Financial Affiliated New and Old Hedge Funds:

an Analysis of Flow-Performance and Survival Probability*

Guillermo Baquero

ESMT Berlin

Vu Binh Le

ESMT Berlin, Berlin School of Economics

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E-mail address: guillermo.baquero@esmt.org, vubinh.le@esmt.org

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Abstract

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1. Introduction

Affiliation of asset management companies with financial groups is a source of potential conflicts of interest with their investors (see e.g. Gaspar, Massa, and Matos (2006), Cohen and Schmidt (2009)). In the hedge fund industry, in particular, affiliation leads to reduced performance, legal or regulatory violations and increased probability of failure (see e.g. Zheng and Yan (2021)). If the survival of affiliated hedge funds is compromised, there is a reason for concern that such associations could destabilize systematically important financial institutions. Recent empirical evidence is, however, at odds with this view, and suggests that hedge fund affiliation with financial conglomerates may have a stabilizing role by providing liquidity to the financial system (see e.g. Franzoni and Gianetti (2018)). In extreme market conditions affiliated hedge funds tend to take more risk and have less liquid exposures, while in booming periods they have lower systematic risk exposures. In this paper we attempt to reconcile these opposite views. Conditional to market states, we analyze the impact of affiliation on performance, investors' flows and survival probabilities of hedge funds and weigh the potential benefits and costs of affiliation.

Hedge funds are complex, leveraged and lightly regulated pooled investment vehicles catered to high-net-worth clients or institutional investors. They have access to the full spectrum of financial instruments, from stocks and bonds to derivatives, futures, commodities, and real estate, and actively leverage their positions. Affiliate hedge funds, in particular, are those owned by larger financial institutions; they can be identified thanks to information on the U.S. Securities and Exchange Commission ADV form.[1] Given these funds' common ownership with another financial institution, investors' reaction to hedge fund performance can vary widely depending not only on performance but also on wider

[1] They only file a mandatory registration with the U.S. Securities and Exchange Committee once their AUM passes $100 million; this regulation is enforced since 2012.

market condition at the time of the investment or divestment decisions. Franzoni & Gianneti (2019) document that 38% of the industry asset are managed by a fund affiliated with a financial conglomerate. Yet, the response of investors' flows and the survival probabilities of this important sub-group of funds are not well-established in the literature.

We employ two different datasets, one is Lipper TASS, also known as Lipper Hedge Fund Database, and the other one is from the United States Securities and Exchange Commission (SEC) ADV form to empirically analyze hedge funds. Lipper TASS has been the standard database for academic papers on hedge funds for years, while ADV is the mandatory registration form for hedge funds operated in the U.S since 2012. Lipper TASS provides important information about funds, such as estimated asset under management, monthly return, management and incentive fee level, and other characteristics of funds. ADV database provides information about funds' legal and operational issues. We describe both datasets in more detail in the section below.

Our paper contributes to the literature of financial affiliated hedge funds in two important ways. First, we find financial affiliation to be an important factor to enhance fund survival probabilities, supporting the view that affiliation has a beneficial effect in the financial system. Affiliation significantly reduces the liquidation probability in all our liquidation models. Affiliated funds, on average, have about 2% probability of liquidating, comparing with about 3% for non-affiliated funds in liquidation probability in any given quarter, showing about 50% reduction. Second, we extend the findings of Franzoni and Giannetti (2019) and differentiate between old and new affiliations in our analysis, by taking advantage of the mandatory registration requirement for hedge funds enforced by the SEC since April 1, 2012. Previous papers on fund affiliation make the assumption that the financial affiliation dated back to when a fund starts operating. We label this type of affiliation as "old." We assume that affiliation status found in the SEC registration from April 1, 2013 (one-year delay from the mandatory filing date) are *new* affiliation, meaning the fund is only owned by a financial institution from that moment. We find this expanded group of affiliated hedge funds to have lower flow-performance sensitivity in all market states. This finding is robust to all controls, including four quarter lags of cash flows, the exclusion of fund of funds[2], and the exclusion of backfilled periods. The support from the larger financial institutions is consistently observed in the analysis for newly affiliate hedge funds in all market states as proxied by annual excess return of the S&P 500. The evidence for the flow-performance sensitivity of old affiliation is weaker, however we observe a flattened flow-performance in extreme market periods, with the inclusion of fund of funds and backfilled data.

Our paper proceeds as follow. The next section reviews the literature about hedge funds, their flow-performance relation, and other aspects related to our study. Section 3 provides some basic information about our dataset, including descriptive statistics and other institutional background. Section 4 presents the empirical results, which consist of the effect of moderate market condition on fund flow-performance sensitivity, the lower flow-performance sensitivity of new-affiliated funds, the liquidation model for old-affiliated funds. Section 5 concludes.

2. Related Literature

Fund investors have to undergo a lengthy and costly due diligence search process to select the appropriate funds to invest. Investors are known to invest in funds which performed well in the last period (Sirri & Tufano, 1998). They direct their money into funds with good past performance to chase after good future performance (Gruber, 1996). Chevalier & Ellison (1997) shows that funds try to maximize the inflows in order to maximize fund managers' compensation, and that the flow-performance relationship depends on the age group of funds.

[2] Aiken, Clifford, and Ellis [2015] show that fund of funds, sometimes known as fund of hedge funds, have economy of scale in doing due diligence in hedge fund investing. We, therefore, conclude that the investment process for hedge funds and those for fund of funds are different and decide to exclude them.

They show that the flow-performance curve is different for old (over 10 years old) versus young (less than 2 years old) mutual funds. The flow-performance curve for old mutual funds is flatter than that of young mutual funds, i.e., investors in old funds are less sensitive to a bad performance than those in young funds. In hedge funds, the investment objective for hedge funds is absolute return rather than relative returns relative to a benchmark (Baquero and Verbeek, 2020). It is unclear how investors react to a bad performance in a young hedge fund compared to a bad performance of an older fund.

There is currently no consensus for the shape of the flow-performance curve in hedge funds. Previous studies have shown this relation to be non-linear. Goetzmann Ingersoll, Ross (2003)find an outflow (negative inflow) not only for bottom-performing funds but also for top-performing funds. On the other hand, several studies, such as Agarwal, Daniel, and Naik, (2004) and Fung Hsieh, Naik, and Ramadorai (2008), find positive inflows for top-performing funds, as proxied by the ranking of the fund net-of-fee return among hedge fund databases. If top-performing funds experience negative inflows, then the shape of the flow-performance curve would be a steep slope for bottom and middle performing fund, while showing a flatter slope for top performing ones; this curve would resemble a concave curve. If top performing funds have positive inflows, the flow-performance curve in that case would have a steeper slope for top performing fund and would resemble a convex curve.

To determine the shape of the flow-performance relationship across the spectrum of fund performance, we adopt the academic standard of piecewise linear regression model as pioneered by Sirri & Tufano (1998). As noted in that paper, this construction allows us to investigate the growth in cash flow for each level of fund performance: low, medium, and high. They divide mutual fund performance into five quintiles, while we only split hedge fund performance into three separate groups. We provide more details about our data and our specifications in the following sections.

There are other factors that can affect the shape of the performance-flow relationship. These factors include market conditions, incentives for fund managers, and frequency of the measured performance. Franzoni & Schmalz (2017) shows that performance-flow sensitivity for mutual funds is higher when the market is in moderate conditions, as proxied by annual return of the S&P 500. The authors define moderate states as when the S&P 500 annual return falls between the third and the seventh deciles of historical return, while the extreme states arise when the return is out of those deciles, i.e., in from the first to third decile (extremely low return), or from the eighth to tenth decile (extremely high return). They find that the sensitivity of inflow to past performance can be twice as high in the moderate states as that in the extreme states of the market. They provide a theoretical model to explain this empirical finding: investors can discern the skill of fund managers better in moderate market; thus, they can make decision to invest/divest faster in that market conditions. Agarwal Daniel, and Naik (2004) shows that hedge fund flow-performance depends not only on manager skills but also on managerial incentives, inclusion of high-water mark provisions, and managerial ownership.

Ownership, either by fund insiders or by a related financial institution, can be a key factor affecting the flow-performance sensitivity. We follow Brown Goetzmann, Liang, and Schwarz (2008), (Franzoni & Giannetti, 2019; Zheng & Yan, 2021), and acquire the necessary information about funds affiliated with other financial institutions from the ADV dataset available through the website of the United States Securities and Exchange Commission (SEC). We provide more information about this dataset in details in following sections.

Prior literature on affiliated hedge funds shows some marked differences between affiliated funds and non-affiliated ones. Zheng and Yan (2021) show that affiliated hedge funds underperformed non-affiliated ones between 2001 and 2014. Franzoni and Giannetti (2019) shows that affiliated funds have lower flow-performance sensitivity than that of unaffiliated ones in the years between 2001 and 2012. Another remark is that Zheng and Yan (2021) have a broader definition of affiliation compared to that of Franzoni and Giannetti (2019), thus a financial affiliation does not necessarily mean the same in the two papers. We discuss the differences in definition, in data, and their implications, in the subsections below.

3. Data and variables

3.1 Lipper Hedge Fund database (TASS)

We use the Trading Advisor Selection System (TASS), also known as Lipper Hedge Fund Database, as our main source of data for hedge funds. Lipper TASS contains company name, raw return, asset under management (AUM), and other fund characteristics, such as fee level (management fee and incentive fee), investment focus and geographical focus, the use of high-water mark, the minimum amount of investment, whether the fund is open-ended or close-ended, and any liquidity restriction imposed by the fund (redemption frequency, redemption notice period, and lock-up period). TASS is the academic standard for research papers on hedge funds, with the number of papers using TASS in the hundreds (Joenvaara, Kauppila, Kosowski, and Tolonen, 2019).

We use data from 1995 onwards to eliminate any survivorship bias in the data by using both liquidated (i.e., dead), known in TASS as "graveyard" funds, and alive funds in our regression. Data on liquidated funds in TASS is available only from 1994. Second, we start from 1995 to ensure the reliability of hedge fund performance indices, an issue acknowledged by Fung and Hsieh (2015).

We perform the following tasks to prepare our dataset for empirical analysis. We exclude funds reporting in currencies other than U.S. dollars and exclude close-ended funds from our data. Hedge fund databases are plagued with the "backfilled" data, which is some initial good periods of performance generated by a young fund before it reports to a data vendor (TASS in our case). Once a fund decides to list on TASS, its purpose is likely to raise more funds

(Jagannathan Malakhov, and Novikov, 2010), TASS would publish the entire return history of that fund from the fund's inception date. If we do not control for this backfill problem, fund returns would be biased upwards due to this voluntary reporting nature of hedge funds. We present our results with and without backfilled data side-by-side to check the robustness of our findings. Although the literature of hedge fund recommends dropping backfilled data, these time periods, also known as the incubation period in the mutual fund literature (Evans, 2010), would show the support that young funds received from large financial institutions. In the dataset without backfilled data, we drop all observations of a fund before the date on which it is added to the TASS database.

We follow the procedure described in detail in (Aggarwal & Jorion, 2010) to keep only one share class among multiple share classes from the same fund. These share classes would be from the same company, with very high correlated series of returns. This purge ensures that one fund does not appear multiple times in our dataset and that we do not double count the AUM of a fund management company.

3.2 ADV database from the U.S. Securities and Exchange Commission

We merge the resulting TASS database with SEC's ADV to identify hedge funds that are registered with the SEC. The timeframe of data is from February 2001 to March 2018 due to the availability of data from the SEC portal. The filing ADV form was not mandatory before the enactment of the Dodd-Frank Act. Since the Dodd-Frank Act enacted to response to the financial crisis of 2008 – 2009, filing this form is a regulatory requirement mandated by the SEC for hedge funds with net asset values equal to or greater than 100 million US dollars.

The ADV consists of three parts: the first part is a multiple-choice, fill-in-the-blank format questionnaire that contains a wealth of information about the fund business, such as the size of the fund, its amount of asset under management, its number of high net-worth clients, institutional clients, its list of owners, and its affiliations with other financial institutions. The second part is a brochure about the business in general. We merge the TASS database with the first part of the ADV data. Brown, Goetzmann, Liang, and Schwarz (2008) is the first paper to shed a light on the availability of this information on ADV data downloadable on the U.S. SEC website, but their focus is on the operational risk of funds. They look at the operational risk, i.e., the risk that the fund personnel commit a crime, and find this risk is not related to the flow-performance of hedge funds. The ADV form has evolved so much since 2008 (when Brown et al. (2008) was written), therefore the definition of certain items on the ADV also change compared to that of the old form. We take advantage of the 2012 ADV form version, which contains affiliation data (the most important information pertaining to our paper).

We create two separate datasets from matching with ADV. For old affiliation, we match funds in TASS with ADV data using only name of the fund. They are matched using fund management company name since there is no common identifier in both datasets. If we identify a fund as affiliated one from the matching, we follow prior literature and assume that the affiliation status starts when the fund starts operating.

For new affiliation, we match the funds by the fund management company name and by the date of the filing, which is extracted from a time stamp showing when the form was submitted.

3.3 *Descriptive statistics about data*

Our final affiliation dataset consists of 2,289 ADV-matched funds with 69,561 fund-period observations between the first quarter of 1995 and the last quarter of 2016. The graveyard contains 2,059 funds, which seems to be a large proportion of the dataset. In that graveyard, 1,619 funds liquidated, and 440 funds self-selected out of the sample. At the beginning of the dataset, the first quarter of 1995, there are 245 funds with the sum of AUM about $7 billion. Those numbers for the end of 2016 are 307 funds and $56 billion, respectively.

We present here a summary statistics table of mean, standard deviation, minimum, maximum values, and difference in mean tests (t-tests) of some important characteristics of funds in our sample. The first panel shows those numbers for non-affiliated funds, while the second one is for new affiliated funds in our dataset. Note that the definition of affiliation is based on an expanded definition of affiliation, discussed in a following subsection.

[Insert Table 1 about here]

Affiliated funds are statistically significant different than non-affiliated ones in the first two important characteristics: their AUM and their age. They have generally more asset under management, approximately quadruple the average size of non-affiliated one, and they are almost twice as old (6 compared to 11 years old). They are similar than non-affiliated funds in other characteristics, except that affiliated funds have much lower redemption notice period, showing they can accommodate withdrawals from clients better than non-affiliated ones do.

3.4 *Two Definitions of Financial Affiliated Hedge Funds*

We consider two separate definitions of financial affiliation for hedge funds in this paper, given that financial companies come in all shapes and sizes, with heterogenous levels of support for their affiliate funds. The SEC's ADV form has asked this question in detail about this matter, and funds can indicate their affiliation with many types of companies in the financial sector. In the ADV form, the key information pertaining to fund financial institution affiliation is under Section 7, question 5 and question 7. Question 5 contains the type of business about the "related person," in SEC parlance. Question 7 asks if the fund and the related company are under common control.

We group the types of affiliation into two groups based on recent literature on affiliated hedge funds. The first group consists of funds affiliated to a broker-dealer, a commercial bank, or an insurance company. This is also known as the "Financial Conglomerate Affiliated Hedge Funds", or FCAHF, based on Franzoni and Giannetti (2019). We consider the fund is an FCAHF if at least one of the following boxes is ticked: "broker-dealer", "banking or thrift institution," or "insurance company or agency." We generated a new variable to identify financial conglomerate affiliated fund if the fund is related to a one of the three types of financial firm listed above and are under common control with that firm, which is shown in question 7.

The second group of affiliation is funds affiliated with other types of financial firms as stated on the ADV form: sponsors of limited liabilities corporations, and sponsors of pooled investment vehicles, commodity trading advisors (or CTAs), other investment advisers (including financial planners), and (rarely) pension consultant. We label the expanded definition of affiliation as SCO (sponsors, CTA, and other investment advisors) and explore this expanded subset of financial affiliation because prior literature from mutual fund has shown that funds distributed through retail-oriented intermediaries, such as financial planners, have weaker incentive to perform (Guercio & Reuter, 2014). Therefore, the flow-performance relationship for hedge funds sharing common ownership retail distribution channels, as proxied by affiliated with "Other investment advisers (including financial planners)" in SEC's original wordings, can be materially different than that of funds without a close relationship to firms with expertise in retail investment.

Based on the new definition, approximately 61% of our TASS-ADV sample has some sort of affiliation with financial firms.

[Insert Figure 1 here]

We show above a Venn diagram showing how the definition of financial affiliation changes the number of observations classified as affiliated. There are many more funds affiliated with other kind of financial firms, as described above.

3.5 *Quarterly Normalized Cash Flow and Controls*

We compute the normalized quarterly cash flow as the growth rate of a fund's AUM minus the raw return of that fund in the same quarter. We also compute the cash flow in dollars, measured as the net change in asset minus the internal growth of last quarter's asset.

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

$$DollarFlow_{t+1} = AUM_{t+1} - AUM_t * (1 + r_{t+1})$$

We winsorize both flows at the 1% and 99% level to prevent problems with outliers that can happen when a fund starts operation, namely a large positive normalized cash flow, or when a fund closes, resulting in a large negative cash flow.

We follow (Baquero & Verbeek, 2021) to select additional control variables that are relevant to explain money flows. These variables consist of a fund's management fee (average around 1.5% of AUM), incentive fee (average about 18% of profit), a binary variable to indicate joint ownership structure (i.e. a fund manager has to invest his/her own capital in the fund), the age and size of fund (in logarithmic form), a binary variable indicating whether the fund is onshore or offshore, and a variable indicating the primary category of the fund, or styles. Styles of funds, such as "dedicated short bias" or "long/short equity," can be an important determinant for money flows because investors also make use of fund investment style classification as one factor to determine the allocation of assets. We exclude fund of hedge funds, also known as "fund of funds", in our analysis because this type of funds caters to a different clientele, who may not be familiar with pure hedge fund investment and is likely to follow a different evaluation process than pure hedge fund investors (Aiken et al., 2014). Fund of funds style also takes up a sizable proportion of affiliated funds (approximately twenty-seven percent of the number of affiliated funds). Our results remain quantitatively the same (in terms of magnitude and significant levels) with or without fund of funds observations.

4. Results

4.1. Flow-Performance Sensitivity in Moderate Market Conditions

Our paper posits that the flow-performance sensitivity of hedge funds might vary proportionally with overall market conditions, as found by Franzoni and Schmalz (2017) for mutual funds. They propose a model for increased flow-performance sensitivity in moderate market: investors, in these environments, are better at inferring the skills of managers and thus allocate their money accordingly. Chen, Goldstein, and Jiang (2010) also present a model based on global game theory about investors observing true fundamentals of funds and some noise. In that model, investors receive some common information about the fund's fundamentals, such as Morningstar rating, but differ on their interpretation. As the noise reduces, investors can infer the true fundamental of funds and make their invest/divest decisions accordingly. To invest in a hedge fund is to buy into the skills and talents of a particular manager, thus the ability of investors to distinguish between a manager's skills and luck is crucial, and investors are better at inferring this in moderate market conditions.

We empirically test this hypothesis by regressing the normalized quarterly cash flow (winsorized) on prior quarter three segments of the flow-performance curve and include an interaction term between those variables and a dummy variable for moderate market condition. The full specification is as follow:

$$
\begin{aligned}
Flow_{it} = \alpha + \ & \beta_1 Bottom30_{it-1} + \beta_2 AnnualRank_{it-1} + \beta_3 Top30_{it-1} + \ \beta_4 ModerateMkt \\
& + \ \beta_5 Bottom30_{it-1} \times ModerateMkt \\
& + \ \beta_6 AnnualRank_{it-1} \times ModerateMkt + \beta_7 Top30_{it-1} \times ModerateMkt \\
& + \ \beta_8 \ln(AUM_{it-1}) + \ \beta_9 \ln(Age_{it-1}) + \gamma' X_{it-1} + \omega_i + \lambda_t + \ \epsilon_{it}
\end{aligned}
$$

We take inspiration from Franzoni and Schmalz (2017) in testing this specification, with one notable change: we interact the variable for moderate market condition with all three segments of the annual ranking of hedge funds, which is a relative performance measure (see β_1, β_3, β_5, and β_7). As discussed in their paper, investors in moderate market conditions are better at separating the skills of managers from the noise generated by the market, thus the actions of investors, empirically proxied by flows, would be more visible at the bottom and the top segment of the industry, i.e., at funds with exceptionally bad or good performance relative to their peers.

We follow prior literature in the selection of independent variables: one-quarter lag of asset under management, one-quarter lag of fund age (both in logarithmic form), the fee level of fund (management fee and incentive fee). All those variables are known to affect the flow-performance curve. We also include other relevant controls, such as the lock-up period and some dummy variables about other important characteristics of a fund: one about personal capital (whether fund managers co-invest in the fund), whether the fund is leveraged or not, and whether the fund is offshore or onshore. Last, we have quarter-time fixed effect and investment style fixed effect (according to TASS classification) to make sure effects from a particular time period or from a style do not bias our estimates.

[Insert Table 2 about here]

Our second table examines the effect of moderate stock market condition on the hedge fund flow-performance sensitivity. We define the moderate and extreme states as follow. First, we obtain annual return of the S&P 500 from 1995 and 2017 and sort them into ten deciles. Moderate states occur when annual market returns are between the fourth and the seventh decile (inclusive), and extreme states are when annual market returns are either in decile one to three (inclusive) or in decile eight to ten (inclusive).

We start by regressing lagged normalized cash flow on three segments of annual rank, interacting with the dummy variable for moderate condition. We then add more controls in the second and the third specification. In the second column, the level of management and incentive fee, the liquidity restrictions (redemption notice period and lock-up period), the lagged value of asset and age, the standard deviation of return are added. Dummy variables, such as one for offshore/onshore funds, for manager co-invest in the fund, and for fund leverage, are presented in the second column. In the last column, we add investment style dummies and quarter time fixed effect to absorb any temporal effect from a period or an investment style, which goes in or out of fashion. Results presented below are from the dataset without backfill problem. In dataset with backfilled observations, we obtain quantitatively similar results (not shown here), often with stronger statistical significance level (higher t-statistics).

From Table 2, moderate market conditions have a robust and visible effect on the flow-performance curve of open-ended hedge funds. In these conditions, funds experience a higher outflow in response to a bad performance, as shown by the steepening of the bottom segment of flow-performance slope in moderate market in all specifications. The coefficient for the bottom segment is positive and statistically significant at 5% level in moderate market, in contrast with the same coefficient in non-moderate market. It is to find that opposite sign of the flow-performance sensitivity for coefficients of the bottom segment for the moderate state and that for the extreme state. This effect of the bottom segment disappears if we pool all observations from all market states into one regression.

The effect remains fully intact (significance at 5% level) after the introduction of the necessary controls shown in prior literature: fund characteristics in column (2), and then fixed effects and four quarter lags of flows in column (3). Baquero and Verbeek (2007) shows that investors also allocate capital at the investment style level, and that lagged flows are an important determinant for future cash flows. Even after accounting for all of these in column (3), the effect of moderate market remains consistent in comparison with the previous two specifications.

The economic magnitude of the change in flow-performance sensitivity is also considerable: the flow-performance sensitivity increases by 50 – 60% in moderate market for those in the bottom 30% of the ranking by annual return. This is a stark contrast with the curve in non-moderate market conditions. In those conditions, this curve's bottom segment is much flatter than the middle and top segment by about 30% to 50%, thus the convex-like shape of the curve. The shape of the flow-performance curve changes from a convex one in non-moderate market to a concave one in moderate market. This presents evidence of drastic change in investors' behavior in response to bad performance when they can discern the skills of fund managers from the noise generated in the market. Overall, we find an increased flow-performance sensitivity for hedge funds in moderate states of the market and can corroborate findings from Franzoni and Schmalz (2017). This shows that hedge fund investors are more sensitive to a bad performance in the moderate state of the market. In that environment, we look for the effects of affiliation on adjusting the flow-performance relationship.

4.2. Flow-Performance Sensitivity for Newly Affiliated Hedge Funds

We differentiate between old and new financial affiliation in our regression analysis. The old affiliation includes funds affiliation reported in 2012, and in the first quarter of 2013 (because some funds received a one-year extension permit to register from the SEC). We label these "old" affiliation because these funds have affiliation long before the mandatory registration requirement enforced by the U.S. SEC since 2012. Given that the old affiliation funds have a very different relationship with financial institutions than the new affiliation ones do, we separate the old from new affiliation to compare the flow-performance sensitivity of newly affiliated funds with that of non-affiliated funds. We consider affiliation reported from April 1, 2013, a new financial affiliation because these funds only disclose their affiliation when they register with the SEC.

We include all controls, the four lags of flow, the quarter time fixed effect, and the style fixed effect, and the clustering of standard errors at the fund level. We check the flow-performance using a dataset free of backfilled bias. In the non-backfilled, non-fund-of-funds dataset, we delete all observations of a funds before the date on which it is added to the Lipper-TASS database and exclude all funds with the primary category as "fund of funds."

We continue to examine flow-performance relation using moderate or extreme market conditions, as proxied by the annual excess return of the S&P 500 over the three-month Treasury bill. As investors take more swift investment/divestment decisions in moderate market conditions, that is when the support of affiliated financial institutions comes into play. The difference between flow-performance sensitivity of non-affiliated and affiliated funds is likely larger in moderate conditions because a parent financial institution have more capacity and/or willingness to support their affiliated funds after they suffer a period of bad performance. Baggati, Fecht, and Maddaloni (2021) finds this evidence for affiliated mutual funds in the European Union.

We and run the following regression to determine the effect of new affiliation on the flow-performance relationship:

$$
\begin{aligned}
Flow_{it} = \alpha + {} & \beta_1 Bottom30_{it-1} + \beta_2 AnnualRank_{it-1} + \beta_3 Top30_{it-1} \\
& + \beta_4 FinancialAffiliation + \beta_5 Bottom30_{it-1} \times FinancialAffiliation \\
& + \beta_6 AnnualRank_{it-1} \times FinancialAffiliation + \beta_7 Top30_{it-1} \\
& + \times FinancialAffiliation + \beta_8 \ln(AUM_{it-1}) + \beta_9 \ln(Age_{it-1}) \\
& + \beta_{10} FlowLag_{t-1} + \beta_{11} FlowLag_{t-2} + \beta_{12} FlowLag_{t-3} + \beta_{13} FlowLag_{t-4} \\
& + \gamma' X_{it-1} + \omega_i + \lambda_t + \epsilon_{it}
\end{aligned}
$$

In this regression, we interact the dummy variable for financial affiliation on all three segments of the flow-performance slope to allow the possibility of different level of support for affiliated funds in the top, middle, and bottom segments of the relative rank of fund annual performance. If that is the case, we would observe a different flow-performance curve between affiliated and independent funds. Quarterly lagged of flows, from one to four quarter, are included in this specification because these are known to have a significant impact to current quarter cash flow. Style fixed effect and quarter time fixed effect are included to absorb any effect from those. We use the standard classification from TASS for investment styles.

We present here three specifications with and without backfilled data. Backfill data coincide with funds' incubation period, in which funds get support from their affiliation with larger financial institutions to attract capital inflows, or support from their fund families as in Evans (2010). The flow-performance relationship might be different by the inclusion of incubation data, thus we run our empirical analysis on both a non-backfill dataset and a dataset with backfilled observations. The result from the dataset with backfill and funds of fund is similar to those without backfill and fund of funds observations. In the dataset free of any backfill bias (results presented on column 4-6), we delete any observation before the fund's date added to TASS to correct for this problem.

[Insert Table 4 about here]

We interact the dummy variable for new affiliation with three segments of the piecewise linear regression to understand the effect of affiliation on the flow-performance relation. The coefficient for new affiliation is positive and statistically significant at 1% level in all market state specifications and moderate market specifications, with or without backfill. This shows a new affiliation fund with zero ranking would have significantly inflow than non-affiliate fund with the same ranking.

The difference in shape of flow-performance curve for affiliated funds is statistically significant in both the moderate and extreme states of market. We find the flow-performance for affiliated funds a mostly convex shape, with the steepened bottom segments, very flat main segment, and a steep top segment. Newly affiliated funds experience the same investors' reaction with non-affiliated ones when they have a bad performance, and they have much more limited reaction at the main segment, where their flow-performance sensitivities approach zero in any state of market. This reduction in flow-performance sensitivity at the main segment shows the benefit of new affiliation.

4.3. Flow-Performance Sensitivity for Old Affiliation

In the previous subsection, newly affiliated hedge fund affiliation with any financial firm shows a practical benefit in moderate market: they have much flatter flow-performance sensitivity at the middle segment (30 percent in ranking to 70 percent in ranking) during any market state, moderate or extreme. One way to interpret this flow-performance sensitivity is that the investors of affiliated funds have a more muted reaction to performance from a new affiliated funds.

We also know, based on the information on ADV data and prior literature, that there are funds with old affiliation status. We classify funds as old affiliation if the affiliation status is declared from April 1, 2012 (the deadline to register with the SEC) until April 1, 2013 (because some funds apply for and receive an extension to the original deadline).

We investigate their flow-performance sensitivity to learn more about the benefits of old affiliation to hedge funds in moderate and extreme market states.

[Insert Table 5 here]

The flow-performance relation of old affiliated funds is different from that of new affiliated funds. It should be noted that these specifications include backfilled and fund of funds observations, thus they are only comparable to column (1) to (3) in the previous table about new affiliation. First, the coefficient for old affiliation is positive and statistically significant at the 1% level in all market state specification and in extreme market state specification. Holding performance rank constant, old-affiliated funds receive more inflows than new affiliated funds in extreme market conditions (annual excess return of S&P 500 either smaller or equal than decile 3 or greater than or equal to decile 8). Second, the bottom segment of flow-performance sensitivity of old-affiliated funds in extreme market flattens almost completely, however the significant level is only at 10%.

4.4. Old Affiliated Hedge Fund Liquidation Model

After observing the not-so-robust change in flow-performance relation for old-affiliated funds, we question why funds still seek to gain an affiliation with another

We present here probit models to model for the probability of a hedge fund liquidation event. We describe here how we create and classify our dependent variable: a dummy variable equals to one if there is a liquidation event when a fund exits the TASS database. We face a challenge in differentiating between the funds forced to liquidate due to poor performance and those self-selecting themselves out of the sample for various reasons (close to new investors, capacity constraints, etc.), given the self-reporting nature of hedge fund data.

First, we obtain the reasons for dropping the fund from TASS database. The variable is set to one if the drop reason from TASS is "fund liquidated." However, TASS also includes other more ambiguous drop reasons, such as "Unable to contact fund", or "Unknown," i.e., the disappearance reason is unknown to us. To separate the liquidated from the self-selected (for example, a fund stops reporting because it is closed to new investment), we calculate an annual dollar flow or an annual cumulative return of each fund. If a fund is dropped from the database with unknown reasons described above and with a negative final annual dollar flow or a negative final cumulative return, we label those cases as liquidation. In our TASS-ADV dataset spanning from 1995 to 2018, there are 1,394 liquidation events for a sample of 2,258 funds. Among them, 1,020 liquidations (approximately 73%) are identified by TASS as "fund liquidated", we classify the remaining 374 cases: 309 (22%) are those TASS identifies as "unable to contact fund" with negative annual dollar flow or annual cumulative return, and 65 "unknown" cases (5%), also with negative metrics as described.

Our dependent variable for liquidation is as follow:

$$y_{it} = \begin{cases} 0 & \text{otherwise} \\ 1 & \text{if fund } i \text{ is liquidated in quarter } t \end{cases}$$

We regress this dummy variable on past quarterly ranks (four quarter lags), a list of fund characteristics, the fund (incentive and management) fee level, its one-quarter lag of asset under management and its one-quarter lag of fund age (both in natural logarithmic form), a dummy variable indicating financial affiliation status, and investment style fixed effect and quarter-time fixed effect:

$$\begin{aligned} \Pr(y_{it} = 1) = {} & \alpha + \beta_1 quarter\_rank_{t-1} + \beta_2 quarter\_rank_{t-2} + \beta_3 quarter\_rank_{t-3} \\ & + \beta_4 quarter\_rank_{t-4} + \gamma' X_{it-1} + \beta_5 IncentiveFee_i \\ & + \beta_6 ManagementFee_i + \beta_7 \ln(AUM_{it-1}) + \beta_8 \ln(Age_{it-1}) + \beta_9 FinAffil \\ & + \omega_i + \lambda_t + \epsilon_{it} \end{aligned}$$

We present the probit estimations below. The first column contains only 4 lags of quarterly rank and their interaction with the dummy variable for old affiliation. The second column adds fund fixed characteristics known from Baquero et al., (2005), such as dummies for high-water mark, offshore, management and incentive fee, one quarter lag of asset under management, one quarter lag of fund age (last two in natural logarithmic form), and the fund's standard deviation of return. The third and last column include all controls in the second and add time and investment style fixed effects.

[Insert Table 6 here]

All lags of quarter ranks are negative and significant, showing that the higher the fund's quarterly rank, the lower the liquidation probability. The dummy variable for old affiliation is also negative and statistically significant at 1% level in all specifications. The magnitude and significance level improves in the last column as we add time and style fixed effects. This shows old-affiliation is a strong and important factor in reducing liquidation probability for funds and explain why funds seek affiliation with other financial institutions.

[Insert Figure 2 here]

We also plot the probability of liquidation for non-affiliated funds (blue line) and old-affiliated funds (red line). The band around each line represents the 95% confidence intervals for each estimation. Two things can be observed from this plot. First, both lines have a uniform, downward slope, showing that an improvement in the first lag of quarterly rank reduces probability of liquidation significantly. Second, we can see from the plot that the confidence intervals for non-affiliated and old-affiliated funds never overlaps. This represents clear graphic evidence of the benefit of hedge funds affiliated with financial institutions: to lower the risk of liquidation.

5. Conclusion

We focus on flow-performance relations of pure hedge funds in moderate or extreme market conditions and show that the flow-performance sensitivity increases drastically for poorly performed funds, as proxied by their annual return ranked in the bottom 30% of our database. This corroborate findings from findings in theoretical models about investors are better at discerning fund managers' skills from luck in moderate market, so that they act accordingly by divesting from funds with low skills.

We identify a new group of affiliation using the timing of registration data from the SEC. The new affiliated, pure hedge funds have lower flow-performance sensitivity than those of non-affiliated funds in any market condition. Both of these findings are robust after controlling for issues plagued the hedge fund database, such as the survivorship bias and the backfill bias.

We then compare the flow-performance of old affiliated funds with that of non-affiliated funds and find similar, although weaker in terms of statistical significance, behavior for old-affiliated funds. They have significant flatter flow-performance relationship for poorly performed funds compared to non-affiliated ones in extreme market state.

After observing weaker effect of old affiliation on flow-performance, we attempt to answer the question of why many funds still seek affiliation. The answer lies in the model for fund liquidation model. Affiliation is an important factor to reduce the probability of liquidation for any fund at any performance rank.

Our research shows the ability of financial institutions to support their affiliated hedge funds through a lower flow-performance sensitivity in any market states. However, there are limitations with our study. First, our new affiliation identification rests on the assumption that hedge funds promptly file their ADV report after acquiring financial affiliation. Second, the unavailable of data on portfolio positions of affiliated funds prevent us from further examining the risk-taking behaviors of affiliated funds in different market states. We reckon that the area of affiliated asset management firms could be promising for further research.

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Figure 1

Venn diagram of different kind of affiliation

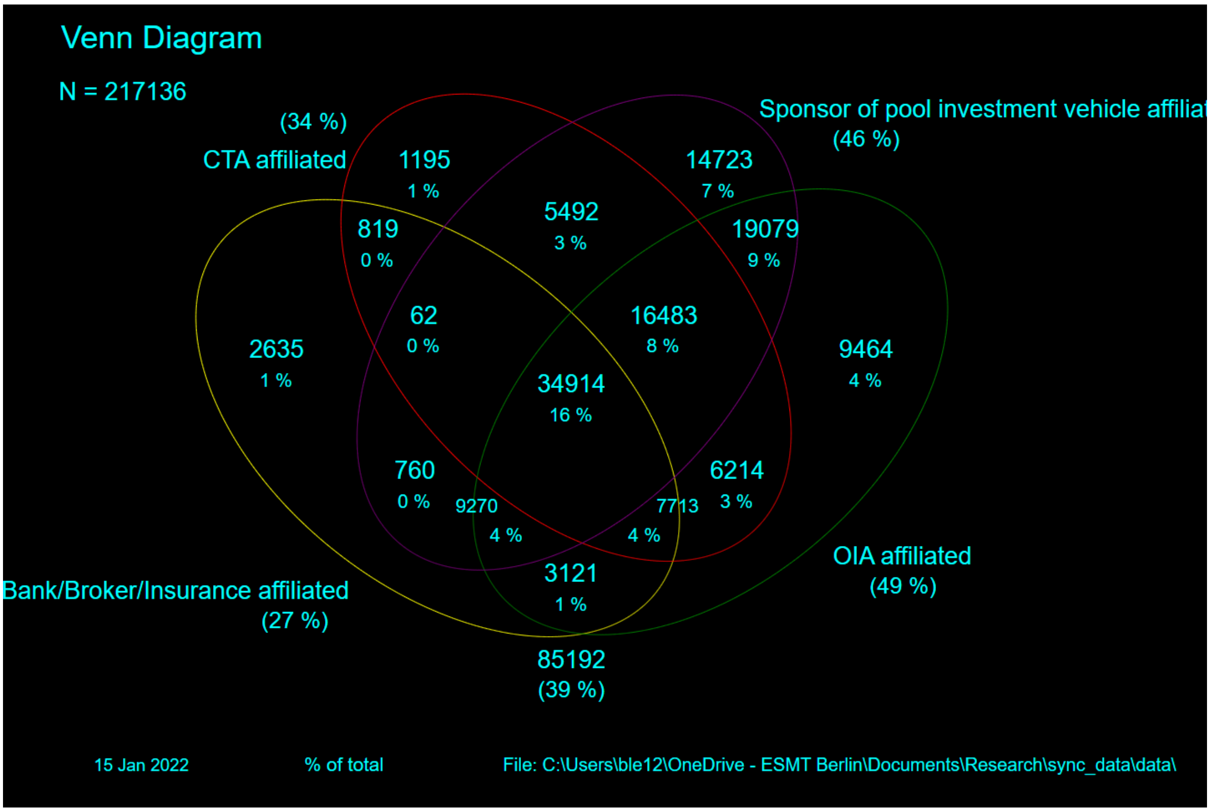

Figure 2

Predictive margins of fund liquidation with 95% confidence interval

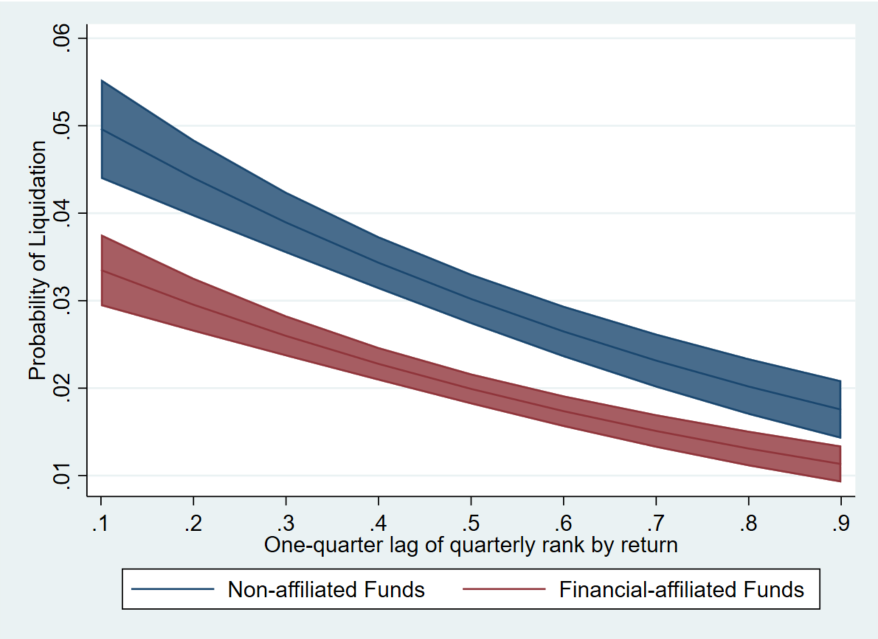

Table 1

Descriptive statistics.

	Non-affiliated funds				New affiliated funds				T-test for difference in mean	
	Mean	Standard deviation	25^{th} Percentile	75^{th} Percentile	Mean	Standard deviation	25^{th} Percentile	75^{th} Percentile	Difference	t-statistic
AUM (in million)	204.77	599.03	17	165	880.60	2406.49	59.55	359.5	-675.82***	(-40.57)
Fund age (in years)	6.135	5.234	2.085	8.836	11.442	6.191	6.833	15.51	-5.307***	(-46.67)
Lock-up period	3.2423	5.9413	0	6	4.0500	8.5268	0	12	-0.808	(-1.16)
Redemption notice period	43.8082	32.7643	30	60	51.7595	38.1499	30	75	-7.951**	(-2.09)
Frequency	68.8228	78.2049	30	90	72.6076	78.1618	30	90	-3.785	(-0.42)
Leveraged	0.6199	0.4856	0	1	0.5750	0.4975	0	1	0.0449	(0.81)
Maximum leverage	128.6559	348.8557	0	156	67.7690	140.5770	0	115	60.89	(1.32)
Average leverage	70.6877	256.5362	0	90	39.8035	78.3350	0	100	30.88	(0.91)
Management fee	1.3931	0.4780	1	1.6	1.4317	0.4582	1	1.875	-0.0386	(-0.71)
Incentive fee	16.6213	6.6597	15	20	17.2152	5.3239	15	20	-0.594	(-0.78)
High-Water mark	0.7024	0.4573	0	1	0.7375	0.4428	0	1	-0.0351	(-0.67)
Personal capital	0.3474	0.4763	0	1	0.3625	0.4838	0	1	-0.0151	(-0.28)
Offshore	0.7045	0.4564	0	1	0.7250	0.4493	0	1	-0.0205	(-0.39)

Table 3

The Effect of Moderate Market Condition on Flow-Performance Sensitivity of Open-Ended Hedge Funds. The table reports a piecewise linear regression of quarterly flow conditional on moderate market conditions. Data starts from the beginning of 1995 until the end of 2018. Moderate market states are quarters in which the annual return of the S&P 500 falls between its 4 and 7 deciles (inclusive) of its historical return. The data consists of funds matched to SEC's ADV database. Cash flows are measured as percentage change of net asset between consecutive quarters, minus the return reported by the fund. Flows are scaled by the fund's asset under management. Flows and fees are winsorized at 1 and 99% level to prevent influence from outlier. Quarter time fixed effects are included in (3) but not shown. We exclude any backfilled data from the dataset. Standard errors are clustered at the fund level. T-statistics based on clustered standard errors are in parentheses.

	Base specification	Including fund characteristics	Including four lag of flows
	(1)	(2)	(3)
	Normalized Flow_t		
$Annual\ Rank_{t-1}$	0.175***	0.177***	0.146***
	(14.50)	(14.68)	(13.27)
$Moderate$	-0.000360	-0.000355	-0.163***
	(-0.06)	(-0.05)	(-12.26)
$Annual\ Rank_{t-1} \times Moderate$	-0.0410**	-0.0439***	-0.0347**
	(-2.43)	(-2.58)	(-2.11)
$Bottom\ 30\%_{t-1}$	-0.0765***	-0.0713**	-0.0616**
	(-2.66)	(-2.43)	(-2.23)
$Bottom\ 30\%_{t-1} \times Moderate$	0.0938**	0.115***	0.0953**
	(2.26)	(2.74)	(2.27)
$Top\ 30\%_{t-1}$	0.0224	0.0102	-0.0441
	(0.71)	(0.32)	(-1.59)
$Top\ 30\%_{t-1} \times Moderate$	0.0369	0.0543	0.0614
	(0.83)	(1.23)	(1.51)
Management fee		-0.00248	-0.00125
		(-0.97)	(-0.62)
Incentive fee		0.000343**	-0.0000243
		(1.99)	(-0.15)
Offshore		-0.00382	0.00381*
		(-1.42)	(1.76)
Personal capital		0.0114***	0.00304
		(4.53)	(1.43)
Redemption restrictions		0.00544	0.00245
		(1.48)	(0.83)
Redemption Notice Period		0.0000231	0.0000898**
		(0.48)	(2.27)
Lock-up period		-0.000255	-0.0000133
		(-1.16)	(-0.08)

$Ln(AUM)_{t-1}$		-0.00731***	-0.0108***
		(-9.79)	(-15.99)
$Ln(Age)_{t-1}$		-0.0354***	-0.00704***
		(-20.10)	(-4.04)
Leveraged		0.00855***	0.00280
		(3.40)	(1.38)
Standard deviation of return		-0.222***	-0.0913**
		(-4.31)	(-2.11)
$Normalized\ Flow_{t-1}$			0.135***
			(16.67)
$Normalized\ Flow_{t-2}$			0.0802***
			(12.56)
$Normalized\ Flow_{t-3}$			0.0385***
			(7.07)
$Normalized\ Flow_{t-4}$			0.0202***
			(3.68)
Constant	-0.0699***	0.114***	0.102***
	(-15.84)	(8.01)	(6.68)
Quarter FE	No	No	Yes
Style FE	No	No	Yes
Observations	66143	65175	54725
Adjusted R^2	0.040	0.059	0.104

Table 4

The Effect of Moderate Market Condition on Newly Affiliated Open-Ended Hedge Funds.

The table reports a piecewise linear regression of quarterly flow conditional on moderate market conditions. Data starts from the beginning of 1993 until the end of 2018. Moderate market states are quarters in which the annual return of the S&P 500 falls between its 4 and 7 deciles (inclusive) of its historical return. The data consists of funds matched to SEC's ADV database. Cash flows are measured as percentage change of net asset between consecutive quarters, minus the return reported by the fund. Flows are scaled by the fund's asset under management. Flows are winsorized at 1 and 99% level to prevent influence from outlier. Quarter time fixed effects are included all specifications but not shown. We exclude any backfilled and fund of funds data from the dataset. Standard errors are clustered at the fund level. T-statistics based on clustered standard errors are in parentheses.

	Include FoF and backfill			Exclude FoF and backfill		
	All market states	Moderate market	Extreme market	All market states	Moderate market	Extreme market
	(1)	(2)	(3)	(4)	(5)	(6)
	Quarterly normalized cash flow					
$Annual\ Rank_{t-1}$	0.143***	0.111***	0.163***	0.166***	0.119***	0.197***
	(11.54)	(5.63)	(9.85)	(10.47)	(5.21)	(8.95)
$New\ Affiliation$	0.0735***	0.0730***	0.0732	0.0677***	0.0676**	0.0733
	(3.16)	(2.75)	(1.63)	(2.71)	(2.22)	(1.52)
$Annual\ Rank_{t-1}$ $\times New\ Affiliation$	-0.138***	-0.145**	-0.138*	-0.170***	-0.153**	-0.191**
	(-2.77)	(-2.20)	(-1.83)	(-3.18)	(-2.08)	(-2.30)
$Annual\ Top30_{t-1}$	-0.0210	0.0339	-0.0498	-0.0847**	-0.00702	-0.131**
	(-0.65)	(0.66)	(-1.18)	(-2.14)	(-0.11)	(-2.49)
$Annual\ Top30_{t-1}$ $\times New\ Affiliation$	0.248*	0.179	0.335*	0.391**	0.293	0.496**
	(1.66)	(0.84)	(1.91)	(2.22)	(1.20)	(2.36)
$Annual\ Bottom30_{t-1}$	0.0106	0.110**	-0.0440	-0.0486	0.113*	-0.153***
	(0.33)	(2.13)	(-1.02)	(-1.23)	(1.78)	(-2.59)
$Annual\ Bottom30_{t-1}$ $\times New\ Affiliation$	-0.0117	0.0676	-0.0967	0.0620	0.0870	-0.00113

	(-0.10)	(0.41)	(-0.46)	(0.47)	(0.47)	(-0.01)
$Normalized\ Flow_{t-1}$	0.148***	0.139***	0.151***	0.145***	0.141***	0.145***
	(14.35)	(8.68)	(12.18)	(10.32)	(6.22)	(8.61)
$Normalized\ Flow_{t-2}$	0.0853***	0.0855***	0.0842***	0.0890***	0.0724***	0.0993***
	(9.96)	(5.95)	(7.76)	(8.34)	(3.51)	(7.73)
$Normalized\ Flow_{t-3}$	0.0354***	0.0367***	0.0347***	0.0478***	0.0462***	0.0496***
	(5.31)	(3.19)	(4.02)	(5.00)	(3.79)	(3.67)
$Normalized\ Flow_{t-4}$	0.0327***	0.0378***	0.0288***	0.0202**	0.0228*	0.0173
	(5.04)	(4.05)	(3.36)	(2.10)	(1.95)	(1.21)
Constant	0.201***	0.102**	0.248***	0.0449	-0.120***	0.0953**
	(7.03)	(2.41)	(7.70)	(1.56)	(-2.90)	(2.56)
Fund fixed characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Investment Style Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	29424	11603	17821	17106	7141	9965
Adjusted R^2	0.138	0.128	0.144	0.125	0.118	0.131

Table 5

The Effect of Moderate Market Condition on Old Affiliated Open-Ended Hedge Funds.

The table reports a piecewise linear regression of quarterly flow conditional on market conditions with old affiliation data. Data starts from the beginning of 1995 until the end of 2016. Moderate market states are quarters in which the annual return of the S&P 500 falls between its 4 and 7 deciles (inclusive) of its historical return. The data consists of funds matched to SEC's ADV database. Cash flows are measured as percentage change of net asset between consecutive quarters, minus the return reported by the fund. Flows are scaled by the fund's asset under management. Flows are winsorized at 1 and 99% level to prevent influence from outliers. Fund time-invariant characteristics (fees, liquidity restrictions, on/offshore, highwatermark) are included as controls but not shown here. Quarter time fixed effects are included all specifications but not shown. Standard errors are clustered at the fund level. T-statistics based on clustered standard errors are in parentheses.

	All market states	Moderate market state	Extreme market state
	(1)	(2)	(3)
	Normalized Flow_t		
$Annual\ Rank_{t-1}$	0.130***	0.103***	0.147***
	(6.96)	(3.69)	(5.99)
$Old\ Affiliation$	0.0297***	0.0138	0.0404***
	(3.00)	(0.78)	(3.21)
$Annual\ Rank_{t-1} \times Old\ Affiliation$	0.0113	-0.00105	0.0209
	(0.46)	(-0.03)	(0.64)
$Annual\ Top30_{t-1}$	0.0948*	0.158**	0.0663
	(1.92)	(2.06)	(1.04)
$Annual\ Top30_{t-1} \times Old\ Affiliation$	-0.0862	-0.0643	-0.107
	(-1.37)	(-0.66)	(-1.33)
$Annual\ Bottom30_{t-1}$	0.0325	0.103	0.00593
	(0.72)	(1.41)	(0.10)

$Annual\ Bottom30_{t-1} \times Old\ Affiliation$	-0.0797	0.00144	-0.139*
	(-1.29)	(0.01)	(-1.69)
$Normalized\ Flow_{t-1}$	0.147***	0.135***	0.152***
	(14.36)	(8.69)	(11.84)
$Normalized\ Flow_{t-2}$	0.0819***	0.0779***	0.0831***
	(10.13)	(6.20)	(7.74)
$Normalized\ Flow_{t-3}$	0.0333***	0.0457***	0.0259***
	(5.05)	(4.14)	(3.35)
$Normalized\ Flow_{t-4}$	0.0342***	0.0310***	0.0363***
	(5.36)	(3.41)	(4.34)
Constant	0.159***	0.0914**	0.214***
	(5.22)	(2.34)	(6.14)
Fund fixed characteristics	Yes	Yes	Yes
Investment Style Fixed Effects	Yes	Yes	Yes
Quarter-time Fixed Effects	Yes	Yes	Yes
Observations	29687	11514	18173
Adjusted R^2	0.139	0.130	0.145

Table 6

Liquidation Model for Old Affiliation Open Ended Hedge Funds.

This table presents a probit model for liquidation, comparing all type of affiliation against non-affiliated funds. Data is from 1995 to end of 2016. Style and time fixed effects are included but not shown. Standard errors are clustered at fund level.

	Base specification	Include fund fixed characteristics	Include controls in (2) and time and style FE
	(1)	(2)	(3)
	$Pr(Liquidation = 1)_t$		
$Quarter\ Rank_{t-1}$	-0.623***	-0.590***	-0.654***
	(-10.08)	(-8.24)	(-8.64)
$Old\ Affiliation$	-0.353***	-0.340***	-0.424***
	(-5.14)	(-4.04)	(-4.86)
$Quarter\ Rank_{t-1} \times Old\ Affiliation$	0.100	0.00732	0.0318
	(1.19)	(0.07)	(0.30)
$Quarter\ Rank_{t-2}$	-0.577***	-0.660***	-0.716***
	(-9.45)	(-9.29)	(-9.63)
$Quarter\ Rank_{t-2} \times Old\ Affiliation$	0.212**	0.276***	0.309***
	(2.55)	(2.80)	(3.01)
$Quarter\ Rank_{t-3}$	-0.409***	-0.436***	-0.434***
	(-6.74)	(-6.27)	(-5.94)
$Quarter\ Rank_{t-3} \times Old\ Affiliation$	0.112	0.111	0.0934
	(1.36)	(1.14)	(0.92)
$Quarter\ Rank_{t-4}$	-0.344***	-0.243***	-0.271***
	(-5.81)	(-3.62)	(-3.88)
$Quarter\ Rank_{t-4} \times Old\ Affiliation$	0.115	0.123	0.119
	(1.42)	(1.31)	(1.21)

Constant	-0.983***	0.782***	0.757*
	(-19.95)	(4.83)	(1.79)
Fund characteristics	No	Yes	Yes
Style FE	No	No	Yes
Time FE	No	No	Yes
Observations	60169	43170	41895
Pseudo R^2	0.049	0.091	0.152