The Convexity and Concavity of the Flow-Performance Relationship for Hedge Funds

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Abstract

The shape of the flow-performance relationship in the hedge fund industry is not constant over time, but varies across market conditions. We employ a switching regression approach to explain quarterly hedge fund flows, based on defining two regimes where either inflows or outflows are dominating, combined with a flexible functional form for each of the equations, allowing for a nonlinear impact of past performance at different lags. We characterize the local and global convexities of the relationship by several measures and investigate how they vary over time. Overall, the flow-performance relationship appears flatter at the one quarter horizon than at the four quarter horizon. Moreover, the curve is not uniformly convex or concave. For most periods, the flow-performance relationship is locally convex for a large subset of funds but becoming concave for the top three deciles of performers. The kink in the top part of the curve is more pronounced in periods when aggregate inflows to the industry are high. This effect seems mostly driven by funds that are restricting new inflows, for example due to capacity constraints or decreasing returns to scale. These results are helpful in understanding the incentives of hedge fund managers due to the implications for manager compensation based on performance fees and management fees.

Keywords: hedge funds, flow-performance relation, convexity, concavity, liquidity restrictions, managerial incentives

JEL-codes : G11, G23, G14

1. Introduction

Over the previous two decades the hedge fund industry has matured into an established segment of financial markets with currently managing an estimated $2 trillion of assets. At the same time, the industry has experienced several impactful events, like the failure of Long Term Capital Management in 1998, the quant quake in 2007 (e.g. Khandani and Lo, 2011), the financial crisis since 2008 and the unmasking of Bernard Madoff's fraud in 2008. Registration requirements for hedge fund managers have also been subject to changes (e.g. Brown et al, 2008), while the initial myth of the industry has been reduced and put in perspective (e.g. Lack, 2012). Partly as a result of all this, it can be expected that, over time, the hedge fund industry has been attracting different types of clientele, hedge fund investors varying in their expertise about the industry, their degree of sophistication and their interpretation of information signals, like past performance and hedge fund fees. Moreover, these circumstances may have led fund managers to change inflow and outflow restrictions (e.g. lockup periods and redemption notice periods) and their behavior with respect to investors, e.g. in their willingness to accept new money. Combining all this, there are many reasons to expect that the shape of the flow-performance relationship of hedge funds, summarizing the aggregate responsiveness of investors to past performance, is varying over time.

Existing studies addressing the flow-performance relationship for the hedge fund industry have reported different results. For example, Goetzmann, Ingersoll and Ross (2003) report a concave flow-performance relationship, while Agarwal, Daniel and Naik (2004) find a convex relationship. Ding et al. (2009) relate the shape of the flow-performance relationship to share restrictions and to whether the hedge funds are "live" or "defunct" (liquidated at a future date). Most of these studies estimate a piecewise-linear regression model, similar to flow-performance analysis for mutual funds by Sirri and Tufano (1998) and employ annual hedge fund data. Baquero and Verbeek (2009) show that the empirical shape of the relationship depends upon the frequency of the employed data (i.e. whether to use annual or quarterly returns and flows), and argue that analyzing annual data hides much of the underlying dynamics explaining inflows and outflows at higher frequencies. The current paper investigates the shape and dynamics of the flow-performance relationship for hedge funds by estimating a switching regression model at the quarterly frequency, distinguishing regimes with net negative and net positive flows, combined with a flexible functional form to address the nonlinearities and dynamics in the different regimes and the switching probabilities. While this allows the shape and location of the flow-performance relationship to depend upon large numbers of model parameters and fund characteristics, we summarize the flow performance relationships in two-dimensional graphs and by calculating a range of measures characterizing the convexity and concavity of the relationship. This way, we obtain a large degree of insight into the shape of the flow-performance relationship and how it differs over time.

What determines the convexity of the flow-performance relationship? For mutual funds, Huang, Wei and Yan (2007) present a simple rational model to highlight the effect of investors' participation costs on the response of flows to past fund performance. Participation costs affect fund flows through three channels. First, there is a relation between the level of financial sophistication of the group of investors that are actively investing in funds and the flow-performance sensitivity. This argument is also exploited in Ferreira, Keswani, Miguel and Ramos (2010) who explore the flow-performance relationship for mutual funds in different countries. Second, participation costs may limit the number of funds investors are actively comparing when making their allocation decisions, increasing the convexity of the curve at higher levels of performance. Third, transaction costs hamper the reallocation of investors' money across funds, thus making flows less sensitive to performance in the middle part of the distribution, particularly so for funds with high transaction costs. For hedge funds, however, we have to be aware that the flow-performance relationship is not simply driven by the behavior of investors but also by institutional constraints (e.g. lock up periods) and the behavior of fund managers (e.g. decision to close to new investors).

What would make the flow-performance relationship time varying for hedge funds? Because hedge funds are not open to the general public, it is typically argued that the industry attracts a sophisticated clientele. Nevertheless, it is conceivable that the degree of financial sophistication varies over time such that, for example, during the booming period of the late 1990s, the industry was attracting relatively more investors with limited understanding (or less critical evaluation) of the industry. That is, investors may have been queuing to get in. The changes in the investor base provide one channel driving the time-variation in the flow-performance relationship. A second channel that could explain why the flow-performance relation varies over time is a change in preferences or expectations of investors. For example, it is conceivable that investors respond more strongly to past performance information if their belief about performance persistence is more pronounced. The third channel we distinguish is the behavior of fund managers. We conjecture that the tendency of funds managers to close for new money (particularly from new investors) varies over time and may be relatively high in booming periods.

This paper makes a number of important contributions. At the methodological level, we introduce an innovative and flexible method to analyze the flow-performance relationship of hedge funds by combining a switching regression framework explaining quarterly money flows from past performance at different lags, with the flexibility of the piece-wise linear specifications that have been used before. This combination creates a large degree of flexibility and allows the flow-performance relationship to vary over time in a structured fashion. Second, we are the first to characterize the shape of the flow-performance relationship and its degree of convexity in different segments of the curve by means of a number of convexity measures, and to analyze the variation of these measures across periods. Most interestingly, we relate to degree of convexity of the flow-performance relationship to the aggregate absolute flows to the industry. We show that, in most periods, the flow-performance is not evidently convex, as it is for mutual funds, nor concave. The form of the relationship varies over time but it typically reasonably close to linear or slightly convex for the first part of the curve, to become concave for the few top deciles of performers. This suggest that the best performing hedge funds are reluctant to accept new money, for example because of decreasing returns to scale (e.g. Getmansky, 2012). This effect is more pronounced in periods when aggregate inflows to the industry are high.

The remainder of this paper is organized as follows. The next section provides the intuition behind a flexible modeling of the flow-performance relation for hedge funds. Section 3 describes our sample of hedge funds, variables, and summary statistics. Section 4 presents the base specification of our econometric model. In section 5 we conduct an analysis of the time-varying nature of the shape of the flow-performance relation, taking into account the effect of liquidity restrictions and managerial incentives. Section 6 presents a number of robustness tests while section 7 concludes.

2. Modeling a flexible flow-performance relationship

Many previous studies have reported a nonlinear flow-performance relationship for mutual funds or hedge funds. The shape of the relationship is driven by how the investor community responds to performance information about individual funds or the entire cross-section of funds. Relative to the median fund, funds in the top percentile, for example, may attract a larger number of investors, experience fewer withdrawals, or receive larger sums of money from their investors. Most existing studies try to capture the potential nonlinearities in this process modeling flows as a piece-wise linear or polynomial function of performance or relative performance, see e.g. Sirri and Tufano (1998). This, however, is potentially restrictive because it (typically) assumes that the nonlinearities are located at fixed breakpoints and do not change over time. For example, in a booming period where most funds are receiving new money, the shape of the flow-performance relation may be quite different from a crisis period where most funds experience outflows.

In this paper we take a different approach. In particular, we start from the observation that in the hedge fund industry inflows and outflows are less flexible. Outflows, on the one hand, are restricted by lock-up periods, redemption notice periods and redemption frequencies. Inflows are constrained by hedge fund managers that are unwilling to take new money, search costs and information disadvantages for new investors (due diligence, e.g. Brown et al, 2012). If inflows and outflows respond differentially to past performance (with higher sensitivity or with more delay), it makes sense to take this into account when modeling the flow-performance relationship. Unfortunately, we do not have data available on gross inflows and outflows, so we estimate a reduced from model that allows differential responses of net inflows and net outflows to past performance.

In the end, modeling money flows as a function of past performance is about finding the appropriate functional form. To illustrate this, let us consider the following simple model. Assume that the probability of a positive inflow (or the proportion of investors with a positive inflow) into a particular fund is given by $p(x,z)$, where x denotes past performance and z denotes other characteristics. Conditional upon having a positive inflow, the expected amount (or relative amount) is assumed to be given by $f_1(x)$. Conditional upon having a negative inflow, the expected amount is assumed to be given by $f_2(x)$. The net inflow to the fund is denoted by y. In this simple setting it follows that the expected inflow y depends upon x as

$$E[y|x] = f_1(x)p(x,z) + f_2(x)(1 - p(x,z)) = [f_1(x) - f_2(x)]p(x,z) + f_2(x). \qquad (1)$$

If $f_1(x) = f_2(x)$, $p(x,z)$ is redundant and the shape of the flow performance relationship is determined by $f_1(x)$. Empirically, this can easily be modelled by a flexible functional form, like a piece-wise linear function. However, if outflows respond differentially from inflows, the situation is different. First $p(x,z)$ will affect the shape of the flow-performance relation and how it does so depends upon z. If some periods or some subgroup of funds are characterized by values of z that lead to low values for $p(x,z)$, the flow-performance relation for this subset of observations is mostly driven by $f_2(x)$. For funds or periods with values of z that lead to high values of $p(x,z)$, the flow-performance relation is mostly driven by $f_1(x)$, with varying combinations of $f_1(x)$ and $f_2(x)$ in between.

As a simple illustration, consider the case where $f_1(x) = a_1 x$ and $f_2(x) = a_2 x$ and $p(x,z) = c(z) + bx$.[1] In this specification, both inflows and outflows respond linearly to performance, and the nonlinearity is driven by $p(x,z)$ as long as $a_1 \neq a_2$. The function $c(z)$ is an overall shift to the probability of positive or negative net flows, e.g. driven by market conditions or liquidity needs. Now,

$$E[y|x] = [a_1 - a_2]x[c(z) + bx] + a_2 x = (a_1 - a_2)bx^2 + (a_1 - a_2)c(z)x + a_2 x \qquad (2)$$

If $c(z)$ is very high in any given period the slope of the linear part is strongly affected by this, as long as a_1 differs from a_2. Also the curvature will be different, because the nonlinear part becomes relatively less important. For any approximation by a piece-wise linear, the breakpoints should be dependent upon z. Typically, this is not implemented in the standard flow-performance models, partly because z may be high dimensional thus involving large numbers of interaction terms.

[1] For simplicity this ignores the requirement that $p(x,z)$ should be between 0 and 1.

The switching regression approach that we follow in this paper is based on the above idea, and tries to capture the differential responses of inflows and outflows to past performance in the hedge fund industry in a relatively parsimonious and more insightful way. In addition to allowing the immediate impact of inflows and outflows to be different, we also allow the response speed to differ.

In order to increase the flexibility of the switching regression approach, we will – for some specifications – combine it with the piece-wise linear modeling of the three functions, f_1, f_2 and p.

3. Data and descriptive statistics

Our hedge fund data are obtained from Lipper TASS Management Limited. For each fund, our dataset provides raw returns and total net assets under management (AUM) on a monthly basis until February 2011. Returns are net of all management and incentive fees, but do not reflect front-end and back-end loads (i.e., sales commissions and subscription and redemption fees). We concentrate on the period between the first quarter of 1995 and the third quarter of 2010, asset information prior to 1995 being too sporadic and data for the last quarter of 2010 still being collected for most hedge funds. Moreover, information on defunct funds is available only from 1994 onwards, although several studies suggest that estimation of the flow-performance relationship is not affected by survivorship biases.[2] We focus on hedge funds that report returns in \$. We exclude 2812 closed-end funds present in our database, subscriptions to which are only possible during the initial issuing period, save for rare exceptions of additional subscriptions offered at a premium. We further exclude 1580 fund-of-funds, clients of which arguably follow a different decision-making process than investors who allocate their money to individual hedge funds. A single-manager selection process might be time consuming and costly, requiring both quantitative and qualitative evaluation and personal contacts with managers. Equivalent expertise and time are not required for investment in a fund-of-funds, which provides investors with a number of benefits that include diversification across several types of hedge funds.[3]

[2] See Sirri and Tufano [1998], Chevalier and Ellison [1997], Goetzmann and Peles [1997], and Del Guercio and Tkac [2002]. We also performed robustness checks estimating our model only for a subsample of survivors.
[3] Fung et al. [2008], in contrast, investigate the flow-performance relationship for the subsample of funds-of-funds.

An important characteristic of our analysis is our use of quarterly data, which enables us to explore the short-term dynamics of investment and redemption behavior. Other studies typically employ annual data (e.g., Agarwal, Daniel and Naik [2006] and Ding et al. [2009]). In the case of hedge funds, however, liquidity restrictions are likely to affect the relationship between asset flows and performance. Most subscription and redemption restrictions are defined on a monthly or quarterly basis, only few on an annual basis. Moreover, quarterly and monthly horizons seem to be typical monitoring frequencies among hedge fund investors.[4] Taken together with the findings of patterns of quarterly performance persistence (see, e.g., Agarwal and Naik [2000] and Baquero, Ter Horst and Verbeek [2005]), these facts suggest that significant numbers of buying and selling transactions can be expected within a year.[5]

In considering quarterly horizons, we take into account the most recently available value of assets under management (AUM) in each quarter.[6] We consider only funds with an uninterrupted series of quarterly AUM in order to be able to compute flows of money as the difference between consecutive AUM, correcting for reinvestments. We further restrict attention to funds with a minimum of four quarters of return history, and with quarterly cash flows available at least for one year. Although they impose a survival condition, the last two selections ensure that a sufficient number of lagged returns and lagged cash flows is available to estimate our model. Moreover, in this way we do not take into account extreme cash inflow rates commonly observed during the first quarters after a fund commences operations. Finally, to reduce the effect of a potential instant-history bias[7], we drop all fund observations taking place before the inception date of a fund.

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[4] In a survey associated with his study of hedge fund marketing, Bekier [1996] found that 50% of institutional investors prefer to receive quarterly and about 30% monthly (or between quarterly and monthly) monitoring information about their non-traditional investments, with only 15% choosing to monitor less frequently than quarterly.

[5] A further advantage is that using quarterly data reduces the impact on the flow-performance relation of potential return smoothing on a monthly basis. Getmansky, Lo and Makarov [2004] argue that patterns of serial correlation found in hedge fund data are induced by return smoothing, funds' exposure to illiquid securities being the most important of a number of sources.

[6] When AUM is not available at the end of a quarter, we take the most recent value of AUM up to two months prior.

[7] Instant-history (or backfilling) bias, documented by Park [1995], Ackermann et al. [1999], and Fung and Hsieh [2002], refers to the possibility that hedge funds participate in a database conditional on having performed well over a number of periods prior to inception.

Our final sample contains 2,451 funds and 34,374 fund-period observations. The graveyard consists of 1,689 funds, 996 of which liquidated, the remaining 693 funds self-selecting out of the database for different reasons (e.g., at the fund manager's request or by being closed to new investors). Table 1 provides an overview of the number of funds in our dataset per quarter, aggregate growth rates, and aggregate net assets under management. The 24 funds in our sample at the end of the first quarter of 1995 accounted for about $ 1.31 billion in net assets. The 706 funds in our sample at the end of the third quarter of 2010 accounted for about $ 134 billion, about 14% of the industry total of approximately $ 1 trillion in assets under management estimated by TASS at the end of 2010.

[PLACE TABLE 1 HERE]

Flows are measured as the growth rate of a fund's total net assets under management (AUM) between the start and end of quarter t+1 in excess of internal growth r_{t+1} for the quarter had all dividends been reinvested. In particular

$$CashFlow_{t+1} = \frac{AUM_{t+1} - AUM_t}{AUM_t} - r_{t+1} \tag{3}$$

which assumes that that flows occur at the end of period *t+1.* [8] Because these growth rates can be quite extreme, particularly for smaller funds, we winsorize them at the 1% tails of the distribution. Table 2 presents some descriptive statistics for assets under management and the alternative measures of cash flows. Interestingly, the distribution appears to be relatively symmetric, similar to findings in the pension fund industry and in sharp contrast to the distributions observed for mutual funds. For example, Del Guercio and Tkac [2002] find the top 5% of dollar inflows in mutual funds to be nearly three times larger than the outflows at the bottom 5%. This suggests that the flow-performance relationships in mutual funds and hedge funds might exhibit different characteristics.

In selecting which performance measure to use, we look at the information available to investors through different channels. Although, from a theoretical perspective, some of these risk and

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[8] See Ippolito [1992] for a discussion of the assumptions that underlie these definitions of flows. Berk and Tonks [2007] and Bris et al. [2007] employ an alternative measure of cash flows using $(1+r_{t+1})AUM_t$ in the denominator rather than AUM_t. Our results are not very different when we use this alternative measure.

performance metrics might not be the most appropriate with which to characterize hedge funds, they might nevertheless underlie investor's decisions. We use the simple performance measures offered by most databases, that is, raw returns, return rankings relative to other funds, and Sharpe ratios. Similarly, a fund's riskiness is usually reported in terms of its total risk (standard deviation of historical returns) and measures of downside risk. A popular measure that captures aversion to negative skewness is the downside-upside potential ratio, which combines downward variation as the numerator and upside potential as the denominator.[9] We measure downside deviations and upside potential with respect to the return of three-month Treasury bills over the entire past history of the fund.

[PLACE TABLE 2 HERE]

Table 3 presents descriptive statistics for fees, ownership structure and styles, and several other variables that might be important determinants of money flows. Below, we briefly explain each of these variables and hypothesize their impact on money flows.

Incentive fees constitute one mechanism in place in the hedge fund industry to mitigate principal-agent problems and align investors' goals with fund managers' incentives (see Ackermann, McEnally and Ravenscraft [1999]). The typical incentive contract aims to enhance managerial effort by paying hedge fund managers a percentage of annual profits if returns surpass some benchmark, and in case past losses have been recovered. According to Table 3, managers receive, on average, an incentive fee of about 18% of profits, a bonus that varies substantially across funds, ranging from 0% to 50%. A higher fee would be more attractive to an investor, as it should translate into higher performance, but possibly with the trade-off of incurring greater risk (see Starks [1987]).

Additionally, an investor pays an annual management fee, defined as a percentage of total assets under management. In our dataset, the average management fee is around 1.5%, and varies between

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[9] We use the following definition of the downside-upside potential ratio:

$$DUPR = \frac{\sqrt{\frac{1}{T}\sum_{1}^{T} \iota^{-}(r_{i,t} - r_{mar})^2}}{\frac{1}{T}\sum_{1}^{T} \iota^{+}(r_{i,t} - r_{mar})}$$

where $\iota^{-} = 1$ if $r_{i,t} \leq r_{mar}$, 0 otherwise, and $\iota^{+} = 1$ if $r_{i,t} > r_{mar}$, 0 otherwise ($r_{i,t}$ is the return of a fund *i* at time *t*, and r_{mar} refers to the minimal acceptable rate of return, or the investor's target return.)

0% and 8%. Management fees might imply an indirect performance incentive in the event that an increase in size is related to an increase in performance. Goetzmann, Ingersoll and Ross [2003], Naik, Ramadorai and Stromqvist [2007] and Getmansky [2012] however, find evidence of capacity constraints and diminishing returns to scale in this industry, in contrast to the mutual fund industry.

Joint ownership structure is another mechanism in place to mitigate principal-agent problems in the hedge fund industry. Intuitively, a fund that requires a substantial managerial investment should enhance manager effort, but possibly at the cost of managers incurring less than the investor's preferred risk level. Therefore, as noted by Ackermann et al. [1999], combining substantial investment of managers' personal capital with high incentive fees might be the most attractive option from an investor's perspective, as managerial effort is greatly enhanced and the degrees of risk-taking implicit in the two approaches counterbalance. Nearly 62% of managers in our sample are required to invest their own capital.

We define fund age as the number of months since its inception that a fund has been in existence. From Table 3, the mean is 55 months (ln(Age) = 4.007). As indicated above, age is truncated at 18 months (six quarters). Investors might perceive older funds to be more experienced at identifying and exploiting mis-pricing opportunities. But the effect of age on money flows is difficult to predict in the event that age is correlated with size and diseconomies of scale are present.

The TASS database distinguishes between onshore and offshore funds. Offshore hedge funds are typically corporations. Because the number of investors is not limited, offshore funds tend to be larger. They represent 62% of the funds in our dataset. Onshore funds, being generally limited partnerships with fewer than 500 investors, tend to be more restricted to new investors and impose more extended redemption periods than offshore funds.

[PLACE TABLE 3 HERE]

Hedge funds invest in different asset classes with different geographical focus and employ a variety of investment techniques and trading strategies. Brown and Goetzmann [2003] find differences in style to account for 20% of cross-sectional variation in performance as well as for a significant proportion of cross-sectional differences in risk, suggesting that, from an investor's perspective, careful assessment of style is crucial. There is, however, no consensus in the hedge fund industry on the use of a unique style classification. TASS provides a classification of mutually exclusive styles based on manager survey responses and information from fund disclosure documents. Self-reporting of styles, albeit subject to self-selection bias, constitutes the most readily available source of investor information concerning styles. We therefore expect styles to be an important determinant of hedge fund investors' preferences, which is the focus of our study. The TASS classification, moreover, closely matches the definitions of CSFB/Tremont Hedge Fund Indices, a set of 10 indices increasingly used as a point of reference for tracking fund performance and comparing funds. Using the TASS classification, we assigned each fund to only one index category. The more general "hedge fund index" category includes funds without a clear investment style (for details, see Baquero, ter Horst and Verbeek [2005]).

4. Estimating the flow-performance relationship

The shape of the flow-performance relationship for hedge funds varies over time. It is the result of investors' response to performance information and other relevant characteristics of hedge funds, combined with hedge fund managers imposing restrictions on outflows and inflows. For example, there are several typical restrictions operating in the hedge fund industry restricting immediate redemptions, such as redemption notice periods and lock-up periods. On the other side, hedge fund managers have some discretion in accepting (or not accepting) new money, and in doing so, may make a distinction between existing investors and new investors. In addition, the information that is available to investors comes with substantial costs, e.g. in the form of due diligence reports, and is typically different between existing investors and new investors in a given funds.

We try to model the flow-performance relationship in a flexible way by combining the typical piecewise-linear specification with two additional features. First, we specify and estimate the model based on quarterly flows and performance information over the previous four quarters. We do so because we conjecture that in the short-run money flows may be less sensitive to performance than in the longer run (e.g. a year). Also, the shape of the flow-performance relationship may be different at the one-quarter horizon and the four-quarter horizon. Second, we model the flow-performance relationship using a switching regression approach, where we estimate three equations. The advantage of this is that the shape of the flow-performance relationship can change over time even if all model coefficients, except the fixed time effects, are constant. This avoids the need to arbitrarily break up the sample period in subperiods or to make some parametric assumption on how the (very many) model coefficients may evolve over time.

The typical approach to investigate the flow-performance relationship is based on a piecewise linear regression (see Sirri and Tufano, 1998). This allows money flows to respond with different sensitivity to past performance, depending upon a particular performance percentile. For example, in the mutual funds literature it is typically found that the responsiveness is much higher for the top 20% past performers than for the bottom 20%. As mentioned above, a drawback of this approach is that the kinks in the flow-performance sensitivities are fixed a priori, are independent upon the level of flows and, moreover, of the question whether inflows or outflows are responsible for the flow-performance relationship of a given fund. This is unfortunate, particularly for hedge funds where inflows and outflows are characterized by different constraints and decision processes. Liquidity restrictions, searching costs, the due diligence process, and the possibility of active monitoring might all result in different sensitivities of inflows and outflows to good and bad past performance.

Therefore, we complement the piecewise linear regression with a more flexible approach. In particular we hypothesize that the flow-performance relationship displays two different regimes depending on whether outflows are more important than inflows (in which case we observe negative net cash flows) or vice versa. This alternative approach to model the nonlinear relationship between money flows and past performance creates additional flexibility. First, we specify the following two equations

$$y_{1,it} = f_1(rnk_{i,t-1}, \dots) + control\ variables + \mu_{1t} + \varepsilon_{1,it} \tag{5}$$

$$y_{2,it} = f_2(rnk_{i,t-1}, \dots) + control\ variables + \mu_{2t} + \varepsilon_{2,it} \tag{6}$$

where $y_{1,it}$ and $y_{2,it}$ denote the rates of cash flows for an individual fund *i* in period *t*, in cases inflows or outflows are dominant, respectively. The variables $rnk_{i,t-1}, \dots$ measure the relative performance rank of the fund (one or more periods ago), and the functions f1 and f2 capture the (hypothetical) sensitivity of net inflows and net outflows with respect to performance in the ultimate case where the corresponding regime is dominant. Let s_{it} be a dummy variable that captures the aggregate investors' decision that takes the value 1 if the observed sign of net cash flows is positive and 0 otherwise. Thus, we observe either

$$y_{1,it} \quad \text{when} \quad s_{it} = 1,$$

$$\text{or} \quad y_{2,it} \quad \text{when} \quad s_{it} = 0,$$

but never both. The first stage consists of estimating a probit model that explains the sign of flows,

$$s_{it}^{*} = f_3\left(rnk_{i,t-1}, \ldots\right) + control\ variables + \lambda_t + \mu_{it} \tag{7}$$

where $s_{it} = 1$ if $s_{it}^{*} > 0$, and $s_{it} = 0$ otherwise. The specification includes (fixed) time effects λ_t. In the second stage, we estimate, by ordinary least squares, the truncated variables $y_{1,it}$ and $y_{2,it}$, while incorporating the generalized residual from the probit model. These additional explanatory variables capture $E[\varepsilon_{1,it} \mid s_{it} = 1]$ and $E[\varepsilon_{2,it} \mid s_{it} = 0]$, respectively, where

$$E\left[\varepsilon_{k,it} \middle| s_{it} = 2-k\right] = \operatorname{cov}\left(\mu_{it}, \varepsilon_{k,it}\right) E[\mu_{it} | s_{it} = 2-k], \quad k = 1,2. \tag{8}$$

The suffix k indexes the relevant regime. k=2 corresponding to negative flows (s_{it}=0) and k=1 to positive flows (s_{it}=1). The latter expectation in (8) reflects the generalized residual of equation (7) (see, e.g., Verbeek [2012], Chapter 7).[10] We do not impose that the coefficients in any of the three equations be identical. The easiest way to interpret our three-equation model is by considering the first two equations as regression models truncated at zero, whereby a common binary choice model, specified in the third equation, explains the appropriate regime. As a result, the two flow equations contain an additional term that captures the truncation. This term is based on the generalized residual of the binary choice model, while its coefficients depend upon the covariances between the equations' error terms (see Maddala [1983] for an extensive treatment of such models).

The three equation switching regression model has many more parameters than the piecewise linear approach and is therefore much more flexible in capturing the subtle nuances underlying the flow-performance relationship of hedge funds. While the parameter magnitudes in the three equations

[10] This analysis assumes joint normality of all unobservable error terms.

cannot be directly compared with those in the single equation approach, both models imply a particular shape for the flow-performance relationship. In the piecewise linear approach the shape of the flow-performance relationship is the same across all periods and all subsets of funds (by assumption). That is, the degree of concavity is the same in all cases, although the overall level of the effect may be different. The switching regression approach is more flexible as the relative importance of the two regimes can change over time or across subsets of funds. Therefore, the degree of concavity can vary. To illustrate this, we will present several graphs and convexity measures to characterize and summarize the aggregate response of investor flows to past (relative) performance, while fixing the fund characteristics to their sample averages. (This is particularly relevant for the three equation case.) This way, we can easily compare the two approaches using economic arguments rather than just statistical ones.

Empirically, the shape of the flow performance relationship in the switching approach is not only driven by the slope parameters in the two regimes and the relative weighting, but also by the overall levels of flows in the two regimes. While expected flows, unconditional upon regime, are a weighted average of the expected flows in each of the two regimes, as shown in equation (1), this logic does not apply to the slope of the flow-performance relationship or its concavity. This occurs because the weighting function itself also depends upon past performance (through equation (5)). This means that the translation of the dynamic and nonlinear responses to past performance in each of the three equations to an aggregate response is much more subtle that may seem at first. The coefficients in each of the two regime equations measure the response of flows to past performance when the probability of the other regime prevailing is zero. Empirically, this typically does not occur, although in some quarters the probability of positive flows is almost zero (2008Q4, 2009Q1). Nevertheless, the coefficients are informative about the responsiveness of inflows and outflows to past performance and its dynamics. For the most relevant cases, the effects upon expected money flows of a marginal change in the performance rank of the fund is driven by the slope parameters in the two regimes (the direct effect) but also by the additional effect through the change in the inverse Mill's ratios, and thus also depend upon the coefficients in (7) as well as the covariances between the error terms from equation (8).

[PLACE TABLE 5 HERE]

Table 5 reports the estimates of the probit model that explain the regime of cash flows (column B). For these results, we do not take into account cash flows that have the value zero (which eliminates less than 3 percent of the fund-period observations – see Table 3). The results show the impact of historical relative performance on the direction of the investment decision to be positive and highly significant, both economically and statistically. Funds with a good track record of performance relative to their peers are likely to experience positive net cash flows, funds with bad past performance more likely to elicit a divestment decision. Although the statistical significance of the lagged performance ranks is typically higher for funds that impose low restrictions to liquidity than for funds that are more restricted, the differences in estimated coefficients between restricted and unrestricted ranks appear limited. Nevertheless, a Wald test on equality of the coefficients for the restricted and unrestricted performance ranks results in a (marginally) significant *p*-value of 0.0221.

From column (A), we observe that investors' decisions to invest or divest are strongly driven by the most recent quarterly performance. The effect attenuates progressively with each lag, dissipating after the fifth lag. The control variables also capture some interesting and significant effects. Younger funds are, ceteris paribus, more likely than older funds to attract money flows. Offshore funds operating in tax havens are, ceteris paribus, more likely than onshore funds to trigger a divestment decision by investors. The dynamics of flows also appear to be an important determinant of the flows regime. Funds that experienced inflows in the past are, ceteris paribus, likely to continue experiencing inflows over the next four quarters. Finally, several investment style dummies also appear to have a significant impact. Long/short equity funds and funds operating in emerging markets have, ceteris paribus, the highest probability of prompting divestment decisions by investors.

5. The shape of the flow-performance relationship

a) *Time-variation of the flow-performance relation*

In the most general switching regression model there are 36 coefficients that measure the direct relation between money flows and performance, corresponding to four different lags, three different segments and three different equations. Moreover, the actual shape of the flow-performance relationship is also driven by the other characteristics in the model, most notably the time effects. For example, if a period is characterized by large aggregate inflows to the entire hedge fund industry, the probability of positive net flows is large and the coefficients of the positive regime are more important in describing the flow-performance relationship. On the contrary, in periods with large outflows, the negative regime is more important. The result of this is not only that the location of the flow-performance relationships shifts up and down, but also that its shape can vary over time. In fact, this is one of the key insights in this paper: the flow-performance relationship is not constant and its shape will be different in different periods (and within different subsets of funds).

Because it is not obvious how the model coefficients translate into the flow-performance relationship, we create a graph summarizing this relationship in a given period while controlling for all other characteristics in the model. We do so at the quarterly frequency. The graphs present the average response to the relative performance (rank) of a fund where the rank in the previous one to four quarters varies between 0 and 1, and all other variables, except the time dummy, are fixed at their sample averages.

[PLACE FIGURES 2 AND 3 HERE]

To illustrate this approach, Figures 2 and 3 present the implied flow-performance relationship for two specific quarters: the first quarter of 2004, corresponding to a period with high inflows, and the third quarter in 2008, a period with large outflows to the industry. The graphs summarize the responsiveness of a hedge fund's quarterly growth rate with respect to the performance rank of the fund over the previous four quarters (fixing all other variables at the sample average). These two figures illustrate the possibility of the more general switching regression approach to imply different shapes in different periods, while the piecewise linear approach is restrictive in the sense that the curve can only move up and down. In 2004Q1, the difference between the two approaches is quite pronounced, while in 2008Q3 the graphs are reasonably similar. The convexity of the curve in the first part of the distribution is stronger in 2004Q1, its slope is larger around median performance, and the kink at the 70th percentile is also larger. We come back to this issue below.

[PLACE FIGURE 4 HERE]

In our next analysis we group divide all quarters in our sample based on total cash flows to the industry. The bottom quintile contains the quarters with the lowest inflows (highest outflows), while the top quintile contains the quarters where inflows are highest. If we aggregate the flow-performance relationship across the quarters within these two quintiles we obtain the results depicted in Figure 4. In periods with high inflows, the convexity in the first part of the curve is larger, the slope of the curve is higher just above the median, and the kink at the 70th percentile is more pronounced. This figure illustrate the added value of the switching regression approach: for the piecewise linear, both curves have the same shape.

b) The dynamics of the flow-performance relationship

The shape of the flow-performance relationship changes if we move from the short-run effect (one quarter) to the mid-run effect (four quarters). Due to the lack of reporting requirements in the hedge fund industry, new investors face information barriers in the short run, which slows down the response of flows to performance. In the mid-run, the response of flows is stronger as investors gather and analyze performance signals and information on managers. To illustrate the response of flows in the short run, specifically for the first quarter of 2004, we obtain the first graph in Figure 5 by varying the rank in the previous quarter between 0 and 1 while all other performance ranks are fixed at 0.5 and all other variables, except the time dummy, are fixed at their sample averages. The remaining graphs in Figure 5 show the response of flows as we move to the mid-run by aggregating two, three and four quarters respectively, while all other performance ranks are fixed at 0.5. The last graph corresponds to our previous approach in Figure 2. At the one quarter horizon the flow-performance relationship is flatter than at the four-quarter horizon, and is relatively close to the piecewise linear regression. As we move to the mid-run, the flow-performance relation increasingly departs from the piecewise linear model.

[PLACE FIGURE 5 HERE]

Thus, the sensitivity of money flows increases when we look at longer horizons. Also, at longer horizons it becomes clear that the flow-performance relationship is not simply convex, concave or piecewise linear. In the first part of the curve, the level of convexity is increasing with the horizon, but there is a clear kink in the second part of the curve (in our specification at the 0.7 percentile) making the flow-performance relationship globally (over the 0.5-1.0 interval) concave, although it may be locally convex still.

c) Convexity measures

Here we further look into the convexity of the curves and how they vary over time. Our estimated model implies a large number of flow-performance curves and, when investigating those, we clearly observe a notable difference in the location and shape of the curve between periods with high aggregate inflows (e.g. 1997/1998) and high aggregate outflows (e.g. late 2007/early 2008). We will first describe the degree of convexity of the flow-performance curve and how it varies over time and, second, focus more on the interpretation.

When a curve is neither uniformly convex or concave there is no obvious single measure that describes the shape of the curve. We look at a number of measures to capture the degree of convexity in these cases.

The first measure we consider is the **convexity ratio**. To explain this, let us consider a given fund that has performance rank 0.4, say. Now, consider what happens to the growth rate of this fund if the performance rank increases or decreases by δ=0.01. We call the curve (locally) convex at 0.4 if the response is the positive direction is, in absolute term, larger than the one in the negative direction. That is, at the margin investors respond stronger to an increase in relative performance than to a decrease of the same magnitude. Next we calculate this measure for every value of the performance rank between 0 and 1 (with steps of 0.01). The convexity ratio is defined as the total number of locally convex points divided by the total number of points. When the convexity ratio is 1, the flow-performance curve is locally convex in each point and the entire curve can be classified as being convex (see e.g. Sati, Marwan and Guy J. Laroye, 1994) .

The convexity ratio described above is based on a local measure where we evaluate what happens to fund flows if the performance rank changes by $\delta= 0.01$ in either direction. We also expand the range of this by evaluating the local convexity over wider windows with changes of 0.05, 0.1 or 0.25.

However, two curves can have the same convexity ratio but can still be quite different in their curvature. We therefore also look at a number of other measures. In particular, we refer to the marginal increment in the slope of the curve for a rank change δ, as *alpha*. If *alpha* is positive, the curve is locally convex. The total sum of *alphas* along the curve captures the degree of *global* convexity (see e.g. Sati, Marwan and Guy J. Laroye, 1994).

[PLACE TABLE 5 HERE]

In Table 5 we present the average convexity measures across subperiods determined by total aggregate flows. To be precise, we sort all periods by the total dollar flows into our hedge fund sample and then divide these periods into five groups (quintiles). Quintile 1 contains the 12 quarters with the largest outflows, while quintile 5 contains the 12 quarter with the largest inflows. Historically, quintile 1 corresponds mostly to 1995Q3 and Q4, 1997Q2, 1998Q4, 2000Q2, 2005Q3 and Q4, and the financial crisis period from 2008Q3 to 2009Q2. Quintile 5 corresponds mostly to 1997Q1, 2001Q2, 2002Q1, the period from 2003Q2 to 2004Q2, 2005Q1and Q3, and 2006Q2 and Q3.

Whichever measure for convexity we employ, it is clear that in quintile 1 the flow-performance relationship is less convex than in quintile 5. For example, in Panel A, when $\delta= 0.01$, the first quintile has on average 76.2% of convex segments along the curve, while the top quintile has on average 92.8% of convex segments. This difference is highly statistically significant with a t-ratio of 4.72.. The bigger convexity in quintile five is mostly located in the first part of the curve (below the median), that is for the relatively low performance ranks. If we move up to the top part of the curve, we observe a clear kink at a rank of 0.7. While the exact location of this curve is determined by our specification (where we allow for kinks in each of the three equations at rank 0.3 and 0.7), it is clear that the shape of the flow-performance relationship alters in the top half of the performance distribution. This marks a notable difference from the relationship that is typically reported for mutual funds. We will argue below that fund managers who are unwilling to accept new money most likely drive the kink at 0.7.

Before the crisis, the difference in the flow-performance relationship between funds that have liquidity restrictions and those that (formally) have not is much bigger than during or after the crisis. This suggests that funds have become less stringent in more recent years.

The flow-performance relationship is not evidently convex, as it is for mutual funds, nor concave. The form of the relationship varies over time but is typically reasonably close to linear. In many periods, the relationship is convex or linear in the first part to become concave for the top deciles of performers. This suggest that the best performing hedge funds are reluctant to accept new money, for example, because of decreasing returns to scale. This effect seems less pronounced during and after the crisis.

The graphs summarize the total response aggregated over the subsequent four quarters. This hides underlying dynamics and asymmetries across the positive and negative cash flow regimes. We investigate this issue in the next section.

d) The effect of restrictions upon inflows and outflows

Supply-side restrictions upon inflows and outflows flatten the flow-performance relationship towards the tails. We conjecture that the kink at the 0.7 percentile is mostly driven by funds that are restricting new inflows, for example, due to capacity constraints or decreasing returns to scale. Recall that the compensation of a hedge fund manager is mostly driven by the incentive fees, so an increase in the size of the fund accompanied by a deterioration in performance, may actually be harmful for the manager's compensation and therefore there will be a clear incentive for a manager to be restrictive on accepting new money, particularly when the fund is already large.

To support our story that the kink at the 0.7 percentile is particularly driven by funds closing to new investors, we perform the following exercise. First, we determine the slope of the flow-performance curve just before the kink point at 0.7. We interpret this slope as describing, at least locally, the direction in which the flow-performance relationship would develop in the absence of restrictions imposed by fund managers. That is, we conjecture a hypothetical flow-performance relationship that expands beyond the kink at 0.7. The actual flow-performance relationship is different because funds are reluctant to take new money. As an example, suppose that once a fund approaches the 0.7 percentile, half of the funds decide to close for new investments. As a result of that, the flow-performance relationship will flatten, and the degree by which this happens depends upon the steepness of the curve just before 0.7. Put differently, the kink at the 0.7 percentile will be more pronounced if the curve is steeper before the restrictions start operating. The kink will become even more pronounced if the proportion of funds that decides to close is larger when the hypothetical curve is steeper. This may make sense. If the hypothetical flow performance relationship is very steep for top performing funds, the potential new inflows to the fund are extremely high, there is a greater risk of hitting capacity constraints and facing decreasing returns to scale, so there is a larger incentive of fund managers to close for new investments.

[PLACE TABLE 6 HERE]

To investigate this, we go back to the grouping of quarters into quintiles based upon aggregate flows, see Table 6. For the quarters with large outflows in quintile 1 the slope just before the 0.7 percentile is 0.420, while it is 0.570 for the quarters with large inflows in quintile 5. That is, in periods with high inflows the curve is steeper than in periods with large outflows. (The difference is highly significant with a t-ratio of 5.336.) We also observe that the magnitude of the kink at 0.7 increases monotonically from quintile 1 to quintile 5. If we relate the magnitude of the kink to the slope of the curve, we also observe a clear pattern: for quarters with high aggregate inflows the reduction in the slope is bigger than for quarters with high outflows. Put differently, the pattern we observe is consistent with funds closing to new investors once they get closer to the top part of the performance ranking, while the tendency of the funds to close is larger is the hypothetical flow-performance curve is steeper.

Even though the kink at the 0.3 percentile is less visible in the graph, we can perform a similar analysis in this region of the performance rank. In the bottom part of the graphs, where outflows are dominating, restrictions imposed by fund managers upon withdrawals become binding and this flattens the flow-performance relationship in the lower segment. If fund managers have some discretion in imposing such conditions or in their treatment of such conditions, the incentives to restrict outflows are larger when the hypothetical flow-performance relationship is steeper. This is exactly the mirror image of what happens in the positive segment. Manager have incentives to try to flatten the flow performance relationship towards the tails of the performance distribution and more so if the flow-performance relationship in the middle range is steeper.

The results in Table 6 confirm our interpretation. For periods with high inflows, the flow-performance relationship is somewhat flatter around the 0.3 percentile than for periods with large outflows. (Note that t=1.823 so significance is weak.) But the kink is much larger for latter quintile.

Note that while outflow restrictions are, to some extent, observable, this only holds for formal constraints. However, the information on these constraints in the TASS database does not vary over time and only the most recent status is available. In addition, the way in which hedge fund managers deal with these constraints may vary across market conditions, for example. That is, under some conditions a fund may be very strict in limiting its outflows, in other conditions they might be more flexible. (Can we give an anecdote here, or link to another paper??)

e) *Cross-Sectional analysis*

The results so far were based on aggregating across all funds within each quarter. The aggregation is probably hiding a large degree of heterogeneity in the flow-performance relationship across funds. In this section, we repeat the previous analysis focusing upon the shape of the flow-performance relationship around the kink points at 0.3 and 0.7, but we separate across one or more characteristics of the funds. Specifically, we use the switching regression model to construct the flow-performance relationship for hypothetical funds where all characteristics but one are fixed at the sample average (not the time dummies). The characteristics that is not fixed is set to two different values e.g. at the 10^{th} and 90^{th} percentile of the distribution. The convexity measures, slopes and kinks are than compared across the two groups. Our preliminary results indicate that the flow-performance relationship is steeper for smaller funds than for larger funds, while the kinks appear to be stronger for funds with higher incentive fees.

6. Robustness tests

In alternative specifications, we estimate separate models before and during the financial crisis (see results in the Appendix). We also checked the sensitivity of our results with respect to chosen kink points. For example, we have repeated our analyses using 0.25 and 0.75, 0.33 and 0.66, 0.20 and 0.80 as kink points. The results remain unchanged with these alternative specifications.

7. Concluding remarks

This paper uncovers a large variation in the shape of the flow-performance relationship in the hedge fund industry across market conditions. The switching regression approach that we follow in this paper, combined with a piecewise linear specification, tries to capture the differential responses of inflows and outflows to past performance in the hedge fund industry in a relatively parsimonious and more insightful way. In addition to allowing the immediate impact of inflows and outflows to be different, we also allow the response speed to differ. We are the first to characterize the shape of the flow-performance relationship and its degree of convexity in different segments of the curve by means of a number of convexity measures, and to analyze the variation of these measures across periods. Most interestingly, we relate to degree of convexity of the flow-performance relationship to the aggregate absolute flows to the industry and fund characteristics.

We show that, in most periods, the flow-performance is not evidently convex, as it is for mutual funds, nor concave. The form of the relationship varies over time but it typically reasonably close to linear or slightly convex for the first part of the curve, to become concave for the few top deciles of performers. This suggest that the best performing hedge funds are reluctant to accept new money, for example because of decreasing returns to scale (e.g. Getmansky, 2012). This effect is more pronounced in periods when aggregate inflows to the industry are high and also depends on the level of managerial incentives.

The shape of the flow-performance relationship, particularly the highly convex shape for mutual funds, is often linked to incentives for fund managers to engage in tournament behavior. In this literature it is argued that fund managers have an incentive to increase their risk taking behavior in the second half of the year when the performance has been poor, because the potential to gain is much larger than the potential to loose. Our results suggest that the time-varying nature of the shape of the flow-performance relation for hedge funds may imply notoriously more complex risk incentives for managers.

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Table 1

Aggregate Cash Flows and Assets Under Management

This table gives the total number of hedge funds in the sample per quarter, aggregate cash flows, total net assets under management and average return. The sample consists of 2451open-end hedge funds taken from TASS database, with a minimum of 4 quarters of quarterly returns history and with computed quarterly cash flows available at least for one year. Funds of funds are not included. The sample period has 63 quarters from 1995Q1 till 2010Q3. Cash flows are computed as the change in total net assets between consecutive quarters corrected for reinvestments. A growth rate is calculated as relative cash flows with respect to AUM of previous period.

	Number of Funds	Aggregate Cash Flows (million dollars)	Aggregate AUM (million dollars)	Average Return		Number of Funds	Aggregate Cash Flows (million dollars)	Aggregate AUM (million dollars)	Average Return
1995Q1	24	-16	1309.00	0.0563	2003Q1	628	1540	85837.00	0.0098
1995Q2	36	64	3392.12	0.0208	2003Q2	646	4530	95083.62	0.0756
1995Q3	57	-119	5102.74	0.0233	2003Q3	662	6040	105619.69	0.0390
1995Q4	83	-598	5991.32	0.0775	2003Q4	677	4850	115879.82	0.0552
1996Q1	107	277	7280.84	0.0159	2004Q1	678	10600	130113.19	0.0399
1996Q2	130	-21	8950.80	0.0604	2004Q2	688	7790	139637.88	-0.0236
1996Q3	150	41	10088.03	0.0092	2004Q3	686	2110	144560.80	0.0118
1996Q4	170	561	15132.53	0.0447	2004Q4	700	1230	158895.29	0.0581
1997Q1	192	1170	18572.39	0.0387	2005Q1	705	3560	165261.48	0.0031
1997Q2	208	-333	21009.81	0.0459	2005Q2	741	-2490	165065.51	0.0119
1997Q3	240	782	24135.02	0.0599	2005Q3	778	-697	179040.80	0.0574
1997Q4	262	-160	24708.09	-0.0270	2005Q4	792	-3470	187689.27	0.0245
1998Q1	289	1300	28018.25	0.0393	2006Q1	806	2480	203329.37	0.0621
1998Q2	316	467	28785.08	-0.0339	2006Q2	816	5880	211827.67	-0.0006
1998Q3	331	131	26179.86	-0.0839	2006Q3	810	4490	221030.58	0.0075
1998Q4	350	-2720	24244.38	0.0599	2006Q4	815	1410	230263.83	0.0552
1999Q1	386	-375	26598.27	0.0333	2007Q1	793	2160	217597.18	0.0228
1999Q2	422	341	30811.60	0.0895	2007Q2	812	8420	233241.59	0.0548
1999Q3	439	44	32104.67	0.0011	2007Q3	800	2640	223875.84	0.0125
1999Q4	445	773	37929.62	0.1406	2007Q4	827	502	235987.04	0.0153
2000Q1	445	694	45334.25	0.0659	2008Q1	812	1540	228997.41	-0.0294
2000Q2	457	-652	41814.54	-0.0354	2008Q2	829	503	232149.68	0.0152
2000Q3	463	-172	43537.92	0.0164	2008Q3	829	-1350	207728.43	-0.1010
2000Q4	468	-360	42598.38	-0.0406	2008Q4	791	-25400	165967.82	-0.0842
2001Q1	468	1800	47923.73	-0.0092	2009Q1	755	-17700	140929.07	0.0046
2001Q2	484	3250	53394.41	0.0406	2009Q2	745	-6360	133231.02	0.1107
2001Q3	529	2350	58848.31	-0.0418	2009Q3	773	1040	154252.25	0.0812
2001Q4	602	537	66467.33	0.0416	2009Q4	773	2380	160268.16	0.0220
2002Q1	595	3100	70285.82	0.0134	2010Q1	763	-836	141515.78	0.0228
2002Q2	604	2100	73655.60	0.0064	2010Q2	739	1260	140517.74	-0.0290
2002Q3	618	740	74942.55	-0.0235	2010Q3	706	-1910	133971.06	0.0631
2002Q4	629	-567	77995.70	0.0245					

Table 2

Distributions of Flows and Assets under Management

This table shows the cross-sectional distribution of cash flows and total net assets under management in our sample of 2451 open-end hedge funds from 1995Q1 till 2010Q3. Cash flows are computed as the change in total net assets between consecutive quarters corrected for reinvestments. A growth rate is calculated as relative cash flows with respect to the fund's AUM of the previous quarter.

Percentile	Cash Flows (growth rate)	Cash Flows (dollars)	Assets Under Management (million dollars)
99%	0.9951	1.76E+08	2500
95%	0.3446	4.63E+07	781.44
90%	0.1872	1.90E+07	425.32
75%	0.0510	2464053	151.60
50%	-0.0003	-2769.16	47.97
25%	-0.0617	-2697553	12.92
10%	-0.1956	-1.74E+07	4.00
5%	-0.3233	-4.12E+07	1.9207
1%	-0.6466	-1.60E+08	0.4489

Table 3

Cross-Sectional Characteristics of the Hedge Fund Sample

This table presents summary statistics on cross-sectional characteristics of our sample of 2451 hedge funds for the period 1995Q1 till 2010Q3. Cash flows are the change in assets under management between consecutive quarters corrected for reinvestments. Returns are net of all management and incentive fees. Age is the number of months a fund has been in operation since its inception. In each quarter, the historical standard deviation of monthly returns, semi deviation and upside potential have been computed based on the entire past history of the fund. Semi deviation and upside potential are calculated with respect to the return on the US Treasury bill taken as the minimum investor's target. Offshore is a dummy variable with value one for non U.S. domiciled funds. Incentive fee is a percentage of profits above a hurdle rate that is given as a reward to managers. Management fee is a percentage of the fund's net assets under management that is paid annually to managers for administering a fund. Personal capital is a dummy variable indicating that the manager invests from her own wealth in the fund. We include 10 dummies for investment styles defined on the basis of the CSFB/Tremont indices.

Variable	Mean	Std. Dev.	Min	Max
Cash Flows (growth rate)	0.0844	0.5010	-0.9653	5.7814
Cash Flows>0 (16686 obs)	0.2569	0.6171	4.50E-10	5.7814
Cash Flows<0 (17680 obs)	-0.1167	0.1601	-1.7473	-6.22E-10
Cash Flows=0 (8 obs)	-2.54E-09	1.87E-08	-1.15E-07	0
Cash Flows (dollars)	2176105	7.26E+07	-2.78E+09	9.07E+09
ln(TNA)	17.1543	1.8971	1.4609	23.2966
ln(AGE)	3.5856	1.0927	0	5.9940
Quarterly Returns	0.0271	0.3382	-1	87.8542
Historical St.Dev.	0.0445	0.0562	0	11.0165
Downside-Upside Pot. Ratio	1.64E+11	4.44E+13	0.00E+00	1.21E+16
Offshore	0.6967	0.4597	0	1
Incentive Fee	18.6183	5.2312	0	50
Management Fees	1.4989	0.7121	0	10
Personal Capital	0.4528	0.4978	0	1
Leverage	0.6899	0.4625	0	1
Convertible Arbitrage	0.0392	0.1941	0	1
Dedicated Short Bias	0.0099	0.0988	0	1
Emerging Markets	0.1324	0.3389	0	1
Equity Market Neutral	0.0533	0.2247	0	1
Event Driven	0.1177	0.3222	0	1
Fixed Income Arbitrage.	0.0439	0.2050	0	1
Global Macro	0.0683	0.2523	0	1
Long/Short Equity	0.3866	0.4870	0	1
Managed Futures	0.1204	0.3255	0	1
Hedge Fund Index	0.0283	0.1658	0	1

Table 4

Switching Regression Model Explaining Positive and Negative Cash Flows

Column A reports OLS coefficients estimates using a piecewise linear model explaining cash flows. Columns B, C and D report the coefficient estimates of the three equations of a switching regression model explaining positive and negative flows. The sample includes 2451 open-end hedge funds for the period 1995 Q1 till 2010 Q3. We measure cash flows as a quarterly growth rate corrected for reinvestments. The independent variables that account for relative performance include six lagged fractional ranks. The fractional rank ranges from 0 to 1 and is defined as the fund's percentile performance relative to all the funds existing in the sample in the same period, based on the fund's raw return in previous quarter. Independent variables accounting for fund specific characteristics include the log of fund's total net assets in the prior quarter, the log of fund's age in months since inception, four lagged measures of flows, downside-upside potential ratio based on the entire past history of the fund and calculated with respect to the return on the US treasury bill, a dummy variable taking value one for offshore funds, incentive fee as a percentage of profits given as a reward to managers, management fee as a percentage of the fund's net assets under management, a dummy taking value one if the manager's personal capital is invested in the fund and seven dummies for investment styles defined on the basis of CSFB/Tremont indices. The model also includes 62 time dummies (estimates not reported). The two models using the truncated samples also incorporate as explanatory variable the generalized residual obtained from a probit model explaining the regime of flows (loglikelihood estimates reported in column A. The dependent variable takes the value 1 if net cash flows are strictly positive). We estimate each model by pooling all fund-period observations. T-statistics based on robust standard errors as well as z-statistics for probit estimates are provided in parentheses.

Parameters	Piecewise Linear Model (A)	Regime Switching Model with Piecewise Linear: Probit model explaining sign of cash flows (B)	OLS for CFlows <0 (truncated sample) (C)	OLS for CFlows > 0 (truncated sample) (D)
Intercept	0.5526 (3.05)	0.1138 (0.42)	0.0760 (1.42)	0.5786 (1.87)
Liquidity Restrictions	0.0108 (2.06)	0.1092 (3.69)	0.0284 (5.43)	0.0481 (4.06)
Rank lag 1	0.1436 (7.85)	0.8430 (12.81)	0.2066 (7.43)	0.4684 (7.80)
Three Bottom Deciles	-0.0249 (-0.59)	-0.3597 (-2.15)	-0.0278 (-0.96)	-0.1303 (-1.68)
Three Top Deciles	-0.0543 (-1.13)	-0.5714 (-3.56)	-0.1405 (-4.32)	-0.2415 (-2.81)
Rank lag 2	0.1284 (7.90)	0.7605 (11.08)	0.2038 (8.14)	0.4181 (7.37)
Three Bottom Deciles	-0.0551 (-1.31)	-0.3010 (-1.78)	-0.0794 (-2.88)	-0.1426 (-1.64)
Three Top Deciles	-0.1401 (-3.41)	-0.7772 (-4.52)	-0.2247 (-6.77)	-0.4396 (-5.46)
Rank lag 3	0.0694 (4.07)	0.6229 (9.22)	0.1621 (7.74)	0.2842 (5.43)
Three Bottom Deciles	0.0027 (0.06)	-0.4815 (-2.88)	-0.1452 (-4.76)	-0.0474 (-0.53)
Three Top Deciles	-0.0073 (-0.18)	-0.7090 (-4.25)	-0.1749 (-5.64)	-0.2236 (-2.64)
Rank lag 4	0.0665 (3.97)	0.4585 (6.81)	0.1294 (7.81)	0.2310 (5.57)
Three Bottom Deciles	-0.0094 (-0.23)	-0.2846 (-1.70)	-0.1296 (-4.78)	-0.0013 (-0.02)
Three Top Deciles	-0.0151 (-0.34)	-0.5016 (-3.08)	-0.1206 (-4.20)	-0.1804 (-2.31)
Ln(TNA)	-0.0245 (-10.42)	-0.0155 (-2.44)	-0.0039 (-3.71)	-0.0511 (-10.19)
Ln(AGE)	-0.0179 (-5.25)	-0.1434 (-9.06)	-0.0054 (-1.10)	-0.0949 (-8.27)
Flows lag 1	0.0875 (9.16)	0.3942 (9.48)	0.1332 (9.32)	0.1764 (8.12)
Flows lag 2	0.0517 (5.93)	0.2119 (8.16)	0.0573 (6.82)	0.1245 (6.58)
Flows lag 3	0.0196 (3.67)	0.1365 (6.31)	0.0341 (4.93)	0.0571 (5.44)
Flows lag 4	0.0138 (2.19)	0.0703 (4.11)	0.0136 (2.94)	0.0419 (3.98)
Offshore	-0.0110 (-2.23)	0.0558 (2.41)	0.0382 (9.53)	-0.0353 (-3.43)
Incentive Fees	0.0002 (0.44)	0.0012 (0.54)	-0.0005 (-1.74)	0.0019 (2.24)
Management Fees	0.0012 (0.26)	-0.0075 (-0.41)	-0.0063 (-2.21)	0.0068 (0.74)
Personal Capital	-0.0011 (-0.24)	-0.0156 (-0.71)	0.0068 (2.01)	-0.0219 (-2.58)
Leverage	0.0051 (1.20)	-0.0127 (-0.53)	-0.0061 (-1.71)	0.0101 (1.23)
Downside-Upside Pot. Ratio	-0.0182 (-6.78)	-0.0366 (-2.84)	-0.0059 (-2.66)	-0.0455 (-7.85)
Emerging Markets	-0.0335 (-4.24)	-0.1161 (-2.63)	-0.0008 (-0.10)	-0.1208 (-7.10)
Equity Market Neutral	0.0083 (0.72)	-0.0126 (-0.25)	-0.0106 (-1.17)	0.0313 (1.36)
Event Driven	0.0043 (0.57)	0.0001 (0.00)	0.0017 (0.25)	0.0069 (0.50)
Fixed Income Arbitrage.	0.0129 (1.16)	-0.0575 (-1.07)	-0.0140 (-1.60)	0.0105 (0.48)
Global Macro	0.0149 (1.36)	0.0791 (1.44)	0.0135 (1.48)	0.0637 (2.97)
Long/Short Equity	-0.0207 (-3.21)	-0.0707 (-1.91)	-0.0129 (-2.03)	-0.0607 (-4.59)
Managed Futures	-0.0048 (-0.45)	0.0154 (0.30)	0.0007 (0.09)	0.0125 (0.61)
Generalized Residual from Probit Model			0.3239 (6.55)	0.7704 (6.86)
Chi^2 (80)		2262.32		
Pseudo R^2	0.0827	0.094	0.0881	0.0739
Number of observations	34374	34366	17680	16686

Table 5

Measuring the Convexity of the Flow-Performance Relation

We sort all 63 periods by the total dollar flows into our hedge fund sample and then divide these periods into five groups (quintiles). Quintile 1 contains the 12 quarters with the largest outflows, while quintile 5 contains the 12 quarter with the largest inflows. For each quintile, *Alpha* is referred to as the marginal change in slope of the average flow-performance relation for a given rank change δ. If *Alpha* is positive, the curve is locally convex. Otherwise, the curve is locally concave. The Table reports two measures characterizing the convexity of the average flow-performance relation for each quintile: first, the convexity ratio, defined as the proportion of convex segments along the curve. Second, the total sum of *Alphas* along the curve. We calculate the convexity ratio and the Σ*Alpha* for the curve overall, for the portion below the median and the portion above the median (standard deviations reported in parentheses). We employ three different values of δ in Panel A, B and C. The Table also reports the convexity difference between the top and bottom quintiles (t-test in parenthesis).

Panel A: Convexity measures of the Flow-Performance Relation for Rank change δ=0.01

Quintile	Average Flows	No Periods	(A) Convexity Ratio Overall	(B) Convexity Ratio BelowMedian	(C) Convexity Ratio AboveMedian	(D) ΣAlpha Overall	(E) ΣAlpha Below Median	(F) ΣAlpha Above Median
1	-8.020	12	0.762 (0.11)	0.649 (0.10)	0.873 (0.15)	-0.075 (0.04)	0.098 (0.03)	-0.173 (0.06)
2	-0.390	13	0.850 (0.06)	0.721 (0.11)	0.977 (0.01)	-0.057 (0.02)	0.115 (0.06)	-0.172 (0.08)
3	1.423	13	0.846 (0.04)	0.714 (0.07)	0.975 (0.02)	-0.054 (0.01)	0.118 (0.03)	-0.172 (0.04)
4	3.318	13	0.894 (0.04)	0.807 (0.09)	0.980 (0.00)	-0.038 (0.02)	0.132 (0.03)	-0.170 (0.04)
5	8.033	12	0.928 (0.04)	0.874 (0.09)	0.980 (0.00)	-0.030 (0.01)	0.149 (0.04)	-0.180 (0.05)
Difference Top-Bottom (t-test)			0.165 (4.72)	0.225 (6.01)	0.107 (2.39)	0.045 (3.42)	0.051 (3.33)	-0.006 (-0.28)

Panel B: Convexity measures of the Flow-Performance Relation for Rank change δ=0.05

Quintile	Average Flows	No Periods	Convexity Ratio Overall	Convexity Ratio BelowMedian	Convexity Ratio AboveMedian	ΣAlpha Overall	ΣAlpha Below Median	ΣAlpha Above Median
1	-8.020	12	0.737 (0.11)	0.694 (0.08)	0.775 (0.16)	-0.077 (0.04)	0.099 (0.03)	-0.176 (0.07)
2	-0.390	13	0.822 (0.06)	0.752 (0.11)	0.885 (0.04)	-0.059 (0.02)	0.111 (0.05)	-0.170 (0.07)
3	1.423	13	0.818 (0.04)	0.735 (0.07)	0.892 (0.03)	-0.057 (0.01)	0.113 (0.03)	-0.170 (0.04)
4	3.318	13	0.866 (0.05)	0.829 (0.11)	0.900 (0.00)	-0.042 (0.02)	0.123 (0.03)	-0.164 (0.04)
5	8.033	12	0.899 (0.04)	0.898 (0.09)	0.900 (0.00)	-0.034 (0.01)	0.137 (0.04)	-0.171 (0.05)
Difference Top-Bottom (t-test)			0.162 (4.70)	0.204 (5.80)	0.125 (2.70)	0.043 (3.30)	0.038 (2.57)	0.005 (0.21)

Panel C: Convexity measures of the Flow-Performance Relation for Rank change δ=0.1

Quintile	Average Flows	No Periods	Convexity Ratio Overall	Convexity Ratio BelowMedian	Convexity Ratio AboveMedian	ΣAlpha Overall	ΣAlpha Below Median	ΣAlpha Above Median
1	-8.020	12	0.704 (0.11)	0.771 (0.07)	0.650 (0.17)	-0.079 (0.04)	0.102 (0.03)	-0.182 (0.07)
2	-0.390	13	0.786 (0.07)	0.808 (0.11)	0.769 (0.08)	-0.063 (0.02)	0.108 (0.05)	-0.171 (0.07)
3	1.423	13	0.778 (0.05)	0.769 (0.07)	0.785 (0.06)	-0.060 (0.01)	0.110 (0.03)	-0.170 (0.04)
4	3.318	13	0.838 (0.06)	0.885 (0.13)	0.800 (0.00)	-0.046 (0.02)	0.114 (0.03)	-0.160 (0.03)
5	8.033	12	0.861 (0.05)	0.938 (0.11)	0.800 (0.00)	-0.040 (0.01)	0.123 (0.03)	-0.163 (0.05)
Difference Top-Bottom (t-test)			0.157 (4.53)	0.167 (4.30)	0.150 (3.00)	0.040 (3.14)	0.021 (1.51)	0.019 (0.77)

Table 6

Switching Regression Model Explaining Positive and Negative Cash Flows

We sort all 63 periods by the total dollar flows into our hedge fund sample and then divide these periods into five groups (quintiles). Quintile 1 contains the 12 quarters with the largest outflows, while quintile 5 contains the 12 quarter with the largest inflows. For each quintile, *Alpha* is referred to as the marginal change in slope of the average flow-performance relation for a given rank change δ. If *Alpha* is positive, the curve is locally convex. Otherwise, the curve is locally concave. The Table reports the average *Alpha* for each quintile at the two kinks in our specification model (70th pc and 30th pc) (Standard deviations in parentheses). We also report the slopes of the curve at the two kinks. Finally, we report the ratio of the kink to the slope, which is an indication of flow restrictions in the demand side of capital. Finally, the table reports the differences between the top and bottom quintiles (t-test in parenthesis). We employ three different values of δ in Panel A, B and C.

Panel A: Rank change δ=0.01

Quintile	Average Flows	No Periods	Kink 70th pc	Kink 30th pc	Slope prior to 70th pc	Slope after 30th pc	Kink/Slope 70th pc	Kink/Slope 30th pc
1	-8.020	12	-0.239 (0.05)	0.123 (0.06)	0.420 (0.07)	0.419 (0.06)	-0.569 (0.04)	0.282 (0.10)
2	-0.390	13	-0.286 (0.08)	0.096 (0.02)	0.489 (0.09)	0.411 (0.06)	-0.578 (0.04)	0.231 (0.04)
3	1.423	13	-0.290 (0.04)	0.095 (0.02)	0.493 (0.05)	0.408 (0.03)	-0.585 (0.03)	0.230 (0.04)
4	3.318	13	-0.318 (0.04)	0.068 (0.02)	0.533 (0.06)	0.388 (0.03)	-0.595 (0.02)	0.172 (0.05)
5	8.033	12	-0.345 (0.05)	0.050 (0.02)	0.570 (0.07)	0.382 (0.04)	-0.603 (0.02)	0.130 (0.04)
Difference (t-test)			-0.106 (-5.08)	-0.073 (-4.10)	0.150 (5.34)	-0.037 (-1.82)	-0.034 (-2.57)	-0.152 (-4.83)

Panel B: Rank change δ=0.05

Quintile	Average Flows	No Periods	Kink 70th pc	Kink 30th pc	Slope prior to 70th pc	Slope after 30th pc	Kink/Slope 70th pc	Kink/Slope 30th pc
1	-8.020	12	-0.227 (0.04)	0.117 (0.06)	0.408 (0.07)	0.410 (0.06)	-0.556 (0.05)	0.275 (0.10)
2	-0.390	13	-0.269 (0.08)	0.093 (0.03)	0.473 (0.09)	0.403 (0.07)	-0.561 (0.05)	0.228 (0.03)
3	1.423	13	-0.273 (0.04)	0.092 (0.02)	0.476 (0.05)	0.401 (0.03)	-0.570 (0.03)	0.228 (0.04)
4	3.318	13	-0.299 (0.04)	0.068 (0.02)	0.515 (0.06)	0.383 (0.03)	-0.579 (0.02)	0.176 (0.05)
5	8.033	12	-0.326 (0.06)	0.053 (0.02)	0.551 (0.07)	0.379 (0.04)	-0.589 (0.03)	0.139 (0.04)
Difference (t-test)			-0.099 (-4.84)	-0.064 (-3.75)	0.143 (5.27)	-0.031 (-1.50)	-0.033 (-2.13)	-0.136 (-4.51)

Panel C: Rank change δ=0.1

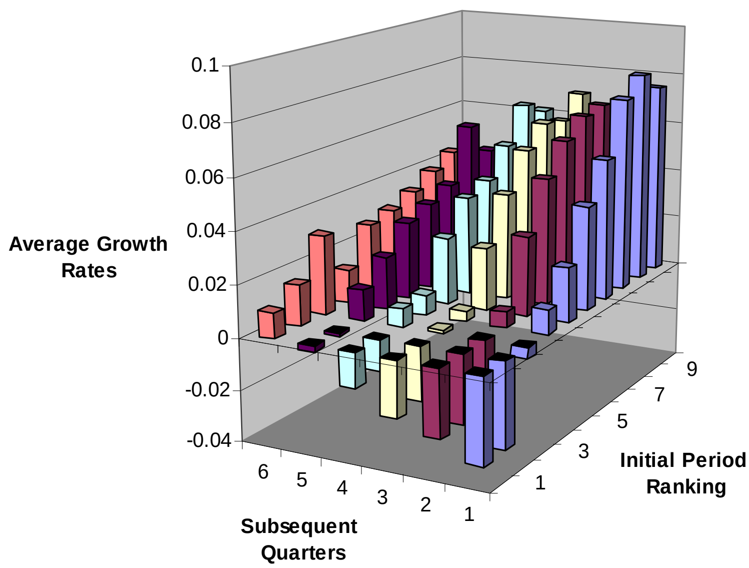
Quintile	Average Flows	No Periods	Kink 70th pc	Kink 30th pc	Slope prior to 70th pc	Slope after 30th pc	Kink/Slope 70th pc	Kink/Slope 30th pc
1	-8.020	12	-0.214 (0.04)	0.111 (0.05)	0.395 (0.06)	0.399 (0.06)	-0.540 (0.05)	0.267 (0.09)
2	-0.390	13	-0.251 (0.08)	0.091 (0.03)	0.455 (0.09)	0.396 (0.07)	-0.541 (0.05)	0.225 (0.03)
3	1.423	13	-0.254 (0.04)	0.090 (0.02)	0.458 (0.05)	0.393 (0.04)	-0.551 (0.03)	0.228 (0.04)
4	3.318	13	-0.277 (0.04)	0.071 (0.02)	0.493 (0.05)	0.379 (0.03)	-0.560 (0.03)	0.184 (0.04)
5	8.033	12	-0.302 (0.06)	0.060 (0.02)	0.528 (0.07)	0.378 (0.04)	-0.569 (0.03)	0.156 (0.03)
Difference (t-test)			-0.088 (-4.41)	-0.051 (-3.20)	0.132 (5.11)	-0.021 (-1.03)	-0.029 (-1.59)	-0.111 (-3.97)

Figure 1

Average Flows across Deciles
Over Subsequent Quarters after Ranking

In each quarter from 1995Q1 to 2010Q3 funds are ranked into decile portfolios based on their past quarter raw returns. For the quarter subsequent to initial ranking and for each of the next 6 quarters after formation, we compute the average growth rate (Panel A) and the average dollar flows (Panel B) of all funds in each decile portfolio. Thus, the bar in cell *(i,j)* represents average flows (net of reinvestments) in the j^{th} quarter after initial ranking of funds ranked in decile *i*. Decile 10 corresponds to the best performers.

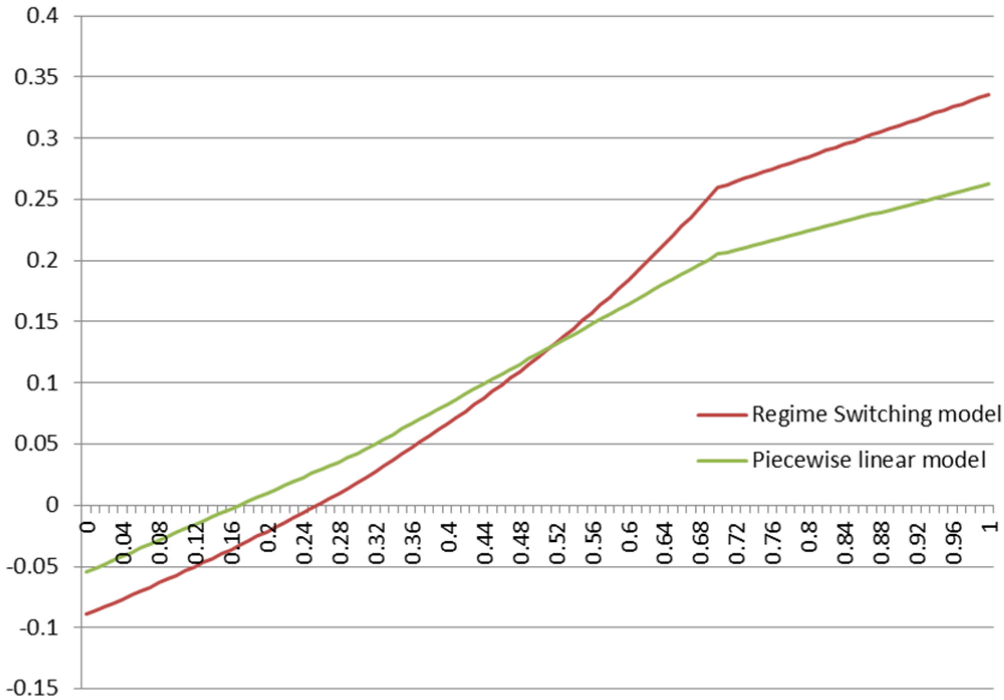
Panel A



Panel B

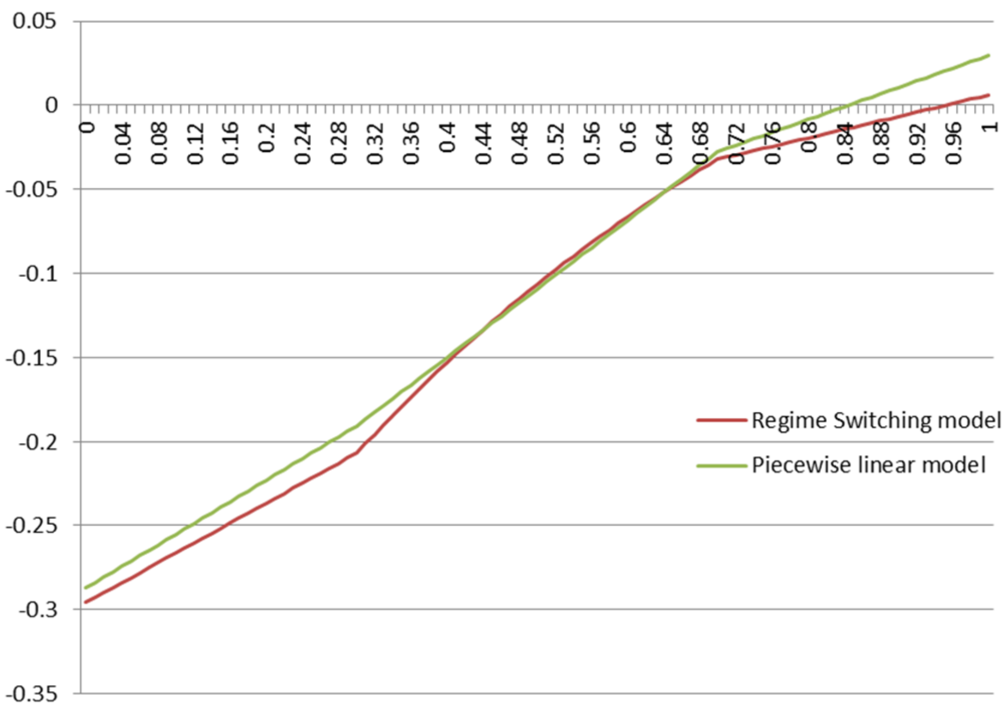
<u>Figure 2</u>

Flow-Performance Relation for Hedge Funds in 2004Q1
Regime Switching model vs Piecewise Linear Model



<u>Figure 3</u>

Flow-Performance Relation for Hedge Funds in 2008Q4
Regime Switching model vs Piecewise Linear Model



<u>Figure 4</u>
Average Flow-Performance Relation for Top and Bottom Quintiles
(Quintiles Based on Total Cash Flows in a Quarter)

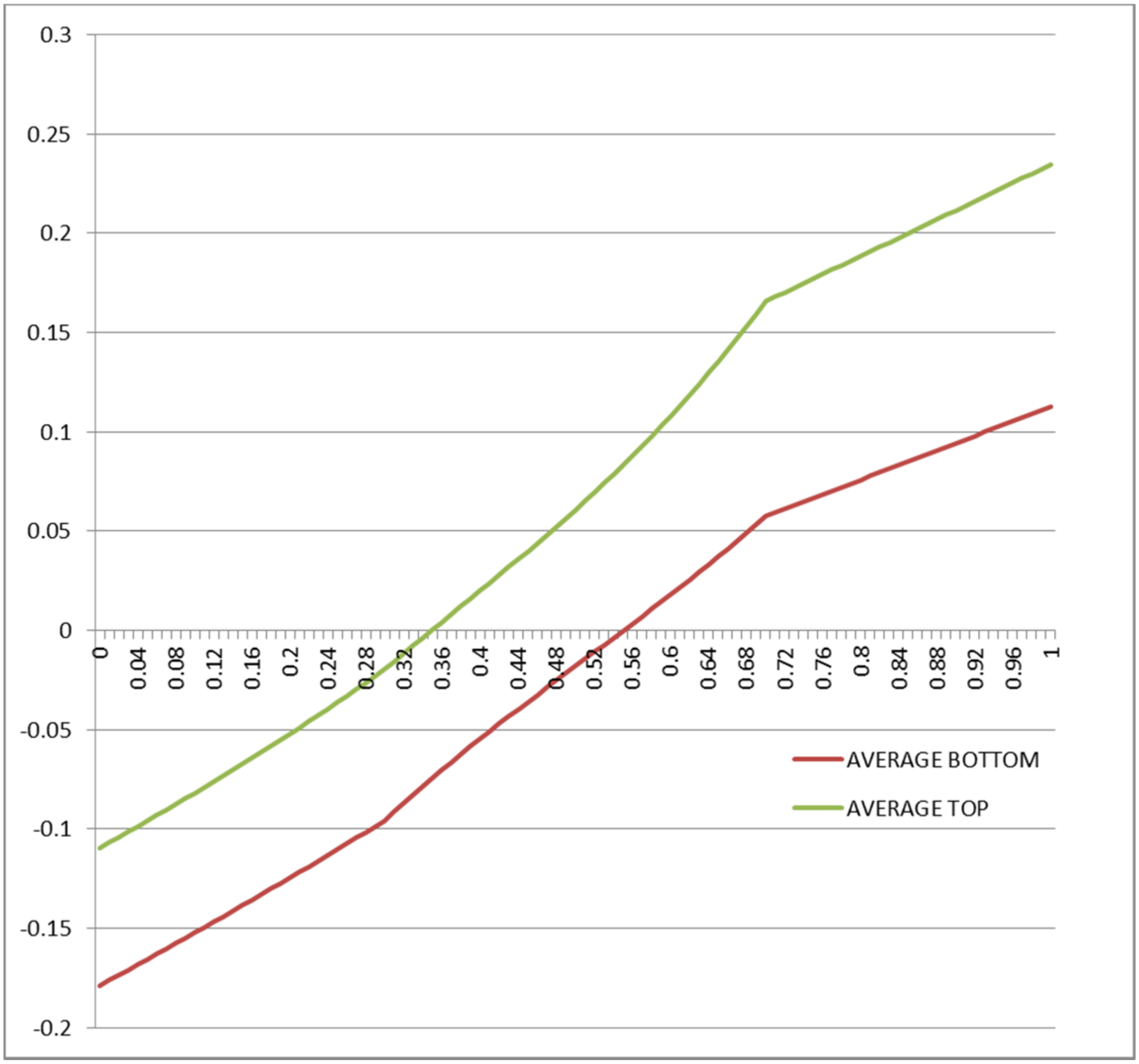
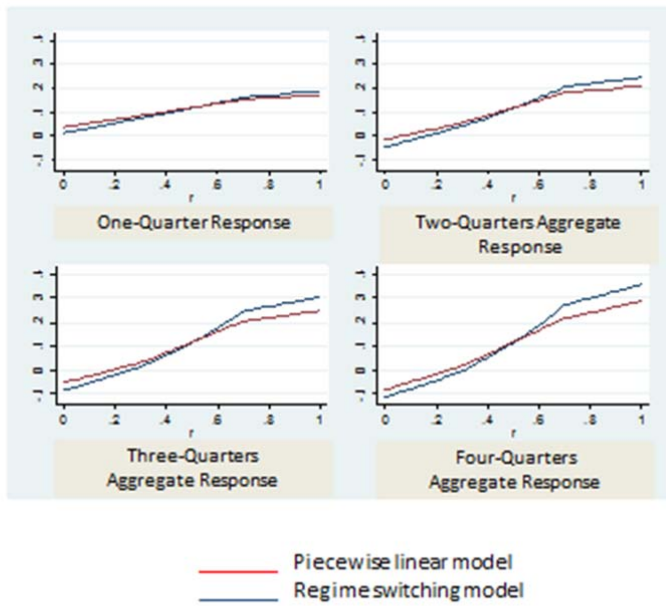


Figure 5

The Dynamics of the Flow-Performance Relation for Hedge Funds (The curves correspond to 2004Q1)



APPENDIX

Table A1

BEFORE THE CRISIS

Switching Regression Model Explaining Positive and Negative Cash Flows

Column A reports OLS coefficients estimates using a piecewise linear model explaining cash flows. Columns B, C and D report the coefficient estimates of the three equations of a switching regression model explaining positive and negative flows. The sample includes 2451 open-end hedge funds for the period 1995 Q1 till 2010 Q3. We measure cash flows as a quarterly growth rate corrected for reinvestments. The independent variables that account for relative performance include six lagged fractional ranks. The fractional rank ranges from 0 to 1 and is defined as the fund's percentile performance relative to all the funds existing in the sample in the same period, based on the fund's raw return in previous quarter. Independent variables accounting for fund specific characteristics include the log of fund's total net assets in the prior quarter, the log of fund's age in months since inception, four lagged measures of flows, downside-upside potential ratio based on the entire past history of the fund and calculated with respect to the return on the US treasury bill, a dummy variable taking value one for offshore funds, incentive fee as a percentage of profits given as a reward to managers, management fee as a percentage of the fund's net assets under management, a dummy taking value one if the manager's personal capital is invested in the fund and seven dummies for investment styles defined on the basis of CSFB/Tremont indices. The model also includes 62 time dummies (estimates not reported). The two models using the truncated samples also incorporate as explanatory variable the generalized residual obtained from a probit model explaining the regime of flows (loglikelihood estimates reported in column A. The dependent variable takes the value 1 if net cash flows are strictly positive). We estimate each model by pooling all fund-period observations. T-statistics based on robust standard errors as well as z-statistics for probit estimates are provided in parentheses.

Parameters	Piecewise Linear Model (A)	Regime Switching Model with Piecewise Linear: Probit model explaining sign of cash flows (B)	OLS for CFlows <0 (truncated sample) (C)	OLS for CFlows > 0 (truncated sample) (D)
Intercept	0.5451 (2.99)	-0.1310 (-0.45)	0.0482 (0.88)	0.6325 (1.99)
Liquidity Restrictions	0.0145 (2.27)	0.1262 (3.52)	0.0350 (5.22)	0.0499 (3.53)
Rank lag 1	0.1695 (7.40)	0.8580 (10.70)	0.2384 (7.02)	0.4325 (7.13)
Three Bottom Deciles	-0.0160 (-0.32)	-0.1537 (-0.76)	0.0165 (0.51)	-0.0319 (-0.35)
Three Top Deciles	-0.1077 (-1.73)	-0.5555 (-2.74)	-0.1535 (-4.00)	-0.2840 (-2.97)
Rank lag 2	0.1453 (7.36)	0.8684 (10.06)	0.2504 (7.58)	0.3955 (6.29)
Three Bottom Deciles	-0.0689 (-1.34)	-0.3668 (-1.75)	-0.0940 (-2.76)	-0.1702 (-1.67)
Three Top Deciles	-0.1203 (-2.37)	-0.7114 (-3.33)	-0.2094 (-5.54)	-0.3336 (-3.78)
Rank lag 3	0.1156 (5.78)	0.7964 (9.26)	0.2254 (7.30)	0.3400 (5.36)
Three Bottom Deciles	-0.0698 (-1.29)	-0.6217 (-2.98)	-0.1915 (-4.80)	-0.1851 (-1.80)
Three Top Deciles	-0.0512 (-0.96)	-0.9770 (-4.61)	-0.2469 (-5.62)	-0.3026 (-2.75)
Rank lag 4	0.0664 (3.35)	0.5509 (6.54)	0.1764 (7.67)	0.1986 (4.10)
Three Bottom Deciles	-0.0129 (-0.25)	-0.3650 (-1.77)	-0.1775 (-5.23)	0.0055 (0.06)
Three Top Deciles	0.0237 (0.41)	-0.6434 (-3.10)	-0.1672 (-4.37)	-0.1099 (-1.13)
Ln(TNA)	-0.0238 (-8.77)	-0.0064 (-0.82)	-0.0012 (-0.99)	-0.0479 (-8.64)
Ln(AGE)	-0.0208 (-5.04)	-0.1631 (-7.93)	-0.0158 (-2.43)	-0.0843 (-6.11)
Flows lag 1	0.0901 (8.02)	0.3694 (7.33)	0.1335 (8.11)	0.1529 (6.94)
Flows lag 2	0.0605 (5.18)	0.2166 (6.67)	0.0643 (5.76)	0.1237 (5.80)
Flows lag 3	0.0174 (2.66)	0.1321 (5.00)	0.0384 (5.04)	0.0414 (3.75)
Flows lag 4	0.0183 (2.33)	0.0685 (3.39)	0.0175 (3.31)	0.0413 (3.13)
Offshore	-0.0163 (-2.80)	0.0697 (2.46)	0.0394 (7.95)	-0.0431 (-3.68)
Incentive Fees	-0.0001 (-0.14)	0.0014 (0.49)	-0.0006 (-1.68)	0.0014 (1.36)
Management Fees	0.0013 (0.23)	0.0103 (0.43)	-0.0054 (-1.63)	0.0164 (1.53)
Personal Capital	-0.0080 (-1.50)	-0.0451 (-1.69)	-0.0029 (-0.67)	-0.0361 (-3.64)
Leverage	0.0033 (0.61)	0.0012 (0.04)	-0.0004 (-0.10)	0.0080 (0.83)
Downside-Upside Pot. Ratio	-0.0180 (-5.64)	-0.0363 (-2.48)	-0.0052 (-2.16)	-0.0451 (-7.05)
Emerging Markets	-0.0430 (-4.14)	-0.1171 (-2.07)	-0.0150 (-1.53)	-0.1100 (-5.46)
Equity Market Neutral	0.0073 (0.54)	-0.0103 (-0.17)	-0.0108 (-1.00)	0.0276 (1.06)
Event Driven	0.0023 (0.26)	0.0076 (0.15)	-0.0008 (-0.10)	0.0077 (0.50)
Fixed Income Arbitrage.	0.0100 (0.89)	-0.0394 (-0.64)	-0.0044 (-0.45)	0.0090 (0.45)
Global Macro	-0.0025 (-0.20)	0.0345 (0.55)	0.0032 (0.28)	0.0161 (0.71)
Long/Short Equity	-0.0266 (-3.51)	-0.0783 (-1.75)	-0.0204 (-2.72)	-0.0605 (-4.01)
Managed Futures	-0.0126 (-0.91)	-0.0136 (-0.20)	-0.0053 (-0.53)	-0.0097 (-0.37)
Generalized Residual from Probit Model			0.3725 (6.50)	0.6164 (5.25)
Chi^2 (80)		1669.03		
Pseudo R^2	0.0932	0.1009	0.0772	0.0846

Number of observations	23420	23415	11457	11958

Table A2

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Switching Regression Model Explaining Positive and Negative Cash Flows

Column A reports OLS coefficients estimates using a piecewise linear model explaining cash flows. Columns B, C and D report the coefficient estimates of the three equations of a switching regression model explaining positive and negative flows. The sample includes 2451 open-end hedge funds for the period 1995 Q1 till 2010 Q3. We measure cash flows as a quarterly growth rate corrected for reinvestments. The independent variables that account for relative performance include six lagged fractional ranks. The fractional rank ranges from 0 to 1 and is defined as the fund's percentile performance relative to all the funds existing in the sample in the same period, based on the fund's raw return in previous quarter. Independent variables accounting for fund specific characteristics include the log of fund's total net assets in the prior quarter, the log of fund's age in months since inception, four lagged measures of flows, downside-upside potential ratio based on the entire past history of the fund and calculated with respect to the return on the US treasury bill, a dummy variable taking value one for offshore funds, incentive fee as a percentage of profits given as a reward to managers, management fee as a percentage of the fund's net assets under management, a dummy taking value one if the manager's personal capital is invested in the fund and seven dummies for investment styles defined on the basis of CSFB/Tremont indices. The model also includes 62 time dummies (estimates not reported). The two models using the truncated samples also incorporate as explanatory variable the generalized residual obtained from a probit model explaining the regime of flows (loglikelihood estimates reported in column A. The dependent variable takes the value 1 if net cash flows are strictly positive). We estimate each model by pooling all fund-period observations. T-statistics based on robust standard errors as well as z-statistics for probit estimates are provided in parentheses.

Parameters	Piecewise Linear Model (A)	Regime Switching Model with Piecewise Linear: Probit model explaining sign of cash flows (B)	OLS for CFlows <0 (truncated sample) (C)	OLS for CFlows > 0 (truncated sample) (D)
Intercept	0.4476 (5.77)	0.8898 (3.62)	0.4263 (3.36)	0.6228 (3.63)
Liquidity Restrictions	0.0048 (0.60)	0.0770 (1.73)	0.0281 (3.72)	0.0342 (1.62)
Rank lag 1	0.0910 (3.02)	0.8202 (7.00)	0.2615 (5.50)	0.4906 (2.86)
Three Bottom Deciles	-0.0486 (-0.65)	-0.8070 (-2.75)	-0.2040 (-3.19)	-0.4425 (-2.09)
Three Top Deciles	0.0609 (0.81)	-0.5618 (-2.08)	-0.1838 (-3.22)	-0.0867 (-0.44)
Rank lag 2	0.0960 (3.29)	0.5449 (4.76)	0.2128 (6.28)	0.3858 (3.12)
Three Bottom Deciles	-0.0206 (-0.28)	-0.1533 (-0.54)	-0.0938 (-2.01)	-0.0237 (-0.15)
Three Top Deciles	-0.1665 (-2.42)	-0.8243 (-2.93)	-0.3319 (-5.56)	-0.6365 (-3.22)
Rank lag 3	-0.0243 (-0.75)	0.3038 (2.70)	0.1214 (5.09)	0.0346 (0.37)
Three Bottom Deciles	0.1601 (1.85)	-0.2007 (-0.72)	-0.1219 (-2.53)	0.4094 (2.18)
Three Top Deciles	0.0988 (1.53)	-0.1364 (-0.49)	-0.0963 (-2.33)	0.1872 (1.44)
Rank lag 4	0.0669 (2.08)	0.2949 (2.52)	0.1034 (4.53)	0.2454 (2.76)
Three Bottom Deciles	-0.0057 (-0.08)	-0.1953 (-0.66)	-0.1100 (-2.38)	-0.0116 (-0.07)
Three Top Deciles	-0.0902 (-1.24)	-0.2266 (-0.81)	-0.0819 (-1.80)	-0.2566 (-1.80)
Ln(TNA)	-0.0267 (-6.20)	-0.0376 (-3.76)	-0.0137 (-5.30)	-0.0654 (-5.70)
Ln(AGE)	-0.0148 (-2.57)	-0.1140 (-4.50)	-0.0050 (-0.73)	-0.1149 (-4.63)
Flows lag 1	0.0724 (4.14)	0.4118 (5.79)	0.1845 (6.89)	0.2078 (3.49)
Flows lag 2	0.0258 (2.46)	0.1815 (4.24)	0.0671 (5.23)	0.0946 (2.85)
Flows lag 3	0.0204 (2.21)	0.1399 (3.97)	0.0423 (2.91)	0.0828 (3.04)
Flows lag 4	-0.0034 (-0.38)	0.0666 (2.03)	0.0114 (1.44)	0.0295 (1.75)
Offshore	0.0019 (0.22)	0.0218 (0.59)	0.0392 (6.98)	-0.0275 (-1.38)
Incentive Fees	0.0005 (0.90)	0.0004 (0.11)	-0.0007 (-1.37)	0.0028 (2.57)
Management Fees	0.0026 (0.44)	-0.0346 (-0.98)	-0.0073 (-1.74)	-0.0198 (-1.25)
Personal Capital	0.0126 (1.75)	0.0449 (1.32)	0.0260 (4.75)	0.0277 (1.56)
Leverage	0.0098 (1.47)	-0.0385 (-1.14)	-0.0179 (-3.22)	0.0122 (0.76)
Downside-Upside Pot. Ratio	-0.0174 (-3.74)	-0.0342 (-1.49)	-0.0115 (-2.82)	-0.0436 (-3.79)
Emerging Markets	-0.0228 (-1.86)	-0.1449 (-2.14)	-0.0053 (-0.40)	-0.1567 (-4.27)
Equity Market Neutral	0.0033 (0.15)	-0.0472 (-0.53)	-0.0242 (-1.65)	0.0154 (0.35)
Event Driven	-0.0049 (-0.38)	-0.0734 (-1.03)	-0.0119 (-1.00)	-0.0450 (-1.44)

Fixed Income Arbitrage.	-0.0011	(-0.05)	-0.2325	(-2.31)	-0.0811	(-3.86)	-0.0609	(-0.80)
Global Macro	0.0464	(2.24)	0.1371	(1.54)	0.0410	(2.75)	0.1514	(3.18)
Long/Short Equity	-0.0216	(-1.83)	-0.1092	(-1.82)	-0.0253	(-2.22)	-0.0974	(-3.14)
Managed Futures	0.0036	(0.23)	0.0266	(0.35)	0.0044	(0.38)	0.0367	(1.17)
Generalized Residual from Probit Model					0.4594	(5.11)	1.0165	(3.38)
Chi^2 (45)			739.38					
Pseudo R^2	0.0651		0.0787		0.1159		0.0634	
Number of observations	10954		10951		6223		4728	