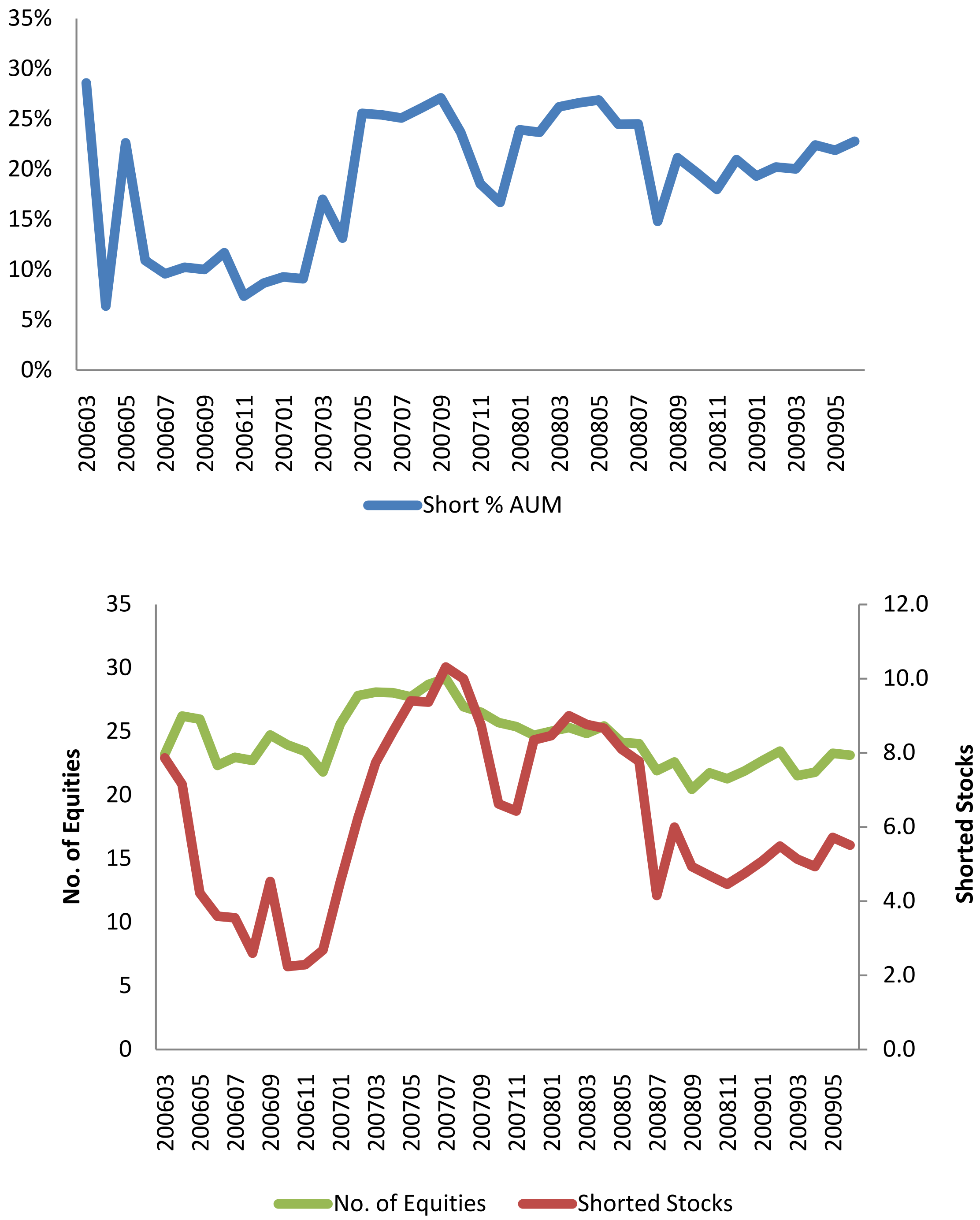


Figure 3.2: Risk Shifting of Long Positions

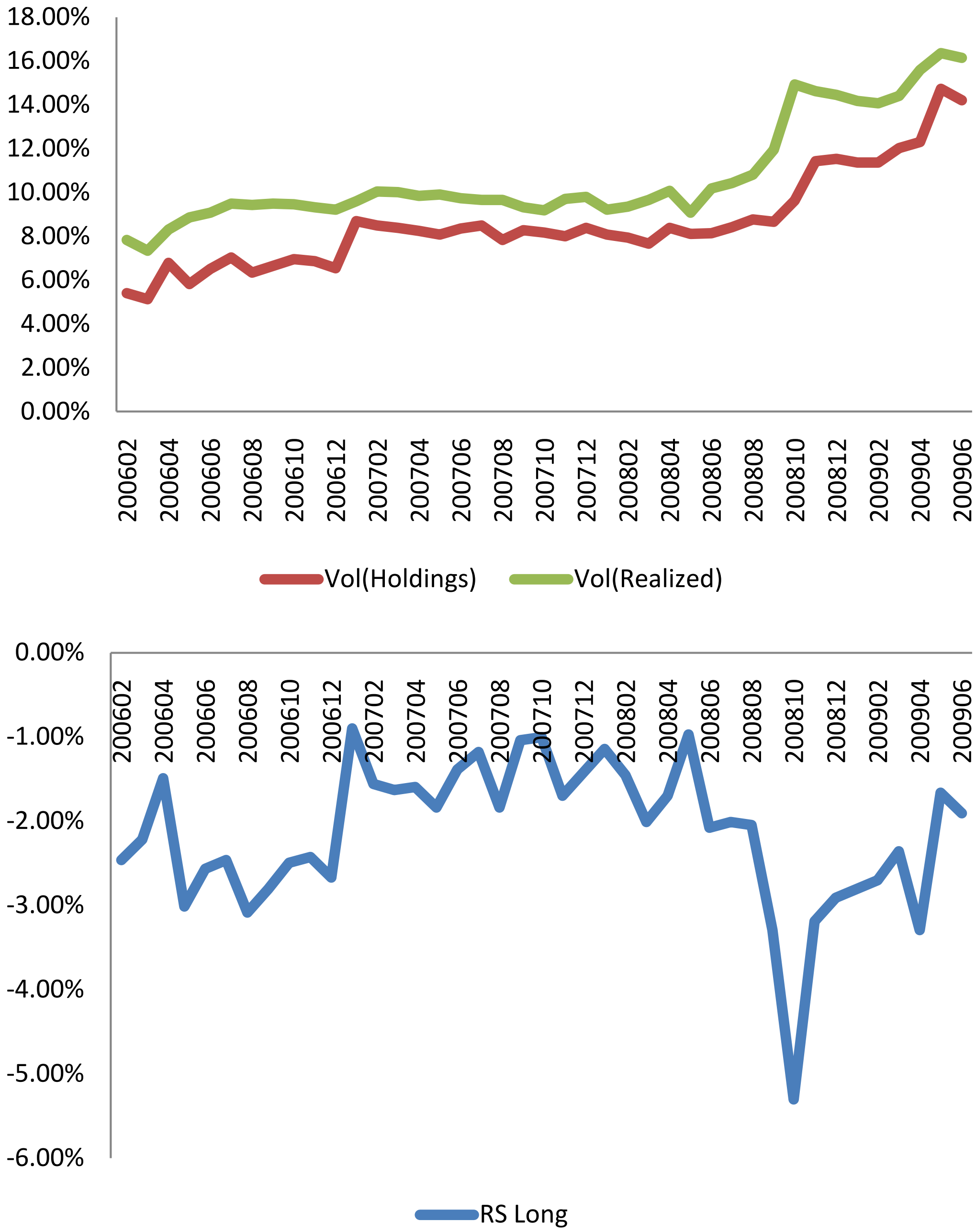


Figure 3.3: Risk Shifting of Short Positions

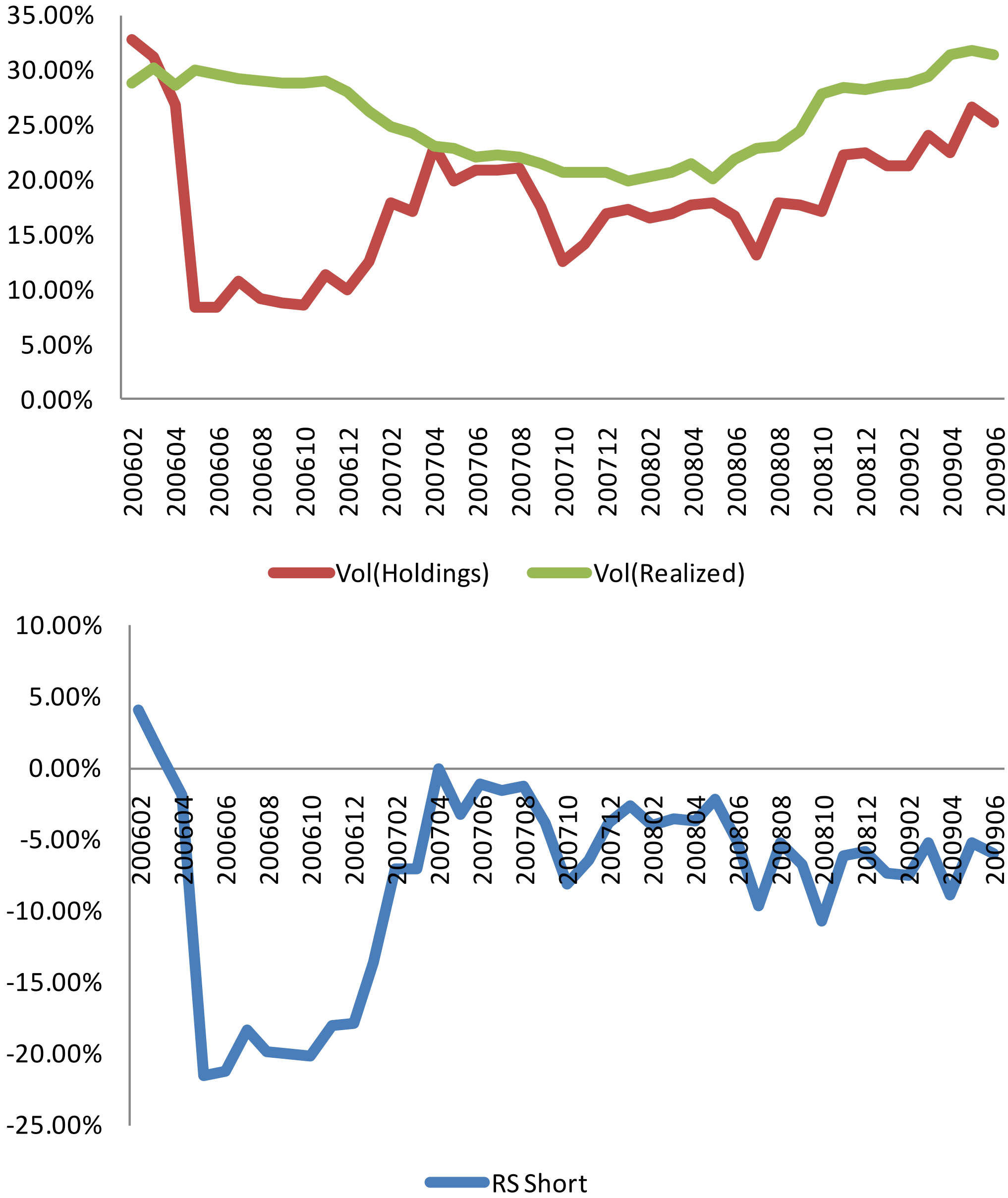


Table 3.1: **Descriptive Statistics**

Variable	**Number of Observations**	**Mean**	**Median**	**Standard Deviation**
Assets under Management	21,279	74,611	18,500	231,937
Age (Years)	21,946	4.86	2.71	5.63
Returns	20,968	0.59%	1.08%	6.95%
Flow	21,572	4.26%	0.00%	22.71%
Matched (% AUM)	24,484	77.20%	80.78%	20.42%
Equity(% AUM)	24,484	48.39%	57.55%	36.01%
Long (% AUM)	24,484	80.22%	82.74%	22.09%
Short (% AUM)	24,484	2.80%	0.00%	7.50%
CDI (% AUM)	24,484	28.62%	4.45%	34.72%
No. Stocks	24,484	19.10	15.00	15.57
No. Stocks Short	24,484	2.40	0.00	6.77
β_{Fund}	24,482	0.52	0.62	0.39
β_{Equity}	24,392	0.83	0.87	0.27
β_{Long}	24,481	0.54	0.62	0.36
β_{Short}	24,484	0.24	0.00	0.41
StDev Realized ($\sigma^H_{f,t}$))	24,482	17.96%	19.64%	13.19%
StDev Realized Equity	24,392	37.88%	27.78%	45.33%
StDev Realized Long	24,481	17.97%	19.55%	12.91%
StDev Realized Short	24,484	7.40%	0.00%	13.29%
Risk Shifting (RS)	24,482	-0.43%	-0.36%	5.34%
RS Equity	24,392	-2.17%	1.17%	66.62%
RS Long	24,481	-0.42%	-0.40%	4.84%
RS Short	24,465	-4.77%	0.00%	12.86%

Table 3.1: **Descriptive Statistics (Cont.)**

This table shows descriptive statistics for the funds that have engaged in short selling at least once between January 2006 and June 2009.

Variable	Number of Observations	Mean	Median	Standard Deviation
Assets under Management	5,433	120,869	38,506	301,524
Age (Years)	5,648	3.52	2.17	3.54
Returns	5,393	1.07%	1.05%	3.68%
Flow	5,591	3.06%	-0.20%	24.11%
Matched (% AUM)	6,412	75.34%	78.24%	21.49%
Equity(% AUM)	6,412	17.13%	7.13%	23.86%
Long (% AUM)	6,412	86.51%	87.61%	25.49%
Short (% AUM)	6,412	10.70%	5.93%	11.42%
CDI (% AUM)	6,412	58.00%	63.38%	30.18%
No. Stocks	6,412	27.22	23.00	18.98
No. Stocks Short	6,412	9.17	5.00	10.62
β_{Fund}	6,412	0.19	0.07	0.29
β_{Equity}	6,399	0.81	0.87	0.42
β_{Long}	6,411	0.27	0.19	0.27
β_{Short}	6,412	0.93	0.94	0.15
StDev Realized ($\sigma^H_{f,t}$))	6,412	8.73%	4.57%	10.48%
StDev Realized Equity	6,399	62.33%	33.92%	80.41%
StDev Realized Long	6,411	8.84%	5.50%	9.44%
StDev Realized Short	6,412	28.25%	26.43%	9.23%
Risk Shifting (RS)	6,412	-2.05%	-2.00%	5.91%
RS Equity	6,399	-6.74%	1.52%	118.89%
RS Long	6,411	-2.18%	-2.14%	4.46%
RS Short	6,393	2.21%	1.33%	6.77%

Table 3.2: **Fund Performance and the Impact of Short Positions**

The table displays regressions of fund returns at time $t+1$ on fund characteristics measured at time t. The sample period ranges from January 2006 to June 2009 and uses Brazilian investment funds that have used short selling as part of their investment strategy at least once during this period. The dependent variables are: $R_i - R_f$, which denotes a fund's monthly return less the Brazilian interbank loan rate (the CDI), and $R_i - R_{CAPM}$, which is the fund's excess return relative to a market model using the Brazilian stock market index. The explanatory variables are all lagged one month and are given by: Δ(% Z) is the monthly change of a particular type of positions, where Z corresponds, respectively to, Long-only, Short-only, Derivatives, and Fixed Income. RS Long and RS Short denote the difference in holdings-volatility and realized-volatility of Long and Short positions. Volatility 6m is the standard deviation of returns in the previous 6 months, Age is fund age since inception, AUM is asset under management, Family AUM is the total AUM of the fund's family, lagged return is the fund's return in the previous month, and Flow is the total monthly net inflow scaled by total net assets in the previous period. All regressions have standard errors clustered at the fund level that are reported in brackets. Significance levels are indicated as follows: ***=statistical significance at the 1% level, **=significant at the 5% percent level, *=significant at the 10% level.

Variable		$R_i - R_f$			$R_i - R_{CAPM}$	
Δ(% Long)	-0.166	0.175	0.185	0.583	0.763	0.782
	[0.562]	[0.571]	[0.571]	[0.595]	[0.603]	[0.611]
Δ(% Short)	0.093	-0.027	0.036	-0.259	-0.358	-0.331
	[0.670]	[0.676]	[0.684]	[0.699]	[0.688]	[0.702]
Δ(% Derivatives)	-0.575	-0.297	-0.457	-0.009	0.2	0.18
	[1.260]	[1.285]	[1.280]	[0.981]	[1.007]	[1.010]
Δ(% Fixed Income)	-0.165	-0.545	-0.534	-0.113	-0.388	-0.377
	[0.402]	[0.405]	[0.401]	[0.397]	[0.394]	[0.391]
Max(0,RS Long)		-0.379***	-0.374***		-0.272**	-0.251**
		[0.146]	[0.132]		[0.132]	[0.120]
Min(0, RS Long)		-0.305***	-0.298***		-0.188***	-0.190***
		[0.084]	[0.084]		[0.057]	[0.056]
Max(0,RS Short)			0.172***			0.079***
			[0.040]			[0.027]
Min(0, RS Short)			0.002			-0.004
			[0.017]			[0.013]
Volatility 6m	0.018***	0.025***	0.026***	0.001	0.005	0.006
	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]
Age	-0.11	-0.068	-0.07	-0.123	-0.072	-0.077
	[0.081]	[0.073]	[0.076]	[0.088]	[0.080]	[0.081]
AUM	0.04	0.048	0.051	-0.009	-0.012	-0.009
	[0.042]	[0.040]	[0.041]	[0.043]	[0.039]	[0.040]
Family AUM	-0.080***	-0.058**	-0.068**	-0.028	-0.018	-0.02
	[0.029]	[0.026]	[0.027]	[0.027]	[0.025]	[0.027]
Lagged Return	0.342***	0.347***	0.344***	0.061***	0.064***	0.064***
	[0.020]	[0.020]	[0.020]	[0.017]	[0.017]	[0.017]
Flow (%)	-0.448*	-0.468*	-0.478*	0.135	0.106	0.096
	[0.234]	[0.245]	[0.250]	[0.170]	[0.171]	[0.171]
Constant	0.423	-0.219	-0.216	0.544**	0.186	0.146
	[0.298]	[0.296]	[0.305]	[0.275]	[0.283]	[0.293]
Obs.	6,656	6,655	6,640	4,276	4,275	4,263
Adj. R^2	0.12	0.13	0.13	0.02	0.03	0.03

Table 3.3: **Fund Performance and the Impact of Short Positions: Alternative Abnormal Return Measures**

The table displays regressions of fund returns at time $t+1$ on characteristics measured at time t. The sample period ranges from January 2006 to June 2009 and uses Brazilian investment funds that have used short selling as part of their investment strategy at least once during this period. The dependent variables are: $R_i - R_{CAPM}^{Holdings}$, which denotes a fund's monthly return less the expected return from the CAPM model based on the portfolio derived from individual holdings, and $R_i - R_{Charac.}$, which is the fund's excess return relative to the average return of a characteristic-based benchmark portfolio matched on lagged AUM and lagged returns. The matching portfolios are created by splitting funds in terciles based on lagged AUM and further sorted on lagged returns. The explanatory variables are all lagged one month and are given by: Δ(% Z) is the monthly change of a particular type of positions, where Z corresponds, respectively to, Long-only, Short-only, Derivatives, and Fixed Income. RS Long and RS Short denote the difference in holdings-volatility and realized-volatility of Long and Short positions. Volatility 6m is the standard deviation of returns in the previous 6 months, Age is fund age since inception, AUM are assets under management, Family AUM is a fund's family AUM, lagged return is the return in the previous month, and Flow is the total monthly net inflow scaled by total net assets in the previous period. All regressions have standard errors clustered at the fund level that are reported in brackets. Significance levels are indicated as follows: ***=statistical significance at the 1% level, **=significant at the 5% percent level, *=significant at the 10% level.

Variable	$R_i - R_{CAPM}^{Holdings}$			$R_i - R_{Charac.}$		
Δ(% Long)	-0.37	-0.197	-0.197	-0.421	-0.353	-0.357
	[0.484]	[0.485]	[0.487]	[0.489]	[0.492]	[0.494]
Δ(% Short)	-0.576	-0.629	-0.614	0.098	0.079	0.085
	[0.553]	[0.549]	[0.555]	[0.618]	[0.618]	[0.620]
Δ(% Derivatives)	-0.9	-0.731	-0.809	-0.367	-0.27	-0.326
	[1.076]	[1.083]	[1.083]	[1.090]	[1.110]	[1.111]
Δ(% Fixed Income)	-0.464	-0.703**	-0.696**	-0.411	-0.552*	-0.548*
	[0.327]	[0.316]	[0.315]	[0.323]	[0.318]	[0.318]
Max(0,RS Long)		-0.297***	-0.279***		-0.248**	-0.243**
		[0.111]	[0.100]		[0.111]	[0.104]
Min(0, RS Long)		-0.139*	-0.139*		-0.032	-0.029
		[0.072]	[0.072]		[0.057]	[0.056]
Max(0,RS Short)			0.046*			0.055**
			[0.025]			[0.027]
Min(0, RS Short)			0.001			0.014
			[0.014]			[0.012]
Volatility 6m	0.004	0.008*	0.008*	0.002	0.005	0.006*
	[0.004]	[0.004]	[0.004]	[0.003]	[0.003]	[0.003]
Age	-0.094	-0.07	-0.068	-0.137**	-0.123**	-0.114*
	[0.075]	[0.069]	[0.070]	[0.064]	[0.061]	[0.062]
AUM	-0.014	-0.014	-0.013	0.058*	0.053*	0.053*
	[0.035]	[0.034]	[0.035]	[0.032]	[0.031]	[0.032]
Family AUM	-0.024	-0.014	-0.016	-0.021	-0.02	-0.026
	[0.023]	[0.022]	[0.022]	[0.022]	[0.022]	[0.022]
Lagged Return	0.083***	0.086***	0.086***	0.071***	0.073***	0.071***
	[0.018]	[0.018]	[0.018]	[0.015]	[0.015]	[0.015]
Flow (%)	-0.601***	-0.614***	-0.614***	-0.680***	-0.685***	-0.675***
	[0.222]	[0.228]	[0.229]	[0.194]	[0.195]	[0.197]
Constant	0.447*	0.175	0.167	0.123	0.089	0.159
	[0.255]	[0.246]	[0.253]	[0.258]	[0.273]	[0.277]
Obs.	6,656	6,655	6,640	6,656	6,655	6,64
Adj. R^2	0.02	0.03	0.03	0.02	0.02	0.02

Table 3.4: **Fund Performance and Short Holdings Positions: Long-Term Performance**

The table displays regressions of monthly fund returns on characteristics measured at different lags. The sample period ranges from January 2006 to June 2009 and uses Brazilian investment funds that have used short selling as part of their investment strategy at least once during this period. Two Months, Three Months and Four months denote, respectively, explanatory variables lagged two, three, and four months. The dependent variables are: $R_i - R_f$, which denotes a fund's monthly return less the Brazilian interbank loan rate (the CDI), and $R_i - R_{CAPM}$, which is the fund's excess return relative to a market model using the Brazilian stock market index. The explanatory variables are all lagged one month and are given by: Δ(% Z) is the monthly change of a particular type of positions, where Z corresponds, respectively to, Long-only, Short-only, Derivatives, and Fixed Income. RS Long and RS Short denote the difference in holdings-volatility and realized-volatility of Long and Short positions. Volatility 6m is the standard deviation of returns in the previous 6 months, Age is fund age since inception, AUM is asset under management, Family AUM is the total AUM of the fund's family, lagged return is the fund's return in the previous month, and Flow is the total monthly net inflow scaled by total net assets in the previous period. All regressions have standard errors clustered at the fund level that are reported in brackets. Significance levels are indicated as follows: ***=statistical significance at the 1% level, **=significant at the 5% percent level, *=significant at the 10% level.

	Two Months		**Three Months**		**Four Months**	
Variable	$R_i - R_f$	$R_i - R_{CAPM}$	$R_i - R_f$	$R_i - R_{CAPM}$	$R_i - R_f$	$R_i - R_{CAPM}$
Δ(% Long)	-1.124	-0.147	-1.13	-0.154	-0.887	-0.414
	[0.706]	[0.612]	[0.878]	[0.466]	[0.810]	[0.685]
Δ(% Short)	2.506***	1.519**	1.386*	0.003	1.222	0.474
	[0.720]	[0.675]	[0.770]	[0.580]	[0.854]	[0.770]
Δ(% Derivatives)	-1.916	-1.869	-0.082	0.673*	-0.503	0.749
	[1.705]	[1.172]	[1.608]	[0.379]	[1.129]	[0.828]
Δ(% Cash)	-0.769**	-0.322	0.297	0.269	-0.852	-0.799***
	[0.377]	[0.597]	[0.406]	[0.292]	[0.553]	[0.304]
Max(0,RS Long)	-0.701***	-0.349***	-0.551***	-0.280***	-0.673***	-0.360***
	[0.155]	[0.096]	[0.168]	[0.081]	[0.171]	[0.109]
Min(0, RS Long)	-0.297***	-0.214***	-0.190*	0.009	-0.112	-0.021
	[0.092]	[0.053]	[0.107]	[0.075]	[0.094]	[0.067]
Max(0,RS Short)	0.133***	0.025	0.110***	0.060*	-0.015	0.007
	[0.043]	[0.028]	[0.041]	[0.031]	[0.050]	[0.031]
Min(0, RS Short)	0.005	-0.008	0.02	0.001	-0.002	-0.004
	[0.019]	[0.013]	[0.021]	[0.011]	[0.022]	[0.013]
Volatility 6m	0.049***	0.008**	0.048***	0.008**	0.049***	0.009**
	[0.005]	[0.004]	[0.005]	[0.004]	[0.005]	[0.004]
Age	-0.151	-0.065	-0.210*	-0.135	-0.268**	-0.155
	[0.109]	[0.082]	[0.118]	[0.090]	[0.128]	[0.096]
AUM	0.074	-0.005	0.041	-0.039	0.012	-0.025
	[0.056]	[0.038]	[0.063]	[0.045]	[0.064]	[0.050]
Family AUM	-0.106***	-0.026	-0.125***	-0.04	-0.130***	-0.047
	[0.037]	[0.027]	[0.041]	[0.029]	[0.046]	[0.034]
Lagged Return	0.202***	0.076***	0.131***	0.058***	0.098***	-0.011
	[0.017]	[0.012]	[0.014]	[0.018]	[0.017]	[0.013]
Flow (%)	-0.325	-0.069	-0.282	0.04	-0.636	-0.406
	[0.235]	[0.204]	[0.309]	[0.205]	[0.392]	[0.255]
Constant	-0.22	0.194	0.68	1.085***	1.328**	1.087***
	[0.474]	[0.322]	[0.543]	[0.397]	[0.579]	[0.406]
Obs.	6,257	4,119	5,890	3,974	5,539	3,833
Adj. R^2	0.07	0.04	0.04	0.02	0.03	0.02

Conclusion

This dissertation uses a seldom used and extremely rich data set of Brazilian funds to shed light into issues relating to incentives and risk-shifting in the fund industry. The first paper shows that using disaggregated data of fund flows at a higher frequency evinces a shape for the fund-performance relationship different than the one suggested in the literature. In particular, although best performing funds still benefit from most of the inflows (convexity on the right tail), I find that the left tail of the distribution is concave, not flat. This result is extremely important as most theoretical papers in incentives and risk-shifting impose strict convexity in the flow-performance relationship, in line with previous empirical papers. Moreover it implies that investors have bad timing, buying high and selling low, as most practitioners argue. My result stems mainly from the fact that investors are quicker than previously thought in punishing the worst performing funds. As most papers use low frequency data, linking flows in a given year with performance in the previous year, they are not able to pick the short-term relation between (bad) performance and outflows. The next step is to verify whether investors indeed get a lower return on their investment than the fund's. For this it is necessary to have a longer series of inflows and outflows.

The second paper in this dissertation analyzes how funds change risk in response to past performance. In particular, I disentangle the incentives generated by an explicit remuneration contract offered to the fund manager from the incentives implicitly generated by the flow-performance relationship. I show that contracts have an asymmetric effect on risk and that the tournament within the fund family is the main driver of risk-shifting. In particular, results are compatible with families actively engaging in the tournament by transferring risk from the worst performing funds to the best and not just performance as other papers in the literature suggest. There is a still incipient literature on strategic interactions between funds within the same family that emphasizes how these family-related agency issues might affect investors.

The results in the first two papers can partly (and should) be tested using US data. The third paper, however, dig into hedge funds portfolio holdings which are usually not available. This paper, co-authored with Pedro A. Saffi, is the first, up to our knowledge, to use portfolio holdings information on short sales. In particular, we examine the impact of long and short positions on performance and test whether changes in long/short positions and their risk can forecast future performance. While we find that funds with large increases in the risk of long-only positions risk relative to the previous 24 months underperform by about 3% per year on average, those that increase the risk of short-only positions overperform their peers by about 1% a year on average, net of fees. Neither monthly changes of long nor short positions can forecast next month's abnormal returns. This paper still needs to be further explored. The uniqueness of the database allows for a much broader analysis which will be carried out in the near future.

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