Costs and Benefits of Financial Conglomerate Affiliation: Evidence from Hedge Funds

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Abstract

This paper explores how affiliation to financial conglomerates affects asset managers' access to capital, trading behavior, and performance. Focusing on a sample of hedge funds, we find that financial-conglomerate-affiliated hedge funds (FCAHFs) have lower flow-performance sensitivity than other hedge funds and that this difference is particularly pronounced during financial turmoil. Arguably, thanks to more stable funding, FCAHFs allow their investors to redeem capital more freely and are able to capture price rebounds. Since investors may value these characteristics, our findings provide a rationale for why financial conglomerate affiliation is widespread, although it slightly hampers performance on average.

Keywords: Hedge Funds, Financial Conglomerates, Risk Taking

JEL Classifications: G2

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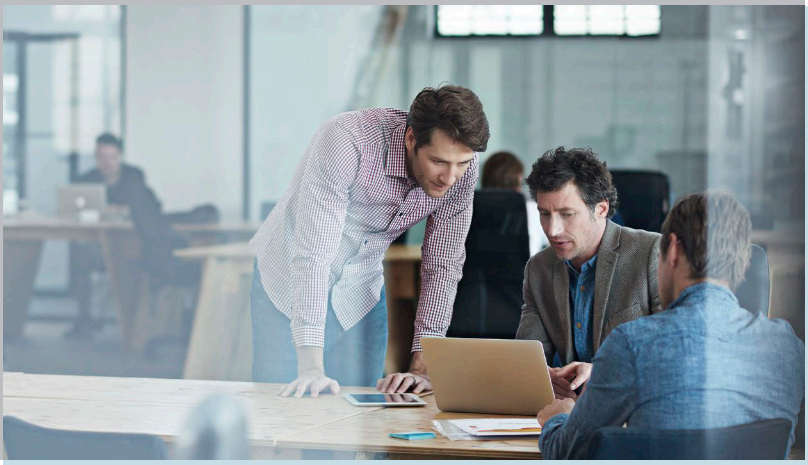

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1. Introduction

About 38% of the hedge fund industry's assets are managed by funds affiliated with a financial conglomerate. Surprisingly, we know little about the costs and benefits of financial conglomerate affiliation in this segment of the asset management industry. The existing literature highlights that mutual funds belonging to a financial conglomerate benefit from information flows (Massa and Rehman, 2008) and from trading with financially constrained subsidiaries of the financial conglomerate (Bhattacharya, Lee and Pool, 2013). These benefits, however, do not accrue to investors because conflicts of interest negatively affect performance (Bhattacharya, Lee, and Pool, 2013; Ferreira, Matos, and Pires, 2015; Golez and Marin, 2015).

Anecdotal evidence suggests that conflicts of interest may handicap also affiliated hedge funds.[1] This raises a puzzle. In the mutual fund industry, underperforming asset managers affiliated with financial conglomerates may survive thanks to their ability to attract and retain unsophisticated investors. However, hedge funds tend to attract sophisticated investors (see, e.g., Ackermann, McEnnally, and Ravenscraft, 1999), who are likely to choose affiliated funds only if they perceive some benefits in this type of institutional setup. This consideration suggests that affiliation with financial conglomerates may have yet-unexplored advantages over stand-alone structures from investors' perspective, and it makes the hedge fund industry an ideal setting to explore the costs and benefits of this institutional arrangement.

This paper studies how affiliation to financial conglomerates is associated with hedge funds' access to capital, contractual characteristics, performance, and trading behavior. The analysis aims to evaluate the costs and benefits of financial conglomerate affiliation from

[1] For example, in 2015, JP Morgan agreed to pay $307 million to the SEC and the CFTC to settle accusations that it steered its private banking clients' assets towards affiliated hedge funds, without giving the clients full disclosure (see, e.g., New York Times, DealBook, December 19, 2015).

investors' point of view. To the best of our knowledge, this is the first paper to document how financial conglomerate affiliation affects asset managers' access to funding and consequently their trading strategies.

To investigate these issues, we assemble a novel dataset of hedge fund ownership, mostly hand-collected from regulatory filings. These data allow us to construct a measure of financial-conglomerate affiliation that relies on ties to banks, insurance companies, and prime brokers. We then show that financial conglomerate affiliated hedge funds (FCAHFs) have access to more stable funding and explore how this fact relates to the nature of the services that FCAHFs are able to offer to their investors and the way they operate in the market.

Following a non-parametric approach similar to Chevalier and Ellison (1997) and Chen, Goldstein, and Jiang (2010), Figure 1 illustrates the main difference between FCAHFs and other hedge funds. The figure shows that FCAHFs' flows are less sensitive to performance. In particular, we find that following low returns, the flow-performance sensitivity of FCAHFs is 58% lower than for other funds. Moreover, as apparent in Figure 2, the sensitivity of flows to poor performance of FCAHFs is even lower in high-VIX periods (top quartile of the VIX distribution), which we label periods of market turmoil.

Lack of investor sophistication is unlikely to explain the weaker sensitivity of flows to performance. If anything, FCAHFs appear to cater to investors that are more sophisticated. In particular, FCAHFs display more financial institutions in their client base. Moreover, these findings are not the result of differences in hedge-fund styles, for which we control in our regressions.

Therefore, we conjecture that the observed differences in flow-performance sensitivity are due to the fact that financial conglomerate affiliation makes financial constraints less binding. Several arguments motivate this conjecture.

First, the typical hedge fund is subject to leverage constraints, which lead to a significant reduction in the demand for risky assets when aggregate market volatility increases, consistent with the theories in Gromb and Vayanos (2002) and Brunnermeier and Pedersen (2009). Benefiting from internal capital markets, FCAHFs may receive funding from the parent company or other subsidiaries of the financial conglomerate in periods of turmoil. This implicit credit line allows FCAHFs to release leverage constraints and have easier access to funding also during periods of market stress.

Second, FCAHFs are likely to benefit from the reputation and visibility of the financial conglomerate. Arguably, the financial conglomerate aims to protect its reputation with investors and avoid fund failures. The conglomerate can also leverage its reputation to convince its clients to invest in the affiliated funds or to remain invested when the funds underperform (Gennaioli, Shleifer, and Vishny, 2015).

Finally, the retention effect of the liquidity backstop and the reputational channels is likely to be magnified due to the strategic complementarities in investors' redemption decisions (Chen, Goldstein and Jiang, 2010; Goldstein, Jiang and Ng, 2015). In particular, expecting more stable funding, investors in FCAHFs have lower incentives to engage in runs on the funds' assets.

Consistent with the conjecture that affiliation to a financial conglomerate provides a liquidity backstop, we find that when FCAHFs experience extreme outflows, the share of financial sector institutions in their capital base increases. Moreover, FCAHFs controlled by severely underperforming financial conglomerates or by financial conglomerates with extremely high leverage, which enjoy worse reputation in the market, do not display lower sensitivity of flows to performance. Similarly, hedge funds belonging to financial conglomerates with rating below prime experience higher sensitivity of flows following poor performance.

A significant benefit of FCAHFs is that they allow their investors to redeem capital more freely. In particular, FCAHFs display a total duration of redemption restrictions that is 22% lower than other funds. This contractual characteristic is valuable because it provides investors with an option to redeem in case of idiosyncratic shocks (Ang and Bollen, 2010). Arguably, affiliated funds can afford this flexibility thanks to a more stable capital base.[2]

Importantly, as Stein (2005) highlights, more stable funding affects FCAHFs' trading behavior. A low sensitivity of flows to performance gives a comparative advantage for holding assets that are vulnerable to transitory price movements. Consistent with this conjecture, we find that FCAHFs are able to capture price rebounds following periods of market turmoil. Using institutional holdings and trade-level data, we provide evidence that FCAHFs acquire undervalued assets during market turmoil. In particular, we show that FCAHFs purchase relatively more volatile and illiquid stocks as well as past losers. In addition, FCAHFs' trades have lower price impact in illiquid, losing, and volatile stocks during high-VIX periods suggesting that FCAHFs provide liquidity to investors who wish to sell these stocks. Finally, the analysis of portfolio turnover of FCAHFs reveals a significantly longer trading horizon during periods of financial turmoil. Arguably as a consequence of this behavior, FCAHFs display significantly higher returns than other hedge funds right after market turmoil. For example, for

[2] During 2008, many hedge funds imposed gates to halt redemptions (Ben David, Franzoni and Moussawi, 2012). While this information cannot be directly observed, financial conglomerates are believed to provide support to their affiliated funds and continued liquidity to investors to avoid negative reputational spillovers (Kacperczyk and Schnabl, 2013).

four months after a crisis period, FCAHFs' monthly returns are at least 14 basis points higher than for other funds.

Financial conglomerate affiliation otherwise involves costs for investors, as in other corners of the asset management industry. We find that FCAHFs have slightly lower unconditional alpha than other funds (by almost 1% annually). To explain this finding, we argue that FCAHFs are likely to attract less skilled managers, as is consistent with their lower management fees (Berk and Green, 2004), and give them weaker incentives to perform, as is consistent with lower incentives fees and probable conflicts of interest arising within the financial conglomerate. Lower sensitivity of flows to performance may also contribute to this underperformance, as redemptions play the beneficial roles of disciplining fund managers and fostering managerial turnover (Fama and Jensen, 1983).

In sum, FCAHFs allow their investors to redeem capital more freely and engage in strategies that provide significantly higher returns than other hedge funds following periods of market turmoil. The characteristics of FCAHFs' strategies are compatible with these funds' more stable funding and can arguably make FCAHFs attractive for sophisticated investors in spite of their slightly lower average performance because investors' marginal utility of consumption is higher following crisis periods. This argument resonates with Glode's (2011) logic that investors prefer mutual funds' strategies that perform better when investors' marginal utility of consumption is high, even if these strategies have negative unconditional alphas.

Overall, our findings may have two not necessarily alternative interpretations. First, financial-conglomerate affiliation may lead hedge funds to provide liquidity during periods of market turmoil thanks to the stability of funding that it provides. Second, hedge fund managers who wish to pursue strategies that involve providing liquidity during periods of market turmoil may seek affiliation with financial conglomerates because of the funding stability associated with financial-conglomerate affiliation. However, irrespective of the interpretation, it remains true that financial-conglomerate affiliation facilitates liquidity provision thanks to stable funding.

This paper belongs to a recent and growing literature exploring different aspects of financial conglomerates. Most existing literature studies conflicts of interest affecting mutual funds affiliated with financial conglomerates and shows that conglomerate affiliation affects negatively performance (see, e.g., Massa and Rehman, 2008; Bhattacharya, Lee and Pool, 2013; Golez and Marin, 2015; Ferreira, Matos, and Pires, 2015). On the other hand, conflicts of interest do not negatively affect the performance of hedge funds affiliated with investment banks in comparison to the ones affiliated with non-bank conglomerates (Berzins, Liu, and Trzcinka, 2013).

Other papers explore the costs and benefits of financial conglomeration in multiple segments of the asset management industry. Kacperczyk and Schnabl (2013) show that money market funds that were part of financial conglomerates were less inclined to take risks during the global financial crisis, presumably because of reputational reasons. Fang, Ivashina, and Lerner (2013) study how bank sponsored private equity deals differ from those that occur without bank affiliation. We are the first to focus on the financing and trading of hedge funds belonging to financial conglomerates.

Our paper also contributes to a growing literature exploring the characteristics of asset managers that favor liquidity provision. For instance, Brunnermeier and Nagel (2004) and Griffin, Harris, Shu, and Topaloglu (2011) find that hedge funds were highly exposed to the IT bubble. A number of recent papers, instead, show that hedge funds tend to provide liquidity and to be contrarian investors (Grinblatt, Jostova, Petrasek, and Philipov, 2016; Akbas, Armstrong, Sorescu, and Subrahmanyam, 2014; Cao, Chen, Goetzmann, and Liang, 2013; Kokkonen and Suominen, 2015; and Jylha, Rinne, and Suominen, 2014). Our paper contributes to this literature by showing that hedge funds are heterogeneous and that the characteristics of their funding relate to their strategies. By exploring the incentives associated with financial-conglomerate affiliation, we complement earlier studies that have shown how hedge funds' share restrictions affect liquidity provision (Hombert and Thesmar, 2014) and long-term risky arbitrage (Giannetti and Kahraman, 2018).

2. Data and Sample

2.1. Identifying FCAHFs

The Investment Advisers Act requires all advisers with more than $25 million in assets under management in the U.S. and with 15 or more U.S. clients to register and file ADV forms with the Securities and Exchange Commission (SEC) or with state securities authorities if they manage less than $100 million. The Act defines an investment adviser as any entity that receives compensation for managing securities portfolios or providing advice regarding individual securities. Thus, firms advising mutual funds, institutional investment funds, and hedge funds in the U.S. use ADV filings to register. The ADV forms are filed once a year or whenever material changes occur to the information provided with the last filing.

Using the Freedom of Information Act, we obtain historical information on ADV filings from the SEC starting from 2000 through the end of 2013. The ADV filings disclose information about the investment advisors' operations, conflicts of interest, disciplinary histories, and other material facts. Several prior studies use ADV filings to explore hedge funds' operational risk and misreporting (Brown, Goetzmann, Liang, and Schwarz, 2008; Dimmock and Gerken, 2012 and 2016).

Crucially for our purposes, Item 7 of the ADV Form requests investment advisers to report information on their industry affiliations and activities. The funds have to report whether any subsidiary or any other entity under common control with the filing adviser provides financial, legal, consulting, or brokerage services.

We define an investment adviser to be part of a financial conglomerate if any subsidiary or entity under common control may be able to directly or indirectly offer financing. We consider banking or thrift institutions, insurance companies, and prime brokers to be able to perform this function. During periods of market turmoil, when leverage constraints bind for hedge funds, the affiliated banks, insurance companies, and prime brokers may provide a liquidity backstop, valuable capital introductions, or at least not tighten the margins as much as for unaffiliated clients, also to protect their reputation with investors. Bear Stearns, whose collapse was partly driven by its exposure to two affiliated hedge funds, provides a suitable example. More generally, banks, insurance companies, and prime brokers can leverage their reputation to convince clients to remain invested in poorly performing funds.

We thus define an investment adviser to be part of a financial conglomerate if the investment adviser declares to be related to a banking or thrift institution, to an insurance company or a broker-dealer in the ADV filings. Since broker-dealers include in a few instances executing agents, we manually purge the list of FCAHFs from any hedge fund affiliated with broker-dealers that are exclusively executing brokers.

We identify hedge funds using three common commercial datasets, Lipper Tass, CISDM/Morningstar, and Hedge Fund Research, from which we also obtain information on hedge funds' characteristics, including returns, assets under management, and other contractual details.

As argued in Agarwal, Fos, and Jiang (2013), the three commercial datasets provide information on largely different subsets of hedge funds. Following their procedure (also see Patton, Ramadorai, and Streatfield, 2015), we manually merge the databases by management company name. Then, after converting returns in dollars, we exclude multiple share classes for the same management company. We end up with a sample of 21,892 distinct funds over the period between 1994 and 2013.[3]

Next, we merge the information from the union of the three datasets with the ADV filings using the management company names. Out of the 8,717 firms in our sample, we are able to find a match in the ADV filings for 2,258 firms (about 26%), which manage 5,513 distinct funds over the period 2000-2013. In our merged sample, there are 1,630 financial-conglomerate-affiliated hedge funds (about 29% of the observations in our panel pertain to FCAHFs). JP Morgan Alternative Asset Management, BNY Mellon ARX Investimentos, or Napier Park Capital Management are among the top FCAHFs by assets under management (AUM) in our sample.

Typically, the financial conglomerate directly invests capital in the affiliated hedge fund. In other cases, the financial conglomerate obtains a share of the affiliated hedge fund's revenues in perpetuity in exchange for the access to marketing and distribution channels. In all these instances, the financial-conglomerate affiliation may facilitate the hedge fund's access to capital.

A case in point is Highbridge Capital Management, a hedge fund in which JP Morgan Chase acquired capital interest in 2004. Even if JP Morgan was forced to dismiss whole or part

[3] The number of hedge funds in our sample is similar to Agarwal, Fos, and Jiang (2013) and Patton, Ramadorai, and Streatfield (2015), after accounting for the fact that we have a more recent sample and therefore more years of data.

of its capital investment by an eventual implementation of the Volker rule, it could transfer Highbridge to its asset management unit and continue to perceive part of the fund's revenues. Overall, these two institutional arrangements are not very different from the point of view of the ultimate owner as in both cases the financial conglomerate has incentives to protect future profits by sustaining the fund at times of crisis. Anecdotal evidence shows that this happens routinely following an affiliated fund's negative performance as the financial conglomerate not only provides a liquidity backstop but also, more crucially, it convinces bank clients to remain invested in the fund (Wall Street Journal, September 8, 2015). JP Morgan Alternative Assets Management also provides an example of the limitations of the financial conglomerate affiliation in incentivizing and retaining talent, as the star managers tend to quit and start their own funds in the quest for a larger share of profits and more visibility (Financial Times, March 4, 2012).

2.2. Sample Representativeness

One may wonder to what extent our sample is representative of the general hedge fund universe. The main concern arises from the fact that up to the introduction of Rule IA-2333 in February 2005, hedge fund advisers could count their private funds as clients, effectively creating an exemption from registration. Rule IA-2333, removed this exemption, leading to the requirement of registration for hedge fund advisors.[4] Following a lawsuit, this rule was revoked and the exemption from registration became effective again. Dimmock and Gerken (2016), however, show that about 70% of the hedge fund advisors in their sample that had registered following the introduction of Rule IA-2333 remained registered after its repeal, arguably because

[4] The SEC reports that a majority of hedge fund advisors was already registered before the introduction of Rule IA-2333, possibly because they were also managing mutual funds, advising 15 or more funds, or voluntarily forgoing the exemption. See: http://www.sec.gov/news/testimony/ts051606sfw.htm.

they had already born the fixed cost of registration and their investors had adjusted their expectations.

With the amendments to the Advisers Act introduced by the Dodd-Frank Act, the exemption for hedge fund advisors from registration has fallen once again, effective September 2011. In the current regulatory environment, U.S. hedge fund advisors with more than $150 million of AUM need to register with the SEC. An exemption from registration survives for foreign hedge fund advisors that have fewer than 15 U.S. clients and less than $25 million of AUM from U.S. clients.

These changes in regulation induce oscillations in the number of reporting funds with the sample of reporting hedge funds been highly representative in 2006 and after 2011. To improve the coverage of our sample, we assume any hedge fund that was affiliated with a financial conglomerate in 2006 to be still affiliated with a financial conglomerate in the following years if the fund status did not change between 2006 and 2011, or if the fund does not appear in the ADV filings again. We also backward impute the financial conglomerate status for hedge funds that only appear in a later part of the ADV sample. Overall, we fill approximately 36% of the observations.

To evaluate whether filling missing ADV observations introduces any biases we perform two types of checks. First, we consider funds that report both in 2006 and 2011 and explore what proportion of them changes status. We find that this is the case for less than 2% of the hedge funds suggesting that our procedure of attributing missing status to hedge funds that report only in a few years should not introduce big biases. This is consistent with anecdotal evidence that hedge funds are often acquired by financial conglomerates when they perform early fundraising activities, which is before they enter commercial databases.

Second, we perform all of our tests in an alternative sample in which we abstain from backward imputation of the financial-conglomerate status. The results we report hereafter are qualitatively unchanged further indicating that our procedure of constructing the panel of hedge funds and their financial-conglomerate affiliations does not introduce large biases.

One may also wonder whether the sample of hedge funds reporting to the commercial dataset that we are able to merge with ADV forms is selected. To evaluate the extent of selection problems, Panel A of Table 1 compares the main characteristics of the funds in the merged commercial datasets and in the final dataset for which we are able to find a match with the ADV filings. We consider unmatched onshore hedge funds because our sample based on U.S. regulatory filings can be representative only of funds active in the U.S. market.

There are no economically significant differences in performance between matched and unmatched funds. Unsurprisingly, given the minimum threshold on assets for mandatory registration, the hedge funds that we are able to match with ADV filings are somewhat larger. The matched funds are also older and require larger minimum investments suggesting that our sample includes relatively more established funds. To the extent that older non-FCAHFs enjoy higher reputation than other funds this may bias our results against finding any differences between FCAHFs and other funds.

2.3. Hedge Fund Holdings and Trades

We perform tests on two other samples, which allow us to explore hedge funds' trading. First, we merge our main dataset with stock holdings from 13F filings in Thomson-Reuters. Since Thomson-Reuters and the hedge funds' databases provide no common identifiers, we merge by management company name as is common in the literature (e.g., Agarwal, Fos, and Jiang, 2013).

Thomson Financial 13F provides the shareholdings of management companies. In case of financial conglomerates, this may include holdings of different subsidiaries. Differently from previous literature, we do not include only "pure-play" hedge funds, as this would imply the exclusion of most FCAHFs. In robustness tests, which we do not report for brevity, we compare the trades of FCAHFs with those of other financial conglomerates without hedge funds. These tests show significant differences in trading between FCAHFs and other financial conglomerates without hedge funds indicating that our findings on FCAHFs vs. other hedge funds are unlikely to be driven by the holdings of other non-hedge-fund subsidiaries of the financial conglomerate.

We are able to match 401 management companies to our sample resulting from the intersection of ADV filings and the commercial databases. Even though the sample is reduced and the funds are older and require higher minimum investment than in the ADV matched sample, in Panel A of Table 1, the 13F matched dataset does not appear to be much different from the unmatched sample and the ADV matched sample. Therefore, we use the 13F-matched dataset to explore how different types of hedge funds rebalance their holdings in stocks with different characteristics during periods of market turmoil.

We also perform tests on a second sample obtained by merging our main dataset with the ANcerno database by management company name. Abel Noser Solutions Ltd., provider of the ANcerno data, is a consulting firm that works with institutional investors to monitor their equity trading costs. The ANcerno data contain trade-level information for individual funds. However, the only recognizable identifier is at the management company level (see, e.g., Jame, 2015; Franzoni and Plazzi, 2015), which is therefore the chosen level of aggregation. We are able to identify 184 hedge fund management companies matching to the intersection of the ADV filings and the commercial hedge fund databases. In Panel A of Table 1, also this sample, albeit reduced, appears similar to the ADV matched and the unmatched samples.

3. Characteristics of FCAHFs

FCAHFs are a sizeable part of the hedge fund industry. As shown in Figure 3, Panel A, the proportion of FCAHFs has been increasing over time, even though it decreases in 2010, possibly in anticipation of regulations related to the Volker rule after the financial crisis.

Figure 3, Panel B, shows the proportion of the hedge funds' AUM managed by FCAHFs. In aggregate, FCAHFs control on average about 38% of the hedge fund industry's AUM, indicating that FCAHFs are larger than other funds. Similarly to what Fang, Ivashina, and Lerner (2013) find for banks' investment in private equity, it appears that the proportion of assets managed by FCAHFs increased in the heyday of easy credit, when presumably banks increased their investments in hedge funds.

Panel B of Table 1 compares a few salient characteristics of FCAHFs and other hedge funds in our ADV matched sample. FCAHFs are larger and belong to larger families. These characteristics are often associated with asset managers' reputation and may result in funding stability. It is thus an empirical question whether FCAHFs have more stable funding than other large funds or funds belonging to large families.

FCAHFs have a lower propensity to use leverage than other funds (variable *Leveraged*), but when they use leverage they do it in somewhat higher proportions (variable *Leverage*). A higher fraction of FCAHFs are funds of funds.[5] We note that funds of funds experienced large redemptions during the financial crisis of 2008 (see, e.g., Indjic and Billieux, 2009). Hence, to the extent that funds of funds affiliated with financial conglomerates shared the destiny of other funds of funds, FCAHFs should appear as having less stable funding. In fact, the evidence that we present points to the opposite result for FCAHFs.

Large redemptions in the styles of FCAHFs go against finding a positive effect of financial conglomerate affiliation on funding stability also because differently from other hedge funds, financial conglomerates, fearing negative effects on their reputation, are expected to be less inclined to impose gates and to suspend redemptions on their funds (Kacperczyk and Schnabl, 2013). In any event, to control for unobserved variation across styles, all our fund-level regressions include style fixed effects.

As is consistent with previous literature on financial conglomerate affiliated asset managers (see, e.g., Massa and Rehman, 2008), FCAHFs appear to underperform stand-alone hedge funds although the differences are not necessarily statistically significant for three out of four measures of performance. FCAHFs also have higher return volatility suggesting that they may be taking more risk. This is also suggested by the fact that FCAHFs have higher market beta and R-squared when we estimate Fung and Hsieh's (2001, 2004) factor model indicating that they have, on average, higher exposure to systematic risk and a smaller idiosyncratic component in returns.[6] The higher negative skewness and negative beta suggests that FCAHFs' exposure to systematic risk factors is particularly high during bad times. FCAHFs also have higher

[5] We refer to Fung, Hsieh, Naik, and Ramadorai (2008) for a detailed treatment of performance and risk of funds of funds.

[6] To be precise, the original Fung and Hsieh (2001, 2004) model included seven factors, but we also include the emerging market factor, as advocated in Edelman, Fung, Hsieh, and Naik (2012). The factors can be found here: http://faculty.fuqua.duke.edu/~dah7/DataLibrary/TF-FAC.xls. They include three trend-following factors for bonds, currency, and commodities, an equity market factor (the S&P 500), the size-spread factor in U.S. equities, a bond market factor, a credit spread factor, and an emerging market index.

autocorrelation of monthly returns (rho), which, according to Getmansky, Lo, and Makarov (2004), may indicate that they hold less liquid portfolios. Our empirical analysis explores these features of FCAHFs' strategies in more detail. Panel C of Table 1 presents the descriptive statistics for our sample. Variable definitions are in Appendix Table A1.

A question arising from the comparison of hedge funds' characteristics in Panel B of Table 1 is whether affiliation to a financial conglomerate is a salient characteristic that affects hedge funds' contractual features and strategies beyond their style, size, and family characteristics. Table 2 reports regressions of hedge fund characteristics on the indicator for FCAHFs, controlling for the fund's age, family size, and style.

Panel A of Table 2 considers cross-sectional variation in some salient characteristics of the contracts that the hedge funds in our sample offer to their investors. Since these contractual features are typically established upon the fund's inception, for these variables, we do not have time-series information. Columns 1 and 2 of Panel A show that FCAHFs charge their investors lower management fee (by about 8 bps) and incentive fee (by about 82 bps) than other hedge funds. These differences are economically significant given that the mean (standard deviation) of these variables is 1% (1%) and 15% (8%), respectively (see Panel C of Table 2).

In the spirit of Berk and Green (2004), the lower fees of FCAHFs may suggest that these funds hire less skilled managers and give them weaker incentives to perform and would be consistent with FCAHFs' worse risk-adjusted performance.

To decrease their flow-performance sensitivity, hedge funds often impose lockup periods during which new investors cannot recover their funds (Agarwal, Daniel, and Naik, 2009). Once the lockup period has expired, investors must often give the fund advance notice (e.g., one month) before redeeming. Investors may also be able to redeem only at fixed dates (e.g., every quarter), which denote the redemption frequency. These contractual impediments to withdrawals are collectively referred to as share restrictions. Given that hedge funds' *monthly* performance is typically reported with a delay of three to eight weeks, in the presence of share restrictions, a seasoned investor in the fund, i.e. one for which the lock-up period has already expired and it is, therefore, not binding, will be able to withdraw after one quarter.[7]

FCAHFs offer their investors strictly shorter lockup periods (by about 19 days, column 3), shorter redemption notice periods (by about 4 days, column 4), and lower distance between redemption dates (by about 5 days, column 5). Again, the economic magnitude is significant given that the means of these variables are 74, 41, and 66 days, respectively. Hence, FCAHFs offer their investors shares with significantly lower total restrictions (column 6).

Thus, FCAHFs offer more liquidity to their investors, a feature that is valuable if investors are subject to idiosyncratic shocks, which lead them to redeem their capital from the fund (Ang and Bollen, 2010). In the next section, we explore whether the greater liquidity that FCAHFs offer to their investors implies less funding stability or, rather, whether FCAHFs can afford to offer greater liquidity to their investors thanks to more stable funding.

Panel B of Table 2 considers differences in client composition between funds, for which we have time series information from the funds' ADVs. Since a fund's assets composition may not vary much over time, we cluster standard errors at the fund level.

Investment advisers report in their ADVs the number of their clients. While some funds may be reporting the number of funds as clients, it appears that just a minority does so as the

[7] An investor whose lock up period has expired needs to give a notice of redemption to the fund before he/she can get the money back. From Panel C of Table 2, the median Redemption Notice period is 30 days (mean: 41 days). After the notice period has passed, the investor will be able to withdraw the funds at the first available redemption date. The median Redemption Frequency is 30 days (mean: 66 days), suggesting that the typical investor is allowed to redeem at the end of each quarter or slightly before.

bottom percentile of registered financial advisors reports 100 clients. We can thus explore whether affiliation with a financial conglomerate allows hedge funds to attract a larger number of clients. It appears that FCAHFs have more clients (Number of Clients) even after controlling for their size (column 1). This result is robust if we restrict the sample to funds with more than 10 or even 100 clients indicating that reporting differences are unlikely to drive our findings. In particular, FCAHFs have nearly 66 more clients than non-affiliated funds, a considerable difference given the mean of this variable (73 clients in Panel C of Table 1).

Unsurprisingly, FCAHFs attract a larger percentage of assets from banks and insurance companies (column 2). The average of the percentage of assets from banks and insurances companies is 8.7% for FCAHFs and can be considered an upper bound on the capital invested by the financial conglomerate in the hedge fund. As we would expect, the average of this variable is lower at 2.5% for non-FCAHFs. FCAHFs also display 6.4% more assets from other institutional investors in the financial industry, which may be associated with the financial conglomerate (column 3).

While FCAHFs also attract more assets from pension funds (column 4) and from foreign investors (column 5), a lower percentage of their assets is from individual investors and high net-worth individuals (column 6), though the difference is not significant. Overall, these results suggest that FCAHFs do not cater to less skilled investors than other funds. Any differences in their flow-performance sensitivity are therefore unlikely to depend on the lack of investor sophistication or on investor inattention, but are more likely to depend on the fact that the financial conglomerate is expected to provide support when the fund experiences financial constraints.

Panel C of Table 2 provides evidence consistent with the view that FCAHFs receive a liquidity backstop from the financial conglomerate in bad times. We regress the percentage of assets from financial institutions on a dummy for whether the fund experiences flows in the bottom quintile of the distribution in the prior quarter. The dependent variable is taken as a proxy for the investment of the financial conglomerate in the affiliated fund. We include fund fixed effects, besides quarter fixed effects, because we are interested in fund-level variation in the dependent variable. The estimates reveal that hedge funds that suffered extreme outflows experience a significant increase in assets from the financial sector. Interacting extreme outflows with the affiliation dummy (column 2), we note that this effect only takes place among FCAHFs, for which the assets from financial conglomerates increase by 9 bps. This finding strengthens the intuition that the parent company or its other subsidiaries step in to provide capital for affiliated funds.

4. Financial-Conglomerate Affiliation and Flow-Performance Sensitivity

In this section, we study the stability of FCAHFs' funding. FCAHFs may be special for several reasons. They may invest the capital of the financial conglomerate and its subsidiaries, which is naturally less volatile. In addition, they may be considered more trustworthy by investors, thanks to the reputation of the financial conglomerate they are affiliated with. Investors may also be less inclined to redeem if they expect the capital coming from within the financial conglomerate not to be withdrawn or the financial conglomerate to provide a liquidity backstop. Thus, runs on the financial intermediaries arising from the payoff complementarities of the fund's investors may be less likely to arise (Chen, Goldstein, and Jiang, 2014). All these elements should contribute to making FCAHFs less financially fragile.

4.1. Estimates of the Flow-Performance Sensitivity

To evaluate the validity of this conjecture, we estimate whether flows are less sensitive to performance for FCAHFs, indicating that they have access to more stable funding. We consider how a fund's performance over quarter q affects the fund's flows during quarter $q+1$.[8] To account for a delayed reaction to performance, we also include performance during quarter *q-1*.

Quarterly net flows are computed as the change in assets under management relative to the prior quarter minus the dollar return on prior quarter assets, divided by prior quarter assets:

$$Flows_{j,q} = \frac{\left[AUM_{j,q} - AUM_{j,q-1} \times (1 + R_{j,q})\right]}{AUM_{j,q-1}}, \tag{1}$$

where $AUM_{j,q}$ is the AUM in quarter q for fund *j*, and $R_{j,q}$ is fund *j*'s quarterly return, which is obtained from compounding the fund's monthly returns.

In the spirit of Sirri and Tufano (1998), we regress the fund's flows in quarter q+1 on the fractional rank of the fund return (FRANK) in quarter q (i.e., the fund return's percentile ranking relative to other funds). While we compute the fractional rank based on reported returns, results are qualitatively and quantitatively unchanged if we unsmooth fund returns, as in Getmansky, Lo, and Makarov (2004).

[8] This is the timing commonly assumed in previous literature (see, e.g., Fung, Hsieh, Naik, and Ramadorai, 2008; Ben-David, Moussawi, and Franzoni, 2012; Getmansky, Liang, Schwarz, and Wermers, 2015; Lim, Sensoy, and Weisbach, 2016; Yin, 2016).

Given the non-linearity in the response of flows to performance that emerges in Figures 1 and 2, we distinguish the effect of flows on performance for funds in the bottom, middle, and top terciles because investors may react differently to extreme performance.

For instance, Goetzmann, Ingersoll, and Ross (2003) report a concave relation between flow and performance for hedge funds indicating that investors react most strongly to poor performance. In a different sample, Agarwal, Daniel, and Naik (2004) instead find a convex relation suggesting that flows are more sensitive to performance for the best performing funds. More recently, Li, Zhang, and Zhao (2011) find the flow-performance relation to be linear. We accommodate any of these functional forms using the following specification

$$Flows_{j,q+1} = a + b_1 FRANK1_{j,q} + b_2 FRANK2_{j,q} + b_3 FRANK3_{j,q}$$

$$+\left(c_1 FRANK1_{j,q} + c_2 FRANK2_{j,q} + c_3 FRANK3_{j,q}\right) \times FCAHF_j$$

$$+d_1 FRANK1_{j,q-1} + d_2 FRANK2_{j,q-1} + d_3 FRANK3_{j,q-1}$$

$$+(f_1 FRANK1_{j,q-1} + f_2 FRANK2_{j,q-1} + f_3 FRANK3_{j,q-1}) \times FCAHF_j$$

$$+eFCAHF_j + controls + \gamma_j + \delta_q + \varepsilon_{j,q+1}, \tag{2}$$

where we define FRANK1=min(FRANK, 1/3), FRANK2=min(FRANK-FRANK1, 1/3), and FRANK3= min(FRANK-FRANK1-FRANK2, 1/3), i.e., we break the variable FRANK into three terciles. Thus, a higher value of the fund's fractional rank here means better performance. We further include one-quarter lags of FRANK1, FRANK2, and FRANK3 and their interaction with $FCAHF_j$ to consider that investors in funds with longer share restrictions may not be able to redeem within one-quarter.

We control for fund size, age, the logarithm of redemption restrictions, and lagged flows. We absorb any quarter-specific differences in styles by including interactions of style and time fixed effects. We also double-cluster standard errors at the fund and time levels to account for the fact that flows may not only be correlated for the same fund, but also subject to contemporaneous shocks across funds (Petersen, 2009, p. 458). Our results are at least as strong if we cluster at the management firm and time level.

Our estimates in columns 1 and 2 of Panel A of Table 3 suggest that being part of a financial conglomerate weakens the relation between flow and performance for bottom-performing hedge funds (FRANK1). Differences for middle and top performing funds are not statistically significant. The less steep relation between flows and performance for FCAHFs is consistent with Figure 1, where we use non-parametric estimation to provide a visual characterization.

Interestingly, the shape of the flow-performance sensitivity for non-FCAHFs is consistent with concavity for low levels of performance and with convexity for higher levels of performance, while it is mostly linear for FCAHFs. This multi-faceted evidence therefore seems to reconcile the literature's prior findings.[9]

Differences in flow performance sensitivity are not only statistically but also economically large. Bottom performing non-FCAHFs have higher sensitivity of flows to performance of about 58% (i.e., 0.07/0.12, in column 2). These differences in coefficients

[9] We separately compute the partial R-squared (i.e., the within R-squared) of the regressions in the Table 3. These statistics give the fraction of the variance of the dependent variable that is explained by our regressors, without taking into account the fixed effects. From comparing the total and partial R-squared of the regressions in Panel A, we note that the contribution of fixed effects to the total R-squared is about 3%. The difference is of similar magnitude in the other panels of Table 3. Hence, we infer that the other regressors explain a fraction of variation that is substantially larger than the fraction captured by fixed effects.

between FCAHFs and other hedge funds have large consequences on flows following changes in performance. A non-FCAHF in the bottom tercile of the ranking has a sensitivity of flows to performance of 0.12. This implies a decrease in net flows of $1.8 million if its fractional rank slides by 10 percentage points (i.e., $0.1 \times 0.12 \times \$151$ million). For a FCAHF in the bottom tercile, the effect of a corresponding drop in fractional rank on outflows is less than half at $0.7 million (i.e., 0.1 × (0.12-0.07) ×$151 million).

These results are robust in columns 3 and 4 when we consider the effects of performance in quarter *q-1* on the flows at *q+1* as well as in column 5 when we estimate the full model in equation (2). It appears that FCAHFs experiences less outflows due to poor performance also when we consider performance two quarters ahead. The explanatory power for the fractional rank at q seems larger than for the fractional rank at *q-1*. This conclusion is confirmed in column 5, showing not only that flows respond less to poor performance for FCAHFs as indicated by the negative and significant coefficient on the interaction term $FRANK1_{j,q} \times FCAHF_j$, but also that the most relevant differences between FCAHFs and other hedge funds emerge already within a quarter.

These findings have important implications because, as Chevalier and Ellison (1997) argue, the shape of the flow-performance relationship affects asset managers' incentives to take risk. In particular, based on their flow-performance relationship, FCAHFs should be less concerned about underperformance than other hedge funds because they experience less outflows following weak returns. As we show below, these incentives are particularly strong during bad times when FCAHFs may take advantage of mispriced securities. We explore this prediction in Section 6.

4.2. Robustness to Alternative Performance Measures

In Panel B of Table 3, we show that our results are robust if we use continuous measures of performance instead of the funds' fractional rank. In particular, in column 1, we measure performance using excess returns, in columns 2 and 3, using the alpha estimated from a capital asset pricing model and from a Carhart (1997) four-factor model, respectively, and in column 4 using the alpha estimated from Fung and Hsieh's (2001, 2004) seven-factor model plus the emerging market factor. In all cases, the flow-performance sensitivity is smaller for FCAHFs. Differences in flow-performance sensitivity are about 10% when we consider excess returns and well in excess of 20% once we consider funds' factor exposures in column 2 to 4.

4.3. Flow-Performance Sensitivity in Periods of Turmoil

Arguably, the financial support from the conglomerate is mostly relevant during periods of market stress, when capital is scarce. Therefore, we explore how the flow-performance sensitivity varies during periods of market turmoil. We capture periods of market turmoil using the VIX index, a measure of implied volatility in S&P 500 index options. The VIX index is often referred to as the "fear gauge index" and is commonly used in the literature to identify periods of market stress and high aggregate market volatility (see, for instance, Nagel, 2012; Cella, Ellul, and Giannetti, 2013). We define high-VIX periods as quarters during which the average VIX index exceeds the 75th percentile of its realizations up to that quarter. This allows us to concentrate on periods of extreme aggregate market volatility, such as the recent financial crisis, without a look-ahead bias. Appendix Table A2 lists the high-VIX periods.

We condition the relation between flows and performance on realizations of the VIX and further control for fund characteristics that could affect this relation. Hence, we estimate the following specification

$$Flows_{j,q+1} = a + b_1 FRANK1_{j,q} + b_2 FRANK2_{j,q} + b_3 FRANK3_{j,q}$$

$$+\left(c_1 FRANK1_{j,q} + c_2 FRANK2_{j,q} + c_3 FRANK3_{j,q}\right) \times High\,Vix_q \times FCAHF_j$$

$$+\left(d_1 FRANK1_{j,q} + d_2 FRANK2_{j,q} + d_3 FRANK3_{j,q}\right) \times High\,Vix_q \times Control_{j,q}$$

$$+\left(e_1 FRANK1_{j,q} + e_2 FRANK2_{j,q} + e_3 FRANK3_{j,q}\right) \times FCAHF_j$$

$$+\left(f_1 FRANK1_{j,q} + f_2 FRANK2_{j,q} + f_3 FRANK3_{j,q}\right) \times High\,Vix_q$$

$$+\left(g_1 FRANK1_{j,q} + g_2 FRANK2_{j,q} + g_3 FRANK3_{j,q}\right) \times Control_{j,q}$$

$$+g_1 FRANK1_{j,q-1} + g_2 FRANK2_{j,q-1} + g_3 FRANK3_{j,q-1}$$

$$+(h_1 FRANK1_{j,q-1} + h_2 FRANK2_{j,q-1} + h_3 FRANK3_{j,q-1}) \times FCAHF_j$$

$$+eFCAHF_j + f High\,Vix_q \times FCAHF_j + hHigh\,Vix_q \times Control_{j,q}$$

$$+Control_{j,q} + controls + \gamma_j + \delta_q + \varepsilon_{j,q+1},$$

(3)

where the variable $Control_{j,q}$ is an indicator denoting: a Large Fund, a Large Family, High Restrictions, a High Age (these variables are defined in detail in Appendix Table A1). Our main focus in Equation (3) is on the triple interactions involving *FRANK1*, High VIX, and the indicator for FCAHF. While we continue to control for performance at *q-1* and the differential effects on FCAHFs, we do not distinguish the effect of VIX as our results in Table 3 show that performance at *q* is the main driver of differences in flows between FCAHFs and other funds at *q+1*.

We report the estimates in Table 4. The main result is that FCAHFs have a lower sensitivity of flows to poor performance during bad times, as proxied by periods of High VIX (slope on *FRANK1×High Vix×FCAHF*). In particular, using the estimates in column 1, the sensitivity of flows to performance is zero for FCAHFs, while it is 15% for non-FCAHFs, implying that FCAHFs' net flows are significantly more stable.[10]

Table 4 further tests the robustness of our main result. The flow-performance sensitivity of FCAHFs remains lower even when we control for the effects of other characteristics, which are included in the regression as indicated on top of each column. Moreover, during bad times, funds belonging to large families, funds with high restrictions, and old funds do not display a lower sensitivity of flows to poor performance (slope on *FRANK1×High Vix×Control*) suggesting that reputation and redemption restrictions are not a substitute for financial conglomerate affiliation.

4.4. Effect of Financial Conglomerate's Health on the Flow-Performance Sensitivity

If the flatter flow-performance sensitivity of FCAHFs is due to the liquidity backstop provided by the financial conglomerate, or to the higher reputational capital originating from the affiliation to a financial conglomerate, we expect this effect to be weaker when the financial conglomerate performs poorly or, more generally, has low reputation vis-à-vis investors.

[10] Using the estimates in column 1 of Table 4, the slope on FRANK1 for FCAHFs in high VIX periods is: 0.10+0.05-0.03-0.12 = 0. The slope on FRANK1 for non-FCAHFs in high VIX periods is: 0.10+0.05 = 0.15. Hence, the sensitivity for FCAHFs is about 100% lower.

Based on this conjecture, we test whether the reputation and performance of the financial conglomerate affect FCAHFs' flow-performance sensitivity. We perform two types of tests. First, using Bloomberg, we search for the S&P, Moody, and Fitch ratings of different debt issuances of the financial conglomerate parent company. We find ratings for 13.3% of our sample of FCAHFs. We identify as having weaker reputation hedge funds affiliated with a financial conglomerate with rating below prime, which represent about 90% of the FCAHFs' observations.

Second, we merge by name the control persons of FCAHFs, as resulting from ADV filings, with Compustat Global. This allows us to compute leverage and quarterly stock returns for about 6% of our sample of FCAHFs. We define a FCAHF to belong to a conglomerate with low returns (high leverage) if it is in the bottom (top) quartile of returns (leverage) for the merged sample during a quarter. We then explore how ratings below prime, poor performance and high leverage of the affiliated financial institutions affect the flows into the fund depending on its fractional rank. In particular, we run the following regression

$$
\begin{aligned}
Flows_{j,q+1} &= a + b_1 FRANK1_{j,q} + b_2 FRANK2_{j,q} + b_3 FRANK3_{j,q} \\
&+ \left(c_1 FRANK1_{j,q} + c_2 FRANK2_{j,q} + c_3 FRANK3_{j,q}\right) \times FCAHF_j \\
&+ \left(d_1 FRANK1_{j,q} + d_2 FRANK2_{j,q} + d_3 FRANK3_{j,q}\right) \times Characteristic_{j,q} \\
&+ g_1 FRANK1_{j,q-1} + g_2 FRANK2_{j,q-1} + g_3 FRANK3_{j,q-1} \\
&+ (h_1 FRANK1_{j,q-1} + h_2 FRANK2_{j,q-1} + h_3 FRANK3_{j,q-1}) \times FCAHF_j \\
&+ eFCAHF_j + fCharacteristic_{j,q} + controls + \gamma_j + \delta_q + \varepsilon_{j,q+1}.
\end{aligned}
\tag{4}
$$

where $Characteristic_{j,q}$ is a dummy variable denoting FCAHFs that belong to a conglomerate with high leverage, low returns, or ratings below prime. We exclude from the analysis FCAHFs for which we do not find a match with the relevant characteristic.

Table 5 reports the results. Being affiliated with a financial conglomerate with ratings below prime, poor performance, or high leverage is always associated with relatively higher flow-performance sensitivity for funds with fractional ranks in the bottom tercile (slope on *FRANK1*×*Characteristic*). For funds with better performance, poor financial conditions of the parents do not necessarily translate in higher sensitivity of flows to performance across different specifications. This is not surprising, as the anticipation of financial support from the conglomerate should matter primarily for poorly performing funds.

Funds affiliated with financial conglomerates with poor past returns and high leverage appear to receive somewhat smaller flows, regardless of their prior performance, as evident from the estimates for the dummies High Leverage and Low Past Return, even though the effect is only statistically significant for High Leverage. This finding is consistent with the evidence in Sialm and Tham (2015) that mutual fund flows depend on the performance of their listed management companies, even after controlling for the mutual fund's returns.

Overall, these tests validate our interpretation that expectations of financial support from the conglomerate and, more generally, trust in the parent institution are important in explaining the funding stability of FCAHFs. Alternative explanations, unrelated to financial conglomerate affiliation, cannot jointly explain the evidence we have presented so far. For instance, while asset managers with less sophisticated investors may have a flatter relation between flow and performance, in Table 3, Panel B, we show that FCAHFs do not appear to cater to less experienced investors. Furthermore, an interpretation in which the difference in flow-performance sensitivities originates from learning about uncertain managerial skill, as in Berk and Green (2004), does not seem to apply in this context because we continue to find a flatter sensitivity of flows to performance when we control for the interaction between performance and age, a proxy for investors' uncertainty about managerial skill (column 5 in Table 4).

In sum, unless the financial conglomerate is performing poorly, FCAHFs have more stable access to funding than other funds and this tendency is even stronger in periods of financial turmoil. This fact can explain our prior finding that FCAHFs offer their investors contracts with weaker share restrictions. Importantly, as implied by the theories of Stein (2005) and Hanson, Shleifer, Stein, and Vishny (2015), funding stability should have an influence on intermediaries' strategy and performance. In what follows, we explore this conjecture.

5. The Performance of FCAHFs

5.1 Unconditional Performance

We study how FCAHFs differ from other funds in terms of unconditional performance. Table 6 reports estimates of the following regression of hedge-fund monthly performance on an indicator for FCAHFs and controls

$$Performance_{j,t} = a + bFCAHF_j + controls + \gamma_j + \delta_t + \varepsilon_{j,t}. \tag{5}$$

We use different measures of performance: excess returns (columns 1-2), alpha from the capital asset pricing model (columns 3-4), alpha from a Carhart (1997) model (columns 5-6), and alphas from a Fung and Hsieh (2001, 2004) model plus the emerging market factor (columns 7-8). We use the usual set of controls: a dummy for large fund family, the log of size, the log of age, the log of total restrictions. Since performance can be correlated for a given fund and across funds at a given date, we double-cluster standard errors at the fund and time levels (Petersen, 2009, p. 458).

The returns of FCAHFs are significantly lower than those of other funds by about 5 to 7 basis points per month (between 0.6% and 0.84% annually) irrespective of the risk adjustment. These effects do not depend on fund or family size, or other funds' characteristics. For instance, we control for share restrictions, which appear to be positively associated with performance as highlighted in previous literature (Aragon, 2007). Moreover, all effects are similar if we control for differences in style by including interactions of style and time fixed effects (columns 2, 4, 6, and 8).

Overall, this evidence indicates that financial conglomerate affiliation hampers performance in the hedge fund industry as in the mutual fund industry (e.g., Bhattacharya, Lee, and Pool, 2013). This may depend on poorer skills and weaker incentives for fund managers in FCAHFs, which would be consistent with the lower fees charged by these funds. It can also be due to conflicts of interest that can lead the affiliated funds to take actions in the interest of the conglomerate to the expense of their investors, such as purchasing losing assets, as found in the context of mutual funds (Bhattacharya, Lee, and Pool, 2013; Ferreira, Matos, and Pires, 2015; Golez and Marin, 2015). The lower flow-performance sensitivity of FCAHFs that we identify in Section 4 can itself be detrimental for performance (Stein, 2005; Fama and Jensen, 1983). If investors are less ready to withdraw capital from poorly performing funds, managers with lower skill or conflicted incentives can survive in the market.

On the other hand, FCAHFs' investors may decide to forgo performance because they attach value to the higher flexibility to redeem their capital allowed by FCAHFs (Ang and

Bollen, 2010). Moreover, we show below that FCAHFs may be attractive to investors because they generate higher returns than non-affiliated funds following periods of market turmoil.

5.2. Conditional Performance

FCAHFs may benefit from stable funding by purchasing undervalued assets during bad times. This would allow them to perform better when turmoil subsides and asset markets recover.

In Table 7, we consider hedge funds' monthly excess returns starting from any month of market turmoil, which we identify as a month in which the VIX index is in the top quartile of its distribution up to that month. Contrary to their lower unconditional performance, FCAHFs have significantly higher excess returns during the following four months.

This evidence suggests that, even with less skilled or incentivized managers, FCAHFs may be able to exploit the advantages associated with stable funding and a lower sensitivity of flows to performance during periods of market turmoil. The higher returns that FCAHFs experience in the following months suggest that they are able to take advantage of reversals and asset undervaluation. Based on the same logic as in Glode (2011), we can argue that this profile of performance can make FCAHFs attractive to investors whose marginal utility is low due protracted losses during a crisis period. Ultimately, for this reason, investors may choose to stick with FCAHFs in spite of their lower unconditional performance.

6. Stock Trading of FCHAFs

The better performance of FCAHFs relative to those of other funds following market turmoil suggest that affiliated funds are able to take advantage of mispriced securities to a larger extent than other funds. To provide more direct evidence on the mechanisms leading to better performance following market turmoil, we investigate FCAHFs' stock trading. In particular, we explore how the proportion of a stock's shares outstanding held by FCAHFs and other hedge funds varies in periods of market turmoil as a function of stock characteristics that are typically associated with more severe mispricing, such as illiquidity, volatility, and low past performance.

We focus on the subsample of hedge funds that we were able to merge with 13F filings. We run the following regressions at the stock-quarter level

$$\%\Delta Stock_{i,q+1} = a + bCharacteristic_{i,qt} + cCharacteristic_{i,t} \times High\,Vix_q$$

$$+dHoldings\ of\ FCAHF_{i,q} + eHoldings\ of\ Other\ Funds_{i,q}$$

$$+controls + \gamma_i + \delta_q + \varepsilon_{i,q+1}, \tag{6}$$

where the dependent variable is the aggregate percentage change in holdings of stock *i* by a given category of hedge funds (either FCAHFs or other hedge funds) during a quarter. We carry out the analysis for normal times and high-VIX quarters. Since purchases of different stocks may be correlated at a given date across hedge funds, we include time fixed effects and double-cluster standard errors at the time and stock level. We also include stock fixed effects to account for the fact that some hedge funds may always trade more in certain stocks and to be able to concentrate on the effect of changes in market conditions.

In Panel A of Table 8, the stock characteristics that we consider are the top-quintile volatility and bottom-quintile of past performance. In Panel B, we consider liquidity, using indicators for top-quintile levels of the Amihud (2002) ratio and the bid-ask spread from CRSP. To control for trading motives based on known anomalies, we include: the log of market capitalization, the book-to-market ratio, and the return on assets. We also include the inverse of price as an additional liquidity control and the total fraction of institutional ownership.

In column 1 in Panel A, Table 8, we find that, in high-VIX quarters, FCAHFs are generally less inclined than other funds to purchase high-volatility stocks (slope on *Characteristic*), but this tendency disappears during periods of market turmoil (slope on *Characteristic×High Vix*). Moreover, in high-VIX periods, FCAHFs increase their purchases in stocks that have been falling in value (slope on *Characteristic×High Vix* in column 4).

Panel B shows that FCAHFs increase the proportion of shares that they hold in highly illiquid stocks. Other funds do not appear to vary their holdings of illiquid stocks nearly as much (columns 2). As columns 3 shows, differences in the changes in portfolio shares between the two types of funds are statistically significant. Results are similar if we measure illiquidity using the bid-ask spread (columns 4-6). The effect is not only statistically, but also economically significant. Using the estimates in column 1, Panel B, Table 8, as well as the summary statistics in Table 1, Panel C, during high-VIX periods, a FCAHF increases its ownership by about 20% of a standard deviation of the dependent variable for a high-Amihud stock (0.26/1.29).

Overall, it appears that when market conditions deteriorate, FCAHFs take risk and purchase stocks that are typically underpriced during these periods relatively more than other funds.

Next, we use the 13F holdings to construct measures of portfolio illiquidity and portfolio turnover at the fund-quarter level. In the first case, we take the average Amihud (2002) ratio of the stocks in the hedge-fund portfolios. For the second measure, we compute equity portfolio turnover, like in Brunnermeier and Nagel (2004), as the minimum of the absolute values of buys and sells made by firm i during quarter q, divided by the total holdings at the end of quarter $q-1$, with buys and sells being measured using end-of-quarter $q-1$ prices. By using the minimum of the absolute values of buys and sells, this proxy has the advantage of capturing trades unrelated to the inflows or outflows experienced by the investor.

We regress these measures on an indicator for FCAHFs, which we interact with the High-VIX dummy. Columns 1-4 of Table 9 show that FCAHFs' tendency to act as contrarian traders during financial turmoil translates into more illiquid portfolios during these periods. The average illiquidity of the stocks held by FCAHFs (as captured by their Amihud ratio) increases with respect to other hedge funds and to the portfolios of FCAHFs in normal times. The effect is not only statistically, but also economically significant as the coefficient of *High Vix×FCAHF* in column 2 implies a 27% (=0.06/0.22) increase in the portfolio illiquidity ratio for a fund with average Amihud ratio (from Panel C of Table 2).

Presumably, FCAHFs can invest in illiquid assets because the lower flow-performance sensitivity allows them to take a longer horizon on their investments during periods of market turmoil (Cella, Ellul, and Giannetti, 2013). To evaluate whether this is the case, we proxy for a hedge fund management firm's investment horizon using its portfolio turnover. Columns 5-9 of Table 9 show that FCAHFs' management firms have lower portfolio turnover than other hedge funds in high-VIX periods. In column 8, the effect is an economically relevant 12% lower turnover for a hedge fund with average portfolio turnover equal to 12.2% (=-1.47/12.2). This evidence indicates that FCAHFs take a longer horizon on their investments and can therefore benefit from long-term reversals.

Finally, we use institutional transaction data in ANcerno to study differences in the price impact of trading across different types of funds. Anand, Irvine, Puckett and Venkataraman (2013) argue that price impact is proportional to the demand for liquidity that a trader imposes upon the market. Similar to these authors, we capture the average price impact over a quarter using the average execution shortfall. Average execution shortfall is measured for buy orders as the execution price minus the market open price on the day of order placement, divided by the market open price (for sell orders, we multiply by -1). A higher execution shortfall indicates higher price impact and corresponds to more liquidity consuming trades. Price impact is aggregated at the stock level for different institution types (either FCAHFs or other funds). Then, using stock-quarter observations we run the following regression

$$\%Price\ Impact_{i,q+1} = a + bCharacteristic_{i,q} + cCharacteristic_{i,q} \times High\ Vix_q$$

$$+controls + \gamma_i + \delta_q + \varepsilon_{i,q+1}, \tag{7}$$

where we use the same stock-level characteristics and controls as in Equation (6).

Table 10 reports the results. FCAHFs appear to trade with less price impact during high-VIX periods in illiquid, volatile, and losing stocks. The economic significance is also important. Based on the estimates in column 1 of Table 10 and summary statistics in Table 1, Panel C, during high-VIX periods, a FCAHF decreases its price impact by about 7.8% of its mean price impact for a stock at the mean level of volatility (-0.43×0.02/0.11). Lower price impact indicates that institutions are absorbing long-term order imbalances and are therefore trading in a contrarian way. These findings suggest that FCAHFs do not rush to sell riskier stocks, rather they trade patiently in these securities, explaining their outperformance following periods of market turmoil. Hence, the evidence from the study of price impact confirms that FCAHFs are more inclined to take risk and to act as contrarian traders than other funds during periods of financial turmoil.

7. Conclusion

This paper focuses on hedge funds that report an affiliation with a financial conglomerate in their SEC mandatory filings. These hedge funds attract a large fraction of AUM in the industry, about 38% on average, despite their affiliation can be detrimental to investors due to potential conflicts of interest.

We show that financial-conglomerate-affiliated hedge funds (FCAHFs) have lower sensitivity of flows to performance than other hedge funds. This finding can explain why FCAHFs are better able to act as contrarians and take on risk at times of crisis performing a stabilizing function on the financial system. Moreover, their ability to generate higher returns right after periods of market turmoil and the fact that they give their investors more flexibility in redeeming their capital provide a rationale for why FCAHFs attract and retain clients notwithstanding they slightly underperform other hedge funds on average.

An interesting area for future research may be to explore how financial conglomerate affiliation affects funding stability and strategies in other corners of the asset management industries.

Our findings can also inform the debate about the Volcker Rule and similar regulations around the world. These regulations aim to separate systemically-important financial institutions from hedge funds in order to contain the threats to financial stability. Since FCAHFs take risk during periods of turmoil, our results support the concern of regulators, especially if financial institutions feel compelled to provide a liquidity backstop.

It has also been argued that limiting proprietary trading by banking institutions could have unintended negative consequences on market making and liquidity in financial markets (Duffie, 2012). Our findings suggest the severing the ties between financial conglomerates and hedge funds may curtail liquidity provision by FCAHFs. We acknowledge, however, that the change in status of a FCAHFs affiliated with banks would not necessarily have negative effects on financial markets, because their assets could flow to hedge funds affiliated with other financial institutions.

Finally, we note that FCAHFs display a lower unconditional alpha than other funds. Thus, on average, FCAHFs allocate capital less efficiently than other institutions and may be detrimental to aggregate welfare when compared to standalone funds.

Because of these tradeoffs, which our work is the first to point out, we think that the optimal regulatory design for affiliated asset managers and the broader effects of financial conglomeration on the functioning of financial markets constitute promising areas for future research.

Appendix Table A1. Variable Definitions

Variable	Description
FCAHF	Indicator variable denoting whether the fund is affiliated to a financial conglomerate. The variable is constructed using information from ADV filings. In particular, a fund is considered to be affiliated to a financial conglomerate if the answer in Part 1A of the ADV form is "Yes" to either item 7_A1 or item7_A8 or item 7_A12, that is, if the financial advisor reports to be related to a banking or thrift institution, to an insurance company or agency, or to a broker dealer. We eliminate manually broker-dealer that are merely executing brokers.
Size	Fund's AUM in million dollars. The variable *Log Size* denotes the logarithm of AUM.
Large Fund	Indicator variable for a fund that belongs to the top quartile of the AUM distribution in a given year.
Age	The number of months since the inception date. The variable *Log Age* denotes the logarithm of Age.
Flows	A fund's quarterly flows, computed as: (AUM(q) – AUM(q-1) × (Returns (q) +1)/ AUM(q-1)
Total Restrictions	The sum of lock-up period (Lock Up Period), the redemption notice period (Redemption Period), and the redemption frequency (Redemption Frequency), measured in days. The variable *Log Totrest* denotes the logarithm of Total Restrictions.
High restrictions (High Rest)	Indicator variable for whether the fund has total restrictions above the sample median.
% Assets Financial Conglomerates	The percentage of client assets coming from banks and insurance companies. The information is obtained from the ADV Form, Item 5, section D, question 1, sub-items c and l.
Excess Return	Fund returns in dollars at the specified frequency computed in excess of the risk free rate.
Alpha (CAPM)	Monthly alpha from a one-factor model using the excess return on the CRSP universe as factor, estimated over a rolling window of 24 monthly observations, with at least 12 monthly observations.
Alpha (Carhart)	Monthly alpha from the Carhart four-factor model, estimated over a rolling window of 24 monthly observations, with at least 12 monthly observations.
Alpha (Fung and Hsieh)	Monthly alpha from the seven-factor model based on Fung and Hsieh (2001, 2004) plus the emerging market factor, estimated over a rolling window of 24 monthly observations, with at least 12 monthly observations.
Frank Frank1, Frank2, Frank3	Fractional rank of the fund in the cross-sectional distribution of fund quarterly returns Frank1 = min(Frank,1/3), Frank2= min(Frank-Frank1,1/3), Frank3= min(1/3, Frank - Frank1-Frank2)
Volatility	A fund's return volatility computed as the standard deviation of monthly returns on a twenty-four-month rolling window
Beta	A fund's exposure to the market return, computed from monthly regressions on a twenty-four-month rolling window.
Negative Beta	A fund's exposure to the negative market return, computed from monthly regressions on a twenty-four-month rolling window.
Skewness	The skewness of a fund's returns computed over a twenty-four-month rolling window.
R-squared	The R-squared of the regression of the fund's monthly returns on the seven Fung and Hsieh (2001, 2004) factors plus the emerging market factor,

	estimated over a twenty-four-month rolling window.
Max Draw Down	Minimum of a fund's cumulative abnormal returns over the past 24 months.
Number of Funds	Number of other funds in the same family in the same month.
Large Family	Indicator variable for whether a fund belongs to a family with more than 10 funds.
High-Vix	Indicator variable denoting a quarter in which the VIX index is in the top quartile of its realizations up to that quarter.
Minimum Investment	Minimum initial investment in the fund.
Number of Clients	Approximate number of clients as reported in the ADV Form, Item 5, section C.
Change in Ownership by Institution Type	The change in shares held by institutions of a given category (FCAHFs, non FCAHFs, other financial conglomerates) in a given stock between quarter ends, divided by the stock's number of shares outstanding, presented in percentages.
(Stock) Volatility	A stock's idiosyncratic volatility computed from the residuals of four-factor model including the three Fama-French factors and the momentum factor, estimated from monthly returns over a twenty-four-month rolling window.
Portfolio Turnover	A fund's portfolio turnover during a quarter computed as the minimum of the absolute values of buys and sells made by hedge fund i during quarter q, divided by the total holdings at the end of quarter $q-1$, with buys and sells being measured using end-of-quarter $q-1$ prices.
Portfolio Amihud	The average of the Amihud illiquidity ratio for all stocks in a fund's portfolio at the end of the quarter.
Low Past Return	Dummy variable denoting FCAHFs whose parent company experienced quarterly return in the bottom quartile of the cross-sectional distribution of parent company returns in the prior quarter.
High Leverage	Dummy variable denoting FCAHFs whose parent company reported book leverage in the top quartile of the distribution of parent company book leverage in the prior year.
Below Prime Rating	Dummy variable denoting FCAHFs whose parent company obtained a rating in the majority of its issues that is below the prime rating.

Appendix Table A2.

Episodes of Financial Turmoil

We define financial turmoil as those periods (months or quarters) in which the VIX index is in the top-quartile of its (monthly or quarterly) distribution, considering only realization of the VIX up to that quarter, to avoid a look-ahead bias. The table lists these episodes

Monthly Frequency		Quarterly Frequency
March	2001	Q4 2000
September	2001	Q4 2001
October	2001	Q3 2002
July	2002	Q4 2002
August	2002	Q1 2003
September	2002	Q1 2008
October	2002	Q4 2008
February	2003	Q1 2009
August	2007	Q2 2009
November	2007	Q2 2010
January	2008	Q3 2011
February	2008	Q4 2011
March	2008	
September	2008	
October	2008	
November	2008	
December	2008	
January	2009	
February	2009	
March	2009	
April	2009	
May	2009	
June	2009	
May	2010	
June	2010	
August	2011	
September	2011	
October	2011	
November	2011	

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Table 1

Descriptive Statistics

Panel A compares the mean of salient fund characteristics for the unmatched funds in the union dataset, our universe, the funds in the union dataset matched with the ADV files, and the match of the latter with 13F filings and the ANcerno dataset, respectively. Panel B compares FCAHFs and other hedge funds in our main sample (ADV matched) and reports the p-value for the test of the hypothesis of equality of the means. Panel C reports summary statistics on the main variables that are used in the analysis. The sample period ranges between 2000 and 2013. Variable definitions are provided in the Appendix Table A1.

Panel A: Characteristics of ADV Matched and Unmatched Samples

	Unmatched		ADV Matched		13F Matched		Ancerno Matched	
	N	Mean	N	Mean	N	Mean	N	Mean
TNA ($ million)	259,839	82	257,713	151	26,019	220	8,135	119
Monthly Excess Return (%)	369,311	0.34	382,641	0.32	31,531	0.37	11,190	0.34
Monthly Alpha (CAPM) (%)	243,015	0.23	285,517	0.25	25,638	0.30	8,560	0.26
Monthly Alpha (Carhart) (%)	242,416	0.12	285,975	0.13	25,765	0.17	8,604	0.08
Monthly Alpha (Fung and Hsieh) (%)	242,074	0.21	286,083	0.14	25,798	0.16	8,604	0.10
Quarterly Flows	212,156	0.05	229,776	0.04	22,871	0.03	6,878	0.03
Fund Age (in months)	384,317	59.50	389,969	68.30	32,202	83.50	11,575	69.80
Lock Up Period (days)	218,740	137.00	326,388	84.80	25,972	130.00	9,822	108.00
Redemption Notice (days)	288,358	39.00	349,140	41.10	30,762	40.60	11,218	32.70
Redemption Frequency (days)	296,594	93.10	351,268	66.70	30,730	80.70	10,296	74.70
Management Fee	384,317	1.50	389,969	1.46	32,202	1.37	11,493	1.26
Incentive Fee	384,317	17.30	389,969	15.50	32,077	18.10	11,282	16.00
Minimum investment	355,614	735,633	363,869	906,867	32,054	1,212,748	11,404	1,098,512
Style:								
Equity Hedge	384,317	0.42	389,969	0.35	32,202	0.59	11,575	0.59
Event Driven	384,317	0.06	389,969	0.07	32,202	0.12	11,575	0.06
Fund of Funds	384,317	0.23	389,969	0.28	32,202	0.06	11,575	0.14
Macro	384,317	0.17	389,969	0.11	32,202	0.08	11,575	0.06
Relative Value	384,317	0.07	389,969	0.12	32,202	0.09	11,575	0.10
Other	384,317	0.05	389,969	0.07	32,202	0.06	11,575	0.06

Panel B: FCAHFs and Other Hedge Funds

	FCAHFs		Other Hedge Funds		H_0: Equality of Means
	N	Mean	N	Mean	p-value
TNA ($ million)	78,721	185	178,992	137	0.02
Number of Funds	121,597	13.90	268,372	10.80	0.00
Age	121,597	61.30	268,372	71.50	0.00
Total Restrictions (days)	86,549	167.00	193,123	210.00	0.00
Leveraged	108,098	0.47	238,836	0.53	0.00
Leverage (%)	66,361	44.90	178,725	43.00	0.65
Monthly Excess Return (%)	119,153	0.30	263,488	0.33	0.29
Monthly Alpha (CAPM) (%)	86,412	0.24	197,300	0.26	0.13
Monthly Alpha (Carhart) (%)	86,233	0.11	199,742	0.14	0.04
Monthly Alpha (Fung and Hsieh) (%)	86,340	0.13	199,743	0.14	0.26
Monthly Volatility (%)	85,486	2.48	197,277	2.31	0.01
Beta	86,004	0.24	199,047	0.23	0.17
Negative Beta	86,387	0.26	199,176	0.24	0.09
Skewness	85,611	-0.21	197,584	-0.17	0.00
Max Draw Down	83,077	0.07	194,235	0.06	0.00
R-squared (Fungh and Hsieh)	85,174	0.34	197,613	0.31	0.00
Rho	85,557	0.15	199,187	0.13	0.00
Style:					
Equity Hedge	121,597	0.29	268,372	0.37	0.00
Event Driven	121,597	0.06	268,372	0.07	0.07
Fund of Funds	121,597	0.39	268,372	0.22	0.00
Macro	121,597	0.10	268,372	0.12	0.02
Relative Value	121,597	0.08	268,372	0.14	0.00
Other	121,597	0.08	268,372	0.07	0.13

Panel C: Summary Statistics of the Regression Samples

	N	Mean	Std Dev	Min	p25	Median	p75	Max
Fund Quarterly Dataset:								
FCAHF	48,425	0.29	0.45	0.00	0.00	0.00	1.00	1.00
TNA ($ million)	48,425	179	649	0	1	34	138	25458
Log Size	48,425	14.70	6.17	-2.98	13.90	17.30	18.70	24.00
Age (months)	48,425	75.20	56.40	7.00	32.00	60.00	105.00	361.00
Quarterly Return	48,425	0.01	0.05	-0.28	0.00	0.00	0.04	0.41
Quarterly Flows	48,425	0.03	0.18	-0.46	-0.04	0.00	0.07	1.11
Lock Up Period (days)	48,425	111	177	0	0	0	360	720
Redemption Notice (days)	48,425	43	27	0	30	30	60	105
Redemption Frequency (days)	48,425	76	77	0	30	90	90	365
Restrictions (days)	48,425	230	222	1	60	120	450	1170
Low Past Return of Control Person	34,073	0.00	0.04	0.00	0.00	0.00	0.00	1.00
High Leverage of Control Person	34,114	0.00	0.04	0.00	0.00	0.00	0.00	1.00
Rating below Prime of Control Person	36,414	0.04	0.20	0.00	0.00	0.00	0.00	1.00
Fund Monthly Dataset:								
% Assets Fin Inst	257,572	3.42	13.60	0.00	0.00	0.00	0.00	100.00
Number of Funds	257,572	10.80	10.30	0.00	2.00	9.00	18.00	99.00
Excess Return (%)	181,114	0.29	2.89	-13.10	-0.48	0.01	1.37	13.50
Alpha (CAPM) (%)	136,096	0.26	0.66	-1.80	-0.16	0.14	0.60	2.74
Alpha (Carhart) (%)	136,265	0.14	0.67	-2.20	-0.25	0.01	0.49	2.68
Alpha (Fung and Hsieh) (%)	136,449	0.15	0.70	-2.34	-0.25	0.02	0.50	3.13
Volatility (%)	129,196	2.28	1.76	0.01	0.85	2.13	3.50	7.19
Beta	129,982	0.22	0.30	-0.61	0.00	0.15	0.38	1.25
Negative Beta	130,374	0.24	0.42	-1.09	0.00	0.13	0.46	1.94
Skewness	128,958	-0.18	0.62	-2.11	-0.57	-0.17	0.21	1.62
R-squared (Fungh and Hsieh)	129,607	0.31	0.30	-0.37	0.07	0.32	0.55	0.89
Fund Annual Dataset:								
Number of clients	13,604	73.00	137.00	0.00	5.00	18.00	63.00	600.00
% Assets Financial Cong.	13,604	3.98	13.80	0.00	0.00	0.00	0.00	100.00
% Assets Financial Industry	13,604	56.30	47.70	0.00	0.00	75.00	90.00	100.00
% Assets Pension Funds	13,604	9.11	17.00	0.00	0.00	0.00	25.00	90.00
% Assets Foreign Investors	13,604	3.95	12.00	0.00	0.00	0.00	0.00	90.00
% Assets Individuals	13,604	14.10	30.00	0.00	0.00	0.00	0.00	100.00
Fund Cross-Sectional Dataset:								
Lock Up Period (days)	5,693	73.90	152.00	0.00	0.00	0.00	0.00	720.00
Redemption Period (days)	5,693	41.10	27.90	0.00	30.00	30.00	60.00	105.00
Redemption Frequency (days)	5,693	66.40	70.80	0.00	30.00	30.00	90.00	365.00
Management Fee (%)	5,693	1.41	1.45	0.00	1.00	1.50	1.75	2.50
Incentive Fee (%)	5,693	15.20	7.64	0.00	10.00	20.00	20.00	50.00
Minimum Investment ($ million)	5,693	6.81	151.00	0.00	0.10	0.50	1.00	5000.00
Stock-Quarter Dataset:								
ΔOwnership by FCAHFs (%)	86,151	-0.05	1.29	-6.04	-0.43	-0.01	0.35	4.09
ΔOwnership by Other HFs (%)	81,229	-0.23	0.99	-5.88	-0.39	-0.05	0.09	2.66
Volatility	86,151	0.02	0.01	0.00	0.01	0.02	0.03	0.65
Quarterly Return	86,151	0.03	0.18	-0.30	-0.08	0.03	0.14	0.40
Amihud Ratio	86,151	0.01	0.04	0.00	0.00	0.00	0.01	0.82
Bid-Ask Spread	86,151	0.00	0.01	0.00	0.00	0.00	0.00	0.21
Price Impact FCAHFs (%)	77,724	0.11	0.34	-1.06	-0.06	0.07	0.25	1.63
Price Impact Other HFs (%)	71,703	0.06	0.18	-0.37	-0.04	0.03	0.16	0.60
Log Mkt Cap	86,151	7.33	1.42	2.73	6.27	7.08	8.13	13.30
Book-to-Market	86,151	0.57	0.42	-0.06	0.30	0.48	0.73	10.10
ROA (Return on Assets)	86,151	0.01	0.05	-4.92	0.00	0.01	0.02	0.55
1/Price	86,151	0.06	0.06	0.01	0.03	0.04	0.06	1.98
IOR (institutional ownership ratio)	86,151	0.73	0.23	0.00	0.59	0.77	0.90	1.27
Management Firm-Quarter Dataset:								
Portfolio Turnover (%)	4,363	12.20	9.06	0.00	5.60	10.30	16.40	98.30
Portfolio Amihud (×100)	3,982	0.22	0.23	0.01	0.07	0.14	0.28	1.25
Log Firm Age	4,363	3.37	0.91	0.00	2.77	3.50	4.04	5.14
Log Firm Size	3,643	15.10	6.46	-2.81	7.24	18.20	19.60	24.20

Table 2
Characteristics of FCAHFs
The table reports estimates from regressions of fund characteristics on an indicator for financial-conglomerate-affiliated hedge funds (FCAHF). The dependent variable is indicated on top of each column. Panel A reports estimates from cross-sectional regressions with style fixed effects. The unit of observation is the fund. Panel B report estimates from pooled regressions at the yearly frequency with time and style fixed effects. Panel C reports estimates from regressions at the quarterly frequency of the percentage of the fund's assets from financial conglomerates on a dummy variable for fund flows in the bottom quintile of the prior-quarter cross-sectional distribution. Standard errors are clustered at the fund level. ***, **, * denote significance at 1%, 5%, and 10% levels, respectively. The sample period ranges between 2000 and 2013.

Panel A. Contractual Characteristics

Dependent Variable:	Management Fee	Incentive Fee	Lockup Period	Redemption Notice Period	Redemption Frequency	Log Totrest
	(1)	(2)	(3)	(4)	(5)	(6)
FCAHF	-0.08***	-0.82***	-19.64***	-4.16***	-4.77**	-0.22***
	(-6.00)	(-4.57)	(-4.58)	(-5.37)	(-2.38)	(-7.04)
Log Size	-0.06***	-0.07	-13.31***	-1.86***	6.20***	0.01
	(-7.18)	(-0.58)	(-4.82)	(-3.73)	(4.81)	(0.53)
Log Age	0.00	0.01	-2.53***	0.24***	0.71***	-0.01***
	(1.09)	(0.99)	(-7.10)	(3.71)	(4.29)	(-3.69)
Number of Funds	-0.00	-0.02**	-1.64***	0.02	-0.11	-0.01***
	(-0.76)	(-2.34)	(-8.47)	(0.47)	(-1.22)	(-3.84)
Style FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,693	5,693	5,693	5,693	5,693	5,693
Adjusted R-squared	0.049	0.332	0.047	0.079	0.043	0.049

Panel B. Clienteles

Dependent Variable:	Number of Clients	% Assets from:				
		Financial Cong.	Financial Industry	Pension Funds	Foreign Investors	Individuals
	(1)	(2)	(3)	(4)	(5)	(6)
FCAHF	65.58***	4.73***	6.37***	2.63***	2.02***	-1.86
	(10.53)	(4.59)	(3.34)	(3.58)	(4.04)	(-1.48)
Log Size	-1.66***	0.02	1.50***	0.01	0.04	-0.78***
	(-2.97)	(0.49)	(10.45)	(0.15)	(1.06)	(-5.69)
Log Age	4.75**	-0.14	0.22	0.36	-0.05	1.21**
	(2.33)	(-0.65)	(0.36)	(1.32)	(-0.30)	(2.35)
Number of Funds	-0.89***	-0.09***	0.40***	0.06**	-0.02	-0.16***
	(-5.34)	(-3.51)	(6.80)	(2.56)	(-1.37)	(-4.34)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,604	13,604	13,604	13,604	13,604	13,604
Adjusted R-squared	0.083	0.036	0.194	0.030	0.033	0.040

Panel C. Asset Composition and Fund Flows

Dependent Variable:	% Assets Financial Conglomerate			
	(1)	(2)	(3)	(4)
Low Flows	0.03***	0.01	0.02**	0.01
	(2.80)	(1.51)	(2.35)	(1.60)
Low Flows×FCAHF		0.09**		0.05*
		(2.38)		(1.84)
FCAHF	0.01**	0.02**	0.02**	0.02**
	(2.33)	(2.36)	(2.35)	(2.37)
Log Size	-0.02	-0.02	-0.03	-0.03
	(-1.25)	(-1.22)	(-1.31)	(-1.31)
Log Age		-0.00		0.01
		(-0.16)		(0.84)
Lag Dep. Variable			0.96***	0.96***
			(212.84)	(216.02)
Quarter FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Observations	48,328	48,328	43,361	43,361
Adjusted R-squared	0.997	0.997	0.998	0.998

Table 3
The Flow-Performance-Sensitivity of FCAHFs
The table reports estimates of the flow-performance sensitivity. We regress fund flows on lagged fund performance and control variables. The frequency of observations is quarterly. In Panels A, a hedge fund's fractional rank (FRANK) represents its percentile performance relative to other hedge funds in the same period. We define FRANK1=min(FRANK, 1/3), FRANK2=min(FRANK-FRANK1, 1/3), and FRANK3= min(FRANK-FRANK1-FRANK2, 1/3). Panel B considers alternative measures of fund performance, estimated using the model indicated on top of each column. All regressions include time and style fixed effects and standard errors are clustered at the quarter and fund level. ***, **, * denote significance at 1%, 5%, and 10% levels, respectively. The sample period ranges between 2000 and 2013.

Panel A. Baseline Results

	Flows (q+1)				
	(1)	(2)	(3)	(4)	(5)
FRANK1(q)×FCAHF		-0.07***			-0.07**
		(-2.88)			(-2.64)
FRANK2(q)×FCAHF		0.03			0.02
		(1.23)			(0.93)
FRANK3(q)×FCAHF		-0.04			-0.05*
		(-1.66)			(-1.73)
FRANK1(q)	0.10***	0.12***			0.11***
	(6.48)	(6.97)			(5.92)
FRANK2(q)	0.05***	0.04***			0.03*
	(3.47)	(2.68)			(1.95)
FRANK3(q)	0.11***	0.12***			0.13***
	(7.20)	(7.51)			(8.22)
FRANK1(q-1)×FCAHF				-0.04*	-0.03
				(-1.93)	(-1.63)
FRANK2(q-1)×FCAHF				0.04**	0.04**
				(2.08)	(2.04)
FRANK3(q-1)×FCAHF				-0.06**	-0.05**
				(-2.10)	(-2.01)
FRANK1(q-1)			0.05***	0.06***	0.06***
			(3.25)	(3.57)	(3.41)
FRANK2(q-1)			0.07***	0.06***	0.05***
			(5.43)	(4.03)	(3.50)
FRANK3(q-1)			0.05***	0.07***	0.04**
			(2.90)	(3.23)	(2.17)
FCAHF	-0.01***	0.01*	-0.01***	-0.00	0.02**
	(-3.51)	(1.79)	(-3.30)	(-0.09)	(2.24)
Flows (q)	0.27***	0.27***	0.26***	0.26***	0.26***
	(25.76)	(25.73)	(24.85)	(24.86)	(25.44)
Log Size	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***
	(-6.93)	(-6.97)	(-6.45)	(-6.43)	(-8.88)
Log Age	-0.03***	-0.03***	-0.03***	-0.03***	-0.03***
	(-17.98)	(-18.00)	(-18.12)	(-18.17)	(-17.07)
Log Totrest	0.00***	0.00***	0.00***	0.00***	0.00**
	(3.04)	(3.03)	(3.75)	(3.74)	(2.35)
Style FE × Quarter FE	Yes	Yes	Yes	Yes	Yes
Observations	48,840	48,840	46,885	46,885	46,885
Adjusted R-squared	0.185	0.186	0.176	0.176	0.189
Partial R-squared	0.143	0.144	0.134	0.134	0.147

Panel B. Alternative Measures of Performance

Dependent Variable:	Flows (q+1)			
Factor Model:	No Adjustment	CAPM	Carhart	Fung and Hsieh
	(1)	(2)	(3)	(4)
Alpha(q)×FCAHF	-0.09**	-0.26**	-0.24**	-0.28**
	(-2.60)	(-2.22)	(-2.02)	(-2.59)
Alpha(q)	0.44***	1.33***	1.08***	0.92***
	(12.27)	(14.86)	(11.66)	(13.33)
FCAHF	-0.01***	-0.00	-0.00	-0.00*
	(-2.74)	(-0.78)	(-1.61)	(-1.90)
Log Size	-0.00***	-0.00***	-0.00***	-0.00***
	(-5.83)	(-7.24)	(-6.02)	(-5.23)
Log Age	-0.03***	-0.01***	-0.01***	-0.01***
	(-18.36)	(-8.26)	(-9.10)	(-9.46)
Log Totrest	0.00***	0.00	0.00	0.00*
	(3.50)	(1.42)	(1.27)	(1.78)
Flows(q)	0.27***	0.25***	0.25***	0.26***
	(25.68)	(18.80)	(18.27)	(18.72)
Style FE × Quarter FE	Yes	Yes	Yes	Yes
Observations	48,840	34,069	34,069	34,116
Adjusted R-squared	0.182	0.149	0.144	0.144

Table 4
Flow-Performance Sensitivity in Periods of Market Turmoil

The table reports estimates of the flow-performance sensitivity in different states of the market. We regress quarterly flows on performance in piecewise linear form. We define FRANK1=min(FRANK, 1/3), FRANK2=min(FRANK-FRANK1, 1/3), and FRANK3= min(FRANK-FRANK1-FRANK2, 1/3). We consider differences in flow-performance sensitivity between periods of high VIX and other periods. We also include interactions with control variables. All regressions include time and style fixed effects and standard errors are clustered at the quarter and fund level. ***, **, * denote significance at 1%, 5%, and 10% levels, respectively. The sample period ranges between 2000 and 2013.

Dependent Variable:	Flows (q+1)				
Control Variable:		Large Fund	Large Family	High Restrictions	High Age
	(1)	(2)	(3)	(4)	(5)
FRANK1(q)×High Vix×FCAHF	-0.12**	-0.12**	-0.13**	-0.12**	-0.11**
	(-2.40)	(-2.34)	(-2.50)	(-2.35)	(-2.21)
FRANK2(q)×High Vix×FCAHF	0.11**	0.10**	0.11**	0.10**	0.10**
	(2.14)	(2.08)	(2.17)	(2.13)	(2.08)
FRANK3(q)×High Vix×FCAHF	-0.07	-0.07	-0.06	-0.07	-0.07
	(-1.16)	(-1.16)	(-1.04)	(-1.15)	(-1.20)
FRANK1(q)×High Vix×Control		-0.02	0.12	0.04	0.01
		(-0.33)	(1.29)	(0.73)	(0.24)
FRANK2(q)×High Vix×Control		0.04	-0.06	-0.02	-0.01
		(0.89)	(-0.82)	(-0.47)	(-0.21)
FRANK3(q)×High Vix×Control		0.03	0.01	0.02	-0.01
		(0.63)	(0.06)	(0.46)	(-0.24)
FRANK1(q)×FCAHF	-0.03	-0.03	-0.03	-0.03	-0.03
	(-1.02)	(-1.06)	(-0.94)	(-1.10)	(-1.09)
FRANK2(q)×FCAHF	-0.01	-0.01	-0.01	-0.01	-0.01
	(-0.37)	(-0.41)	(-0.44)	(-0.35)	(-0.31)
FRANK3(q)×FCAHF	-0.03	-0.02	-0.02	-0.02	-0.03
	(-0.76)	(-0.72)	(-0.45)	(-0.75)	(-0.87)
FRANK1(q)×Control		0.01	-0.03	-0.04	-0.04
		(0.30)	(-0.53)	(-1.47)	(-1.55)
FRANK2(q)×Control		0.01	0.00	0.02	-0.03
		(0.40)	(0.04)	(1.02)	(-1.63)
FRANK3(q)×Control		-0.03	-0.08	-0.02	-0.08**
		(-1.01)	(-1.43)	(-0.83)	(-2.61)
FRANK1(q)×High Vix	0.05	0.05	0.02	0.03	0.04
	(1.21)	(1.12)	(0.52)	(0.60)	(0.89)
FRANK2(q)×High Vix	-0.10***	-0.11***	-0.08**	-0.09**	-0.09**
	(-2.84)	(-2.75)	(-2.05)	(-2.05)	(-2.15)
FRANK3(q)×High Vix	0.04	0.03	0.03	0.03	0.05
	(1.21)	(0.69)	(0.95)	(0.68)	(1.10)
FRANK1(q)	0.10***	0.09***	0.10***	0.12***	0.12***
	(4.27)	(3.49)	(4.70)	(4.90)	(3.96)
FRANK2(q)	0.06***	0.06**	0.07***	0.05***	0.08***
	(3.18)	(2.62)	(3.53)	(2.87)	(3.49)
FRANK3(q)	0.12***	0.13***	0.13***	0.13***	0.17***
	(6.61)	(6.80)	(6.58)	(6.30)	(6.44)

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Table 4 *(Continued)*

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Dependent Variable:	Flows (q+1)				
Control Variable:		Large Fund	Large Family	High Restrictions	High Age
	(1)	(2)	(3)	(4)	(5)
FRANK1(q-1)×FCAHF	-0.03	-0.03	-0.03	-0.03	-0.03
	(-1.17)	(-1.19)	(-1.11)	(-1.14)	(-1.10)
FRANK2(q-1)×FCAHF	0.05**	0.04**	0.04**	0.04**	0.04**
	(2.07)	(2.04)	(2.02)	(2.02)	(2.02)
FRANK3(q-1)×FCAHF	-0.06**	-0.06**	-0.06**	-0.06**	-0.06**
	(-2.41)	(-2.39)	(-2.39)	(-2.33)	(-2.41)
FRANK1(q-1)	0.06***	0.05***	0.06***	0.05***	0.06***
	(3.15)	(2.99)	(3.14)	(3.08)	(3.06)
FRANK2(q-1)	0.05***	0.06***	0.06***	0.06***	0.05***
	(3.57)	(3.65)	(3.68)	(3.62)	(3.57)
FRANK3(q-1)	0.05**	0.05**	0.04**	0.05**	0.05**
	(2.29)	(2.38)	(2.23)	(2.30)	(2.33)
High Vix×FCAHF	0.02*	0.02*	0.02*	0.02*	0.02
	(1.86)	(1.80)	(1.95)	(1.82)	(1.68)
FCAHF	0.01	0.01	0.01	0.01	0.01
	(1.08)	(1.17)	(1.00)	(1.11)	(1.14)
High Vix×Control		-0.01	-0.03*	-0.01	0.00
		(-0.80)	(-1.83)	(-0.88)	(0.34)
Control		0.01	0.01	0.02***	0.02***
		(0.93)	(0.97)	(2.93)	(3.64)
Flows(q)	0.26***	0.26***	0.26***	0.26***	0.26***
	(25.45)	(25.07)	(25.58)	(25.44)	(25.43)
Log Size	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***
	(-9.33)	(-8.90)	(-8.69)	(-9.30)	(-9.48)
Log Age	-0.03***	-0.03***	-0.03***	-0.03***	-0.03***
	(-16.95)	(-17.51)	(-16.66)	(-17.05)	(-11.94)
Log Totrest	0.00**	0.00**	0.00**	-0.00	0.00**
	(2.36)	(2.25)	(2.19)	(-1.22)	(2.44)
Style FE × Quarter FE	Yes	Yes	Yes	Yes	Yes
Observations	46,885	46,885	46,885	46,885	46,885
Adjusted R-squared	0.190	0.190	0.190	0.190	0.191

Table 5

Parent Company Characteristics and Flow-Performance Sensitivity

The table reports estimates of the effect of measures of parent company characteristics on the flow-performance sensitivity of FCAHFs. We regress quarterly flows on the terciles of the hedge fund's fractional rank (FRANK), which represents its percentile performance ranking relative to other hedge funds. We define FRANK1=min(FRANK, 1/3), FRANK2=min(FRANK-FRANK1, 1/3), and FRANK3= min(FRANK-FRANK1-FRANK2, 1/3). We interact performance with a dummy variable denoting FCAHFs whose parent company reported ratings worse than prime ratings in the majority of its issues (Below Prime Rating), book leverage in the top quartile of the distribution of parent company book leverage in the prior year (High Leverage), or FCAHFs whose parent company experienced quarterly returns in the bottom quartile of the cross-sectional distribution of parent company returns in the prior quarter (Low Returns). All regressions include time and style fixed effects and standard errors are clustered at the quarter and fund level. ***, **, * denote significance at 1%, 5%, and 10% levels, respectively. The sample period ranges between 2000 and 2013.

Dependent Variable:	Flows (q+1)					
Characteristic:	Below Prime Rating		High Leverage		Low Returns	
	(1)	(2)	(3)	(4)	(5)	(6)
FRANK1(q)×Characteristic	0.34**	0.29*	0.63**	0.61**	1.31**	1.26**
	(2.31)	(1.80)	(2.51)	(2.26)	(2.27)	(2.31)
FRANK2(q)×Characteristic	-0.46***	-0.41**	-0.64***	-0.65***	-1.04***	-1.04***
	(-3.29)	(-2.38)	(-3.03)	(-2.93)	(-3.19)	(-3.27)
FRANK3(q)×Characteristic	0.39**	0.52**	0.74**	0.76**	0.33	0.30
	(2.06)	(2.41)	(2.50)	(2.44)	(1.58)	(1.48)
FRANK1(q)×FCAHF	-0.31**	-0.39**	-0.15	-0.13	-0.21*	-0.22**
	(-2.41)	(-2.67)	(-1.33)	(-1.16)	(-1.85)	(-2.02)
FRANK2(q)×FCAHF	0.38***	0.42***	0.32**	0.32**	0.29**	0.29**
	(2.84)	(2.76)	(2.61)	(2.64)	(2.32)	(2.47)
FRANK3(q)×FCAHF	-0.39**	-0.57***	-0.38***	-0.38***	-0.22*	-0.20
	(-2.08)	(-2.70)	(-3.38)	(-2.68)	(-1.76)	(-1.49)
FRANK1(q)	0.12***	0.11***	0.12***	0.11***	0.12***	0.11***
	(7.16)	(6.15)	(7.22)	(6.11)	(7.17)	(5.77)
FRANK2(q)	0.05***	0.04*	0.05***	0.04**	0.05***	0.04**
	(2.75)	(1.99)	(2.89)	(2.15)	(2.92)	(2.06)
FRANK3(q)	0.12***	0.13***	0.12***	0.13***	0.12***	0.13***
	(7.47)	(8.25)	(7.43)	(7.64)	(7.44)	(7.93)
FCAHF	0.02	0.06**	-0.00	0.01	0.01	-0.00
	(0.90)	(2.21)	(-0.02)	(0.09)	(0.49)	(-0.01)
Characteristic	-0.02	-0.03	-0.11**	-0.10*	-0.21	-0.20
	(-0.84)	(-1.01)	(-2.28)	(-1.85)	(-1.46)	(-1.44)
FRANK1(q-1)×FCAHF		-0.02		-0.03		0.07
		(-0.28)		(-0.12)		(0.52)
FRANK2(q-1)×FCAHF		0.03		-0.02		-0.03
		(0.43)		(-0.22)		(-0.64)
FRANK3(q-1)×FCAHF		-0.03		0.04		0.04
		(-0.38)		(0.41)		(0.45)
FRANK1(q-1)		0.06***		0.06***		0.06***
		(3.28)		(3.29)		(3.28)
FRANK2(q-1)		0.06***		0.06***		0.06***
		(3.48)		(3.22)		(3.42)
FRANK3(q-1)		0.05**		0.04**		0.05**
		(2.39)		(2.18)		(2.11)
Log Size	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***
	(-6.58)	(-6.34)	(-4.93)	(-6.94)	(-6.59)	(-5.66)
Log Age	-0.03***	-0.03***	-0.03***	-0.03***	-0.03***	-0.03***
	(-18.81)	(-17.78)	(-15.52)	(-14.70)	(-13.22)	(-14.02)
Log Totrest	0.00*	0.00	0.00*	0.00	0.00	0.00
	(1.76)	(1.30)	(1.82)	(1.22)	(1.47)	(1.13)
Lagged Flows	0.26***	0.25***	0.26***	0.25***	0.26***	0.25***
	(23.16)	(22.43)	(22.33)	(20.34)	(22.58)	(21.71)
Style FE × Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	36,414	34,170	34,114	32,677	34,161	32,730
Adjusted R-squared	0.188	0.190	0.186	0.189	0.186	0.189

Table 6
The Performance of Financial-Conglomerate-Affiliated Hedge Funds
The table reports regressions of hedge fund performance on the FCAHF dummy and controls. The dependent variables are alternative measures of fund performance (in percent): the monthly excess return and the monthly alphas from the capital asset pricing model, from the Carhart (1997) model, and from Fung and Hsieh (2001) model plus the emerging market factor. The unit of observation is the fund-month. All regressions include time and style fixed effects. Standard errors are double-clustered at the time and the fund level. ***, **, * denote significance at 1%, 5%, and 10% levels, respectively. The sample period ranges between 2000 and 2013.

Dependent Variable:	Excess Return		Alpha (CAPM)		Alpha (Carhart)		Alpha (FS)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FCAHF	-0.06**	-0.05**	-0.06***	-0.06***	-0.06***	-0.06***	-0.07***	-0.07***
	(-2.40)	(-2.23)	(-3.76)	(-3.59)	(-3.88)	(-3.80)	(-4.04)	(-4.16)
Large Family	-0.02	-0.02	-0.00	0.00	-0.00	0.00	0.02	0.02
	(-0.36)	(-0.37)	(-0.11)	(0.12)	(-0.21)	(0.18)	(0.78)	(0.95)
Log Size	0.04***	0.04***	0.04***	0.04***	0.03***	0.03***	0.03***	0.03***
	(5.13)	(5.38)	(18.31)	(18.85)	(14.98)	(15.64)	(17.37)	(17.41)
Log Age	-0.08***	-0.08***	-0.11***	-0.11***	-0.11***	-0.10***	-0.10***	-0.10***
	(-5.76)	(-5.66)	(-8.74)	(-8.37)	(-8.49)	(-8.13)	(-7.05)	(-7.11)
Log Totrest	0.05***	0.05***	0.04***	0.04***	0.04***	0.04***	0.04***	0.04***
	(2.89)	(2.93)	(5.07)	(4.96)	(5.63)	(5.54)	(4.92)	(4.83)
Month FE	Yes	No	Yes	No	Yes	No	Yes	No
Style FE	Yes	No	Yes	No	Yes	No	Yes	No
Style×Month FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	181,114	181,113	136,096	136,095	136,265	136,264	136,449	136,448
Adjusted R-squared	0.174	0.205	0.195	0.217	0.166	0.190	0.136	0.160

Table 7

Performance following High-VIX Periods

The dependent variable is the monthly fund return in excess of the risk free rate in percent. Fund returns are unsmoothed using Getmansky, Lo, and Makarov (2004) procedure. The main explanatory variable is an interaction the financial-conglomerate-affiliated hedge fund dummy (FCAHF) and a dummy denoting the fact that the lagged VIX index was in the top quartile of the VIX distribution (Lagged High Vix). We consider seven different monthly lags of High Vix, starting from lag 0 (the high-VIX month). All regressions include style times month fixed effects. Standard errors are clustered at the time and fund level. ***, **, * denote significance at 1%, 5%, and 10% levels, respectively. The sample period ranges between 2000 and 2013.

Dependent Variable:	Monthly Excess Return						
Monthly Lag:	0	1	2	3	4	5	6
FCAHF × Lagged High Vix	-0.07	0.14**	0.14**	0.14**	0.16**	0.10	0.02
	(-0.82)	(1.99)	(2.09)	(2.22)	(2.30)	(1.33)	(0.33)
FCAHF	-0.04	-0.08***	-0.08***	-0.07***	-0.09***	-0.08***	-0.06**
	(-1.22)	(-3.36)	(-3.12)	(-2.77)	(-3.35)	(-2.93)	(-2.21)
Large Fund		5.47**	3.16	6.84***	3.03	1.93	-0.03
		(2.23)	(1.29)	(2.87)	(1.27)	(0.78)	(-0.02)
Large Family	-0.04	-0.04	-0.04	-0.03	-0.03	-0.04	-0.04
	(-1.06)	(-1.06)	(-1.12)	(-0.86)	(-0.69)	(-0.99)	(-0.88)
Log Size	-0.01	0.01	0.00	-0.00	0.00	0.02	0.02
	(-0.16)	(0.09)	(0.03)	(-0.00)	(0.02)	(0.26)	(0.35)
Log Age	0.04***	0.04***	0.04***	0.04***	0.04***	0.04***	0.04***
	(4.51)	(4.41)	(4.39)	(4.03)	(4.15)	(4.34)	(4.37)
Log Totrest	-0.08***	-0.07***	-0.07***	-0.07***	-0.07***	-0.06***	-0.06***
	(-5.05)	(-4.28)	(-4.06)	(-3.79)	(-3.73)	(-3.23)	(-2.83)
Excess Return at Lag 0	0.05***	0.05**	0.05***	0.05**	0.05**	0.05**	0.05**
	(2.63)	(2.47)	(2.71)	(2.58)	(2.51)	(2.55)	(2.53)
Style×Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	180,499	173,731	170,386	167,507	164,199	161,262	158,538
Adjusted R-squared	0.205	0.210	0.209	0.212	0.209	0.207	0.207

Table 8

Comparison of Trading Behavior in Crisis Times

The table reports estimates from regressions of the changes in ownership (in percent) on stock characteristics interacted with an indicator for high-VIX quarters. The unit of observation is the stock quarter. In Panels A and B, the dependent variable in columns 1 (2) and 4 (5) is the change in ownership of stock *i* held by FCAHFs (other hedge funds) between quarter *q* and *q*+1. In columns 3 (and 6), the dependent variable is the difference between the dependent variables in columns 1 and 2 (and 4 and 5). In all columns, the change in ownership is standardized by the number of shares outstanding. We control for the proportion of shares held by FCAHFs (other hedge funds) at the end of quarter *q*, Holdings of FCAHFs (Holdings of non FCAHFs). Stock characteristics are expressed as indicator variables for the underlying variable being in the top quintile of the cross-sectional distribution in a given quarter, except for returns for which we take the bottom quintile. In all regressions, we control for the log of market capitalization, book-to-market ratio, the return on assets (ROA), and the inverse price ratio, all measured at the end of the prior quarter. Standard errors are clustered at the time and stock level. ***, **, * denote significance at 1%, 5%, and 10% levels, respectively. The sample period ranges between 2000 and 2013.

Panel A. Stocks with Different Volatility and Past Returns

Dependent Variable:	Change in ownership of stock *i* by institution type					
Institution Type:	FCAHFs	Other HFs	FCAHFs - Other HFs	FCAHFs	Other HFs	FCAHFs - Other HFs
Characteristic:	High Volatility			Low Prior Quarterly Return		
	(1)	(2)	(3)	(4)	(5)	(6)
Characteristic×High Vix	0.14**	-0.00	0.14*	0.09**	-0.01	0.10**
	(2.12)	(-0.08)	(1.91)	(2.32)	(-0.29)	(2.10)
Characteristic	-0.13***	-0.05***	-0.09*	-0.07***	-0.01	-0.07**
	(-3.80)	(-3.05)	(-1.98)	(-3.19)	(-0.97)	(-2.40)
Holdings of FCAHFs	-14.56***		-14.65***	-14.56***		-14.67***
	(-20.39)		(-20.60)	(-20.45)		(-20.68)
Holdings of Other HFs		-22.62***	20.32***		-22.69***	20.18***
		(-24.70)	(20.63)		(-24.69)	(20.42)
Log Mkt Cap	0.06**	-0.04***	0.10***	0.06**	-0.04***	0.10***
	(2.16)	(-2.75)	(3.72)	(2.16)	(-2.71)	(3.61)
Book-to-Market	-0.01	-0.02	0.01	0.00	-0.02	0.02
	(-0.21)	(-1.07)	(0.21)	(0.13)	(-0.93)	(0.59)
ROA	0.08	-0.04	0.14	0.07	-0.03	0.13
	(0.85)	(-0.56)	(1.09)	(0.81)	(-0.53)	(1.06)
1/Price	0.11	-0.03	0.13	0.11	-0.06	0.16
	(0.31)	(-0.17)	(0.33)	(0.31)	(-0.38)	(0.38)
IOR	-0.06	-0.02	-0.01	-0.04	-0.01	0.01
	(-0.98)	(-0.29)	(-0.10)	(-0.72)	(-0.15)	(0.13)
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	86,144	81,119	80,295	86,144	81,119	80,295
Adjusted R-squared	0.150	0.197	0.153	0.150	0.197	0.153

Panel B. Stocks with Different Liquidity

Dependent Variable:	Change in ownership of stock *i* by institution type					
Institution Type:	FCAHFs	Other HFs	FCAHFs - Other HFs	FCAHFs	Other HFs	FCAHFs - Other HFs
Characteristic:	High Amihud			High Spread		
	(1)	(2)	(3)	(4)	(5)	(6)
Characteristic×High Vix	0.26*	0.04**	0.25*	0.23*	-0.02	0.26*
	(1.98)	(2.26)	(1.69)	(1.72)	(-1.48)	(1.95)
Characteristic	0.02	0.07***	-0.06	-0.07	0.02	-0.09
	(0.23)	(4.56)	(-0.79)	(-0.97)	(1.59)	(-1.33)
Holdings of FCAHFs	-14.59***		-14.65***	-14.62***		-14.69***
	(-20.66)		(-20.56)	(-20.66)		(-20.59)
Holdings of Other HFs		-22.57***	20.33***		-22.58***	20.32***
		(-25.29)	(21.29)		(-25.27)	(21.29)
Log Mkt Cap	0.07***	-0.03*	0.10***	0.06**	-0.04**	0.09***
	(2.73)	(-1.89)	(3.73)	(2.52)	(-2.18)	(3.85)
Book-to-Market	-0.01	-0.03	0.01	-0.02	-0.02	0.00
	(-0.43)	(-1.46)	(0.26)	(-0.50)	(-1.26)	(0.02)
ROA	0.07	-0.03	0.12	0.08	-0.03	0.14
	(0.81)	(-0.39)	(1.01)	(0.90)	(-0.38)	(1.07)
1/Price	-0.11	-0.16	0.00	-0.06	-0.04	-0.05
	(-0.33)	(-1.10)	(0.01)	(-0.19)	(-0.29)	(-0.13)
IOR	-0.02	0.02	0.01	-0.04	-0.01	0.01
	(-0.28)	(0.30)	(0.12)	(-0.68)	(-0.23)	(0.12)
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	86,151	81,229	80,409	86,151	81,229	80,409
Adjusted R-squared	0.151	0.195	0.153	0.152	0.195	0.154

Table 9

FCAHFs' Investment Horizon and Portfolio Liquidity

The table reports estimates from regressions of the average Amihud illiquidity ratio of the stocks in a fund portfolio during a quarter (columns 1 to 4) and the fund portfolio turnover during a quarter (columns 5 to 8). We control for the log of management firm's Age and Size (i.e. AUM). Quarter and management firm's effects are included. Standard errors are clustered at the time and management firm level. ***, **, * denote significance at 1%, 5%, and 10% levels, respectively. The sample period ranges between 2000 and 2013.

Dependent Variable:	Portfolio Amihud (×100)				Portfolio Turnover (%)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FCAHF	-0.05	-0.06	-0.09**	-0.09**	0.52	0.69	0.68	0.94
	(-1.21)	(-1.42)	(-2.38)	(-2.55)	(0.33)	(0.43)	(0.34)	(0.47)
FCAHF × High Vix		0.06**		0.05**		-0.84*		-1.47**
		(2.60)		(2.37)		(-1.87)		(-2.43)
Log Firm Age			0.00	0.00			-0.19	-0.18
			(0.30)	(0.24)			(-0.53)	(-0.49)
Log Firm Size			-0.01	-0.01			0.29	0.29
			(-0.95)	(-0.92)			(1.28)	(1.27)
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,958	3,958	3,310	3,310	4,363	4,363	3,639	3,639
Adjusted R-squared	0.630	0.632	0.619	0.620	0.498	0.498	0.503	0.503

Table 10

Price Impact

The table reports estimates from OLS regressions of the price impact of trading from ANcerno (in %) on stock characteristics interacted with an indicator for high-VIX quarters. The unit of observation is the stock quarter. Price impact is computed as percentage difference in execution price and opening price and it is the volume-weighted average across all the trades in the quarter. In both panels, the dependent variable is the average price impact of FCAHFs (column 1 and 4), other hedge funds (columns 2 and 5), and the difference in price impact between FCAHFs and other hedge funds (columns 3 and 6). Characteristics are measured as continuous variables. In all regressions, we control for the log of market capitalization, book-to-market ratio, the return on assets (ROA), and the inverse price ratio, all measured at the end of the prior quarter. All models are estimated by ordinary least squares and include time and stock fixed effects. Standard errors are clustered at the time and stock level. ***, **, * denote significance at 1%, 5%, and 10% levels, respectively. The sample period ranges between 2000 and 2013.

Panel A. Stocks with Different Volatility and Past Returns

Dependent Variable:	Price Impact in stock *i* by institution type					
Institution Type:	FCAHF	Other HF	FCAHF - Other	FCAHF	Other HF	FCAHF - Other
Characteristic:	Volatility			Low Past Return		
	(1)	(2)	(3)	(4)	(5)	(6)
Characteristic×High Vix	-0.43***	-0.20***	-0.26**	-0.02*	0.01	-0.03**
	(-3.98)	(-3.16)	(-2.14)	(-1.83)	(1.21)	(-2.32)
Characteristic	0.77***	0.35***	0.31***	0.02	0.01	0.02
	(8.02)	(5.80)	(2.87)	(1.03)	(0.39)	(0.81)
Log Mkt Cap	-0.01***	-0.00	-0.01***	-0.01**	0.00	-0.02**
	(-5.53)	(-0.29)	(-5.23)	(-2.43)	(0.25)	(-2.48)
Book-to-Market	-0.01***	-0.00**	-0.01***	-0.01	-0.00	-0.01
	(-3.02)	(-2.45)	(-2.81)	(-1.26)	(-0.63)	(-0.72)
ROA	-0.01	0.01	-0.01	0.02	0.06**	-0.09
	(-0.33)	(1.28)	(-0.51)	(0.26)	(2.13)	(-1.19)
1/Price	-0.02	-0.06***	0.02	0.12	-0.06	0.20
	(-0.67)	(-3.19)	(0.38)	(1.02)	(-0.99)	(1.45)
IOR	0.00	0.01	0.00	-0.02	0.02***	-0.06***
	(0.76)	(1.34)	(0.59)	(-1.29)	(2.92)	(-3.07)
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	65,602	65,564	48,668	69,153	64,223	63,311
Adjusted R-squared	0.077	0.056	0.065	0.059	0.043	0.057

Panel B. Stocks with Different Liquidity

Dependent Variable:	Price Impact in stock *i* by institution type					
Institution Type:	FCAHF	Other HF	FCAHF - Other	FCAHF	Other HF	FCAHF - Other
Characteristic:	Amihud			Spread		
	(1)	(2)	(3)	(4)	(5)	(6)
Characteristic×High Vix	-0.31***	0.03	-0.27***	-3.02***	0.40*	-1.78***
	(-4.52)	(0.95)	(-2.81)	(-6.95)	(1.70)	(-3.74)
Characteristic	-0.11	-0.14***	-0.12	1.33***	-0.68***	1.09***
	(-1.56)	(-4.13)	(-1.32)	(3.39)	(-3.24)	(2.59)
Log Mkt Cap	-0.01***	-0.00	-0.01***	-0.01***	-0.00	-0.01***
	(-5.39)	(-0.46)	(-5.14)	(-5.02)	(-0.23)	(-4.82)
Book-to-Market	-0.00	-0.00	-0.01**	-0.00	-0.00	-0.01**
	(-1.55)	(-1.10)	(-2.20)	(-1.26)	(-1.18)	(-2.15)
ROA	0.00	0.01*	0.00	0.00	0.01*	0.00
	(0.09)	(1.81)	(0.07)	(0.17)	(1.78)	(0.13)
1/Price	0.05	-0.04**	0.07	0.03	-0.05**	0.05
	(1.45)	(-2.05)	(1.40)	(0.86)	(-2.44)	(1.07)
IOR	0.00	0.00	0.00	0.01	0.00	0.01
	(0.26)	(0.33)	(0.60)	(1.17)	(0.87)	(1.54)
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	65,452	65,325	48,514	65,035	65,051	48,172
Adjusted R-squared	0.075	0.054	0.064	0.077	0.055	0.064

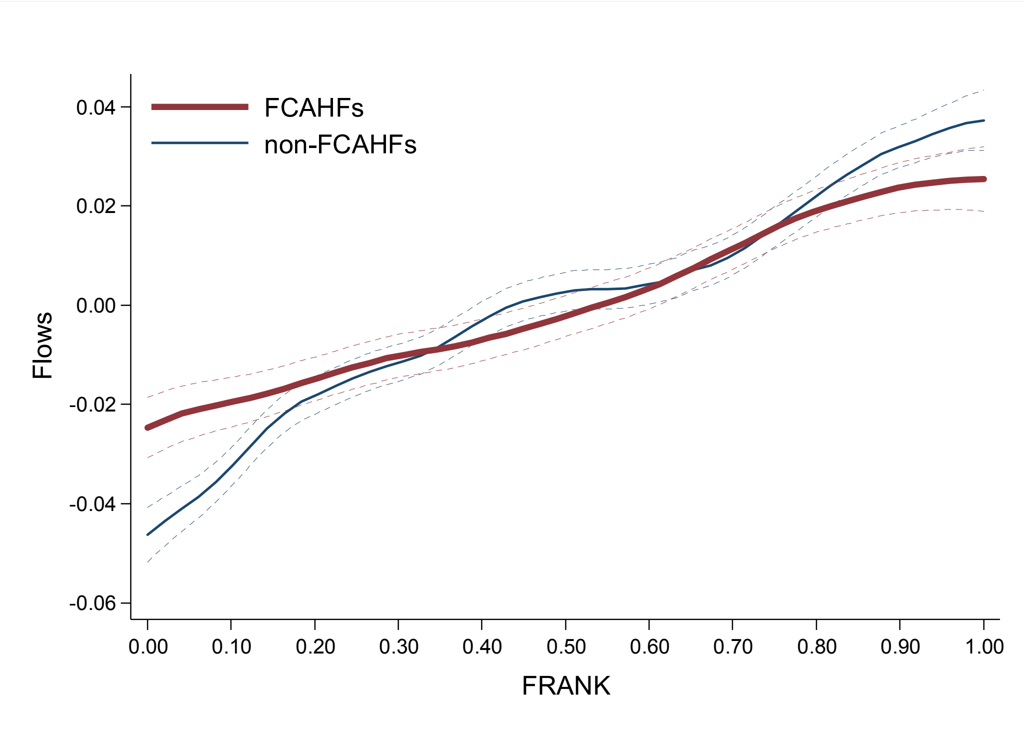
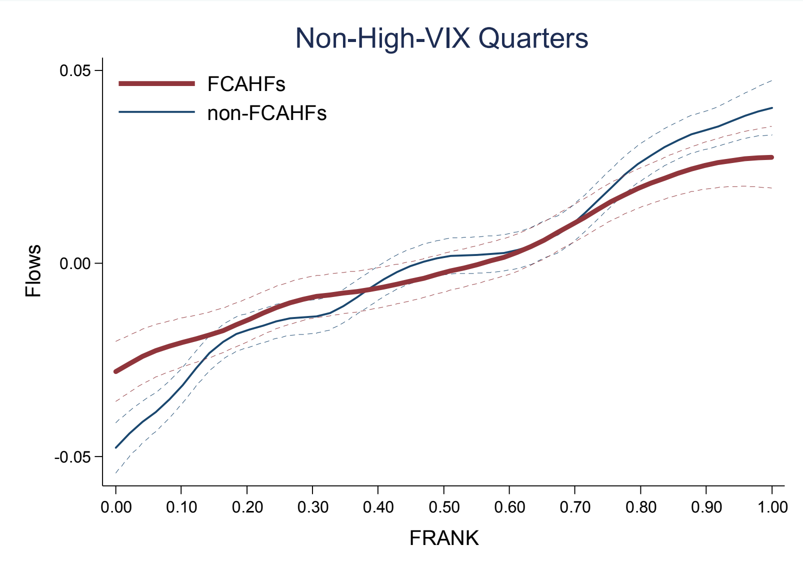


Fig. 1. Flows and Performance of FCAHFs and Other Hedge Funds. Note: The figure plots the fitted values from a local polynomial smoother applied to hedge-fund flows, where the independent variable is the hedge fund's fractional performance rank in a given quarter. The thick red line denotes FCAHFs, the blue line non-FCAHFs. In particular, the figure plots the non-parametric function $f(.)$ in the following semi-parametric specification run at the fund level and quarterly frequency: $Flows_{j,q+1} = a + bf(FRANK_{j,q}) + controls + \gamma_j + \delta_q + \varepsilon_{j,q+1}$. The estimation uses a kernel-weighted local polynomial smoothing. The controls include: fund size, age, the logarithm of redemption restrictions, style and time fixed effects. We perform the analysis for financial-conglomerate-affiliated hedge funds (FCAHFs) and non-affiliated funds (non-FCAHFs). The dashed lines represent 95% confidence intervals. The smoother uses the Epanechnikov (1969) kernel with optimal bandwidth chosen with a rule-of-thumb estimator as described in Fan and Gijbels (1996). The sample period ranges between 2000 and 2013.



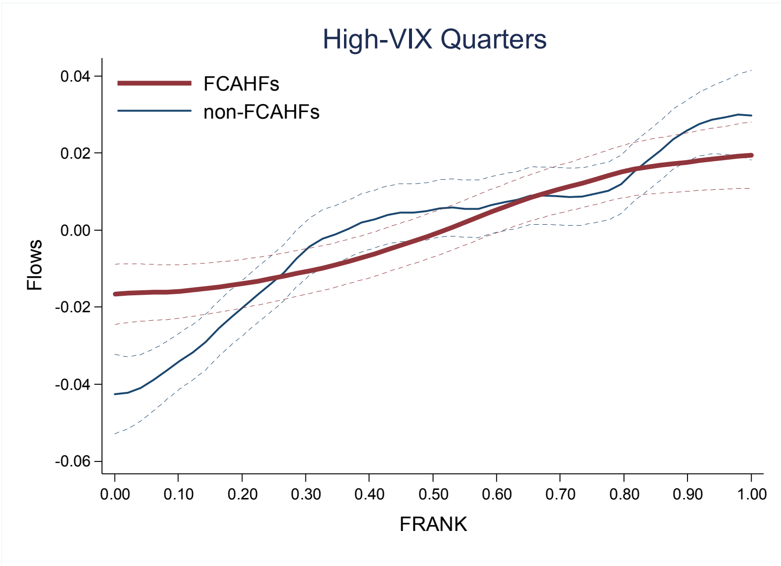


Fig. 2. Flows and Performance across Types of Funds and Market Conditions. Note: The figure plots the fitted values from a local polynomial smoother applied to hedge-fund flows, where the independent variable is the hedge fund's fractional performance rank in a given quarter. The thick red line denotes FCAHFs, the blue line other HFs. In particular, the figure plots the non-parametric function $f(.)$ in the following semi-parametric specification run at the fund level and quarterly frequency: $Flows_{j,q+1} = a + bf\left(FRANK_{j,q}\right) + controls + \gamma_j + \delta_q + \varepsilon_{j,q+1}$. The estimation uses a kernel-weighted local polynomial smoothing. The controls include: fund size, age, the logarithm of redemption restrictions, style and time fixed effects. We perform the analysis for financial-conglomerate-affiliated hedge funds (FCAHFs) and non-affiliated funds (non-FCAHFs). We also distinguish between non-high-VIX quarters (top chart) and high-VIX quarters (bottom chart), as defined in Appendix A2. The dashed lines represent 95% confidence intervals. The smoother uses the Epanechnikov (1969) kernel with optimal

bandwidth chosen with a rule-of-thumb estimator as described in Fan and Gijbels (1996). The sample period ranges between 2000 and 2013.

Fig. 3. *Panel A. The Proportion of FCAHFs over Time*

Fig 3. *Panel B. The Proportion of Assets Managed by FCAHFs over Time*

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