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The Value of Funds of Hedge Funds: Evidence from Their Holdings

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We examine the portfolio holdings of funds of hedge funds (FoFs) to identify the channels through which FoFs add value for their clients. FoFs offer access to a diversified portfolio of funds that would be costly for constrained investors to manage on their own. Although we find only limited evidence that FoFs exhibit skill when selecting hedge funds, we find strong evidence that FoFs make skillful termination decisions. After FoFs divest from a hedge fund, those hedge funds subsequently underperform and fail more often. Our evidence indicates that FoFs learn and skillfully process information about their portfolio funds after they become investors, enabling them to forecast poor future performance. Our study suggests that FoFs serve an important role as intermediaries in a market characterized by significant frictions and transactions costs.

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1. Introduction

Because it is both difficult and costly to directly invest in hedge funds, funds of hedge funds (FoFs) are an important intermediary in the market for hedge fund capital, providing investors access to a diversified portfolio of hedge funds in exchange for an additional layer of management and performance fees. As of 2009, FoFs managed an estimated 43% of the over $2 trillion in total hedge fund assets and were used as an investment vehicle by nearly 70% of institutional investors making hedge fund allocations.[1] Yet, despite their relative importance in allocating hedge fund capital, we know little about how FoFs manage their portfolios and do not fully understand why investors use them as intermediaries. In this paper, we examine the investment decisions of FoFs and explore the various ways in which FoFs could add value for their investors.

Hedge funds pursue complex and illiquid trading strategies, yet they are lightly regulated and face only limited disclosure requirements. Moreover, hedge funds typically have high minimum investments and place restrictions on investor access and redemptions. These unique features of the hedge fund industry suggest at least three possible channels through which FoFs could add value for their investors. First, by pooling investor capital, FoFs could provide intermediary services that permit access to a private and restricted industry. Second, because FoFs specialize in hedge fund investing and have the economies of scale to perform the necessary due diligence on prospective hedge funds, they could skillfully select better hedge funds than an uninformed or constrained investor could. Third, FoFs may acquire informational advantages that improve their ability to actively monitor their hedge fund investments, enabling them to skillfully terminate funds that are more likely to become poor performers or blow up. This monitoring function could be especially important, because hedge funds are often exposed to large left-tail risk associated with their trading strategies (Kelly and Jiang 2012) or high operational risk (Brown et al. 2008b).

Our paper examines each of these channels using a unique subset of FoFs that disclose their holdings to the U.S. Securities and Exchange Commission (SEC). We examine the composition of FoF portfolios as well as the factors that lead FoFs to select new hedge funds for (hire) and remove existing funds from (fire) their portfolio. We test whether these hiring and firing decisions appear skillful on the part of the FoF manager by comparing the postdecision performance of hired and fired funds to the performance of various hedge

[1] See eVestment (2009) and Preqin (2010).

fund indices, constructed to reflect measures of the opportunity cost of capital for hedge fund investors.

We find evidence supporting the idea that FoFs offer a valuable intermediary service to constrained investors. The average FoF in our sample holds 23 different hedge funds, each with an average minimum investment of over $2 million. By pooling investor capital, FoFs could add value by assembling a portfolio of funds that would be difficult for smaller investors to assemble on their own. We estimate that an investor would need to allocate just under $50 million in capital to duplicate the composition of the average FoF portfolio, nearly 100 times the average minimum investment of FoFs themselves. This represents a lower bound of replication costs because it assumes zero search and monitoring costs. Factoring in these costs, the intermediary role of FoFs may be of significant value to constrained investors that lack the resources to actively screen and monitor hedge fund managers.

We next examine how FoFs make their hiring decisions. We find mixed evidence that FoFs select funds with observable characteristics that are known to predict better future performance. When we compare the characteristics of hedge funds selected by FoFs to the rest of the hedge fund universe, we find that FoFs select funds with more restrictive withdrawals and lower operational risk, characteristics that have been found to predict higher future performance (Aragon 2007, Brown et al. 2009). However, FoFs also select larger hedge funds that have had high recent performance and large capital inflows, characteristics that, because of diminishing returns to capital, have been shown to predict lower future performance (Joenväärä et al. 2014).

We test whether FoFs exhibit skill in their hiring decisions using a calendar-time portfolio approach similar to Goyal and Wahal (2008). We form monthly portfolios of hedge funds hired by FoFs and compare their posthired returns to the average performance of the hedge fund universe. Our results suggest that, despite being among the best performers before they are hired, FoF selections do no better than the average hedge fund after they are hired. As such, we lack evidence to support the hypothesis that FoF managers can skillfully select superior hedge funds, at least when compared with the average fund.

However, our primary framework for relative performance evaluation defines the benchmark cost of capital using an unconstrained opportunity set of hedge funds. This benchmark may obscure FoF skill if FoFs, or their investors, face investment constraints that limit their access to some funds. For example, some hedge funds respond to perceived capacity constraints by limiting capital inflows or prohibiting new investors from joining the fund. In addition, some hedge funds may be too small, or have such a limited track record, such that FoFs (and, perhaps, their clients) may be constrained from investing in them. We find some evidence that FoFs select better funds when we omit hedge funds that are small, young, and closed to new investment from the benchmark.

Although we find only limited evidence of selection ability, we find strong evidence that FoFs make skillful termination (firing) decisions. After termination, fired funds exhibit significantly lower performance than the average fund in the hedge fund universe. This underperformance does not appear to be caused by the FoF withdrawal itself and instead suggests that FoF terminations predict future poor performance. Furthermore, fired funds are significantly more likely to suffer extreme negative returns and are more likely to delist from hedge fund databases and liquidate their operations. Following the scandal of Bernard Madoff, the ability of FoFs to screen and monitor managers has received considerable scrutiny.[2] Our evidence suggests that, on average, FoFs do play an important role in monitoring their hedge fund investments by terminating managers that are likely to be poor performers in the future.

Finally, we find evidence suggesting that learning improves the quality of the FoFs' investment decisions. The fact that FoFs make more skillful decisions when they fire funds than when they hire funds suggests that they learn more about hedge fund quality after investing in the fund. This is consistent with the idea that the opacity of private funds creates informational advantages for incumbent investors as compared to prospective investors (Hochberg et al. 2014). In addition to learning about specific hedge funds, we also find evidence that FoFs gain from general experience, suggesting that they "learn by doing." Our performance tests indicate that older FoFs make better hiring and firing decisions than younger funds, suggesting that inexperienced hedge fund investors not only have limited information about each fund but also have a limited set of data from which to draw their prior beliefs *across* hedge funds.

This paper contributes to a large literature that examines the investment decisions of intermediaries that delegate their portfolios to other asset managers.[3] Although ours is the first, to our knowledge, to directly study FoF investment decisions, a number of previous studies have examined the aggregate performance of FoFs, coming to the general consensus that their lackluster performance and additional layer of fees call into question their value as an intermediary.[4]

[2] For example, see Ross (2009).

[3] For example, see Bhattacharya et al. (2013) for funds of mutual funds, Andonov et al. (2012) and Goyal and Wahal (2008) for plan sponsors, and Brown et al. (2010) for university endowments.

[4] See, for example, Brown et al. (2004), Agarwal and Kale (2007), Agarwal et al. (2012), and Brown et al. (2012a).

Table 1 FoF Portfolio Summary Statistics

Variable	Mean	Median	10th percentile	90th percentile	Std. dev.
Number of holdings	23.12	21.00	8.00	42.00	13.21
Number of database holdings	10.30	10.00	3.00	18.00	6.06
Holding size ($ millions)	10.06	4.96	1.13	26.20	13.46
Portfolio weight (%)	6.89	4.76	2.38	12.50	8.24
Number of styles	4.57	4.97	1.94	7.00	2.10
Number of capital additions	2.80	1.00	0.00	8.00	4.23
Number of capital reductions	5.18	4.00	0.00	12.00	5.58
Number of hires	3.01	2.00	0.00	7.00	3.87
Number of fires	1.94	1.00	0.00	5.00	2.85

Notes. The table describes the characteristics of 1,313 quarterly portfolios of FoFs from 2002 to 2009. The unit of observation is an FoF/quarter. *Number of holdings* is the number of hedge fund positions held by an FoF. *Number of database holdings* is the number of hedge funds held by an FoF that actively report performance to the union of three commercial databases: Lipper TASS, BarclayHedge, and HFR. *Holding size* is the value (in millions of dollars) of each FoF's hedge fund holding, and *Portfolio weight* (%) is the holding's fraction of total FoF portfolio value. *Number of styles* is the number of Lipper TASS hedge fund styles held by an FoF. *Number of capital additions* and *Number of capital reductions* measure the frequency with which an FoF rebalances its portfolio weights. *Number of hires* and *Number of fires* measure the frequency with which an FoF invests in new funds (hires) and divests from existing funds (fires), respectively.

We too find only limited evidence that FoFs select hedge funds with superior performance. However, our results are consistent with studies suggesting that FoFs may offer other valuable intermediary and monitoring services to constrained investors. Ang et al. (2008) argue that the benchmark for whether FoFs add value should not be their average performance compared to stand-alone hedge funds but rather what hedge fund investors could achieve based on their own monitoring ability and search costs. Brown et al. (2008a) argue that large FoFs have a competitive advantage because their scale allows them to more easily pay for and perform costly due diligence in order to avoid funds likely to fail as a result of operational risk. Additionally, Sialm et al. (2012) find evidence that FoFs gain an informational advantage from being in close proximity to their investments. The asymmetry between hiring and firing skill we document suggests that FoFs also gain an informational advantage once they invest in the fund and can more closely monitor the behavior of the fund manager.

2. Data and Summary Statistics

2.1. SEC Registered FoFs

In this paper, we employ a data set of FoF holdings disclosed to the SEC by 79 different registered FoFs. We use SEC Forms N-Q, N-CSR, and N-CSRS to capture each FoF's portfolio holdings at a quarterly frequency. These filings disclose the name of each underlying hedge fund position in the portfolio, as well as each position's cost basis and current value. The time-series combination of these filings allows us to create a panel of quarterly hedge fund holdings for each FoF.

To obtain FoF holdings data, we must rely on a sample of FoFs that choose to register with the SEC. The main incentive for an FoF to register is to avoid legal restrictions that unregistered FoFs face when raising capital. For instance, registering removes limitations on the type and quantity of the fund's investors and allows funds to solicit money through retirement plans covered by the Employee Retirement Income Security Act of 1974 without triggering costly regulatory constraints. Funds that choose to register also bear costs, such as legal fees and the subsequent disclosure of fund-level information, to access this additional clientele.

We argue, however, that the drawbacks of registration are unlikely to dramatically hinder the investment process pursued by registered FoF managers compared with other large FoFs.[5] Because the market for hedge fund capital is characterized by relatively high transactions costs, investors cannot use the holdings disclosures of FoFs to easily mimic their strategies.[6] As such, FoFs typically disclose their positions to their limited partners and potential investors, regardless of whether or not they are registered with the SEC. Additionally, the registered funds are run by large institutional money managers, such as Morgan Stanley, Credit Suisse, and BlackRock. A registered product creates an economy of scope for these institutions, enabling them to offer hedge fund access to a larger part of their client base. The relative size and influence of these institutions should facilitate their access to a wide array of hedge funds.[7]

Table 1 provides a first look into the details of how a typical FoF in our sample forms its portfolio.

[5] Aiken et al. (2013) compare the characteristics of registered FoFs to those of the larger set of FoFs that voluntarily choose to report to commercial hedge fund databases and find that registered FoFs and database FoFs have similar performance.

[6] This stands in contrast to the portfolio disclosures of hedge funds themselves, which can contain proprietary information about trading strategies that is easily appropriable by competitors (Agarwal et al. 2013).

[7] The 10 most frequently hired hedge fund advisors in our sample are Canyon Capital Advisors, Avenue Capital Group, Brevan Howard Asset Management, Perry Capital, York Capital Management, Stark Investments, GoldenTree Asset Management, Sloane Robinson, Jana Partners, and Paulson & Co.

Table 2 Hedge Fund Summary Statistics

Panel A: Hedge fund universe

Variable	N	Mean	Median	10th percentile	90th percentile	Std. dev.
Annual return (% per year)	171,748	9.29	7.99	−12.17	30.82	21.08
Standard deviation (% per month)	171,748	3.41	2.56	0.82	7.03	2.95
Sharpe ratio (annualized)	184,215	0.93	0.78	−1.19	3.05	1.85
Operational risk (0 | 1)	170,435	0.33	0.00	0.00	1.00	0.47
Quarterly flow (% per quarter)	189,995	5.87	0.00	−12.60	24.88	31.82
Redemption notice (days)	197,787	37.66	30.00	5.00	90.00	30.51
Withdrawal frequency (days)	197,025	67.65	30.00	30.00	90.00	71.99
Lockup (days)	201,066	125.46	30.00	0.00	365.00	189.63
Minimum investment ($ million)	200,438	1.08	0.50	0.10	2.00	2.92
AUM ($ million)	201,214	158.82	54.90	3.60	333.00	307.38
AUM missing (0 | 1)	201,214	0.22	0.00	0.00	1.00	0.41
Age (years)	201,214	4.80	3.50	0.58	10.83	4.55
Management fee (%)	200,337	1.50	1.50	1.00	2.00	0.60
Incentive fee (%)	199,899	18.42	20.00	12.00	20.00	5.49
Big 4 accounting (0 | 1)	201,015	0.60	1.00	0.00	1.00	0.49
Highwater mark (0 | 1)	200,899	0.86	1.00	0.00	1.00	0.35

Panel B: Held by FoF

Variable	N	Mean	Median	10th percentile	90th percentile	Std. dev.
Annual return (% per year)	7,935	9.65	9.29	−7.90	25.90	16.54
Standard deviation (% per month)	7,935	2.57	2.00	0.79	4.91	2.09
Sharpe ratio (annualized)	8,075	1.22	1.09	−0.98	3.47	1.83
Operational risk (0 | 1)	7,917	0.28	0.00	0.00	1.00	0.45
Quarterly flows (% per quarter)	8,019	4.12	0.00	−12.10	20.69	23.42
Redemption notice (days)	8,112	50.92	45.00	20.00	90.00	29.83
Withdrawal frequency (days)	8,139	106.79	90.00	30.00	365.00	99.09
Lockup (days)	8,156	188.61	30.00	0.00	365.00	211.31
Minimum investment ($ million)	8,173	2.11	1.00	0.25	5.00	5.09
AUM ($ million)	8,173	512.34	241.18	44.65	1,625.85	596.66
AUM missing (0 | 1)	8,173	0.14	0.00	0.00	1.00	0.35
Age (years)	8,173	6.48	5.42	1.83	12.67	4.40
Management fee (%)	8,152	1.48	1.50	1.00	2.00	0.48
Incentive fee (%)	8,151	19.58	20.00	20.00	20.00	2.70
Big 4 accounting (0 | 1)	8,173	0.68	1.00	0.00	1.00	0.47
Highwater mark (0 | 1)	8,153	0.93	1.00	1.00	1.00	0.26

Notes. The table presents descriptive statistics of the hedge funds in our sample. Panel A describes the hedge fund universe, which we define as the superset of funds found in the union of three commercial databases: Lipper TASS, BarclayHedge, and HFR. Panel B describes the subset of hedge funds held by the FoFs in our sample. The unit of observation is a hedge fund/quarter. The variables are defined in the appendix.

On average, FoFs own 23.12 unique hedge funds, each with an average position value of $10.06 million. On average, FoFs hold hedge funds from 4.57 of the 10 Lipper TASS styles defined as convertible arbitrage, emerging markets, market-neutral equity, long/short equity, event driven, global macro, managed futures, fixed-income arbitrage, short bias, and multistrategy. FoFs vary their investment choices over time because they select (hire) 3.01 new funds and divest from (fire) 1.94 funds each quarter on average. Furthermore, FoFs actively rebalance their portfolio weights and on average add capital to 2.80 funds and withdraw capital from 5.18 funds each quarter.

Given that the minimum investment of the average FoF holding is $2.11 million, for an investor to match the portfolio composition of the average FoF in our sample (23.12 hedge funds), that investor would need to allocate roughly $50 million, or nearly 100 times the minimum investment of the average registered FoF ($530,000). Thus, FoFs invest in a diversified number of hedge funds across a broad range of investment styles, giving investors access to a portfolio of funds that would be very difficult for them to replicate on their own. This represents a lower bound of replication costs because it assumes zero search and monitoring costs. Factoring in these costs, the intermediary role of FoFs may be of significant value to constrained investors that lack the resources to actively screen and monitor hedge fund managers.

2.2. Hedge Fund Database Sample

To obtain performance and contract characteristics of FoF holdings (as well as the other funds in the hedge fund industry), we focus our subsequent analysis on hedge funds that report to one of three major commercial hedge fund databases: Lipper TASS, BarclayHedge, and Hedge Fund Research (HFR).[8] Throughout the paper, we refer to the union of these databases as the *hedge fund universe*. In Table 2, we present descriptive statistics for both the hedge fund universe (panel A) and for only those hedge funds held by FoFs (panel B). Our sample period is 2002–2009, and the unit of observation is a hedge fund/quarter. We define our variables in the appendix.

An interesting feature of the hedge fund universe is that the distribution of hedge fund size (assets under management, or AUM) is heavily skewed; the mean fund in the universe manages \$158.82 million, whereas the median fund manages only \$54.90 million, or 18% of the average FoF allocation. Thus, it is not surprising that the median hedge fund selected by an FoF is significantly larger (\$241.18 million) than the median fund in the universe. Hedge fund reporting standards vary across funds, and as such, a sizeable fraction of funds do not consistently report AUM to the databases. Furthermore, this reporting decision is related to the probability of being held by an FoF. AUM is missing for 22% (14%) of the fund/quarters in the hedge fund universe (FoF holdings sample). We include these observations in our analysis, along with an indicator variable that captures whether the fund reports AUM.[9] Finally, we note that many of the characteristics of the universe are meaningfully different from the subsample held by FoFs. In what follows, we more fully examine these differences in a multivariate framework in an effort to understand how FoFs select their hedge fund investments.

3. Hiring Decisions

Hedge fund information is scarce and due diligence is costly (Brown et al. 2012a). Because FoFs specialize in hedge fund investing and have the economies of scale to perform the necessary due diligence of prospective hedge funds, they may have a comparative advantage in selecting hedge funds. An FoF could add value for its clients if it can make better hedge fund selections than an uninformed or constrained investor could. The goal of this section is to understand what characteristics are related to an FoF's decision to select (hire) a hedge fund and to test whether those hiring decisions reflect evidence of skill on the part of the FoF.

Table 3 Determinants of Hiring Decisions

Variable	Model 1 (Hired)	Model 2 (First hire)	Model 3 (Hiring intensity)
Style-adjusted return	1.19***	1.20***	0.43***
	[3.59]	[2.94]	[3.20]
Standard deviation	0.67***	0.67***	−1.06***
	[−5.24]	[−4.42]	[−5.26]
Operational risk	0.71***	0.69***	−0.96***
	[−3.86]	[−3.23]	[−4.03]
Quarterly flow	1.22***	1.22***	0.56***
	[8.28]	[6.46]	[7.57]
Share illiquidity	1.27***	1.26***	0.71***
	[6.03]	[5.99]	[6.31]
AUM missing (0 | 1)	0.70**	0.64***	−1.08***
	[−2.42]	[−3.53]	[−2.84]
AUM (ln)	2.83***	2.35***	2.86***
	[16.62]	[15.92]	[16.78]
Age (ln) (years)	1.03	0.93	0.11
	[0.58]	[−1.33]	[0.73]
Minimum investment (ln)	1.65***	1.57***	1.48***
	[6.97]	[6.82]	[7.29]
Management fee (%)	1.07	1.07*	0.21*
	[1.50]	[1.81]	[1.70]
Incentive fee (%)	1.15***	1.14***	0.38***
	[2.93]	[2.84]	[2.63]
Big 4 accounting (0 | 1)	1.16	0.98	0.43*
	[1.57]	[−0.21]	[1.66]
Highwater mark (0 | 1)	1.21	1.29	0.57
	[0.95]	[1.55]	[1.08]
Style FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Observations	154,319	147,353	154,319
Pseudo R-squared	0.16	0.13	0.12

Notes. In the table, we model the FoF's decision to hire a hedge fund. The unit of observation is a hedge fund/quarter. Models 1 and 2 are logit regressions, and the coefficients are reported as odds ratios. In Model 1, the dependent variable equals 1 in each quarter that an FoF hires a hedge fund and 0 otherwise. The dependent variable is similar in Model 2, yet we remove all subsequent fund observations after the first instance the hedge fund was hired by any FoF. To allow for the possibility that a hedge fund is hired by multiple FoFs at the same time, in Model 3 we estimate a Tobit regression where the dependent variable is the percentage of FoFs that purchased the hedge fund in the quarter, conditional on the fact that they do not already own the fund. The variable definitions can be found in the appendix. All continuous, independent variables in the model have been lagged one quarter and standardized with mean zero and unit variance. To control for unobserved heterogeneity, we include both time and style fixed effects (FE). Our standard errors are clustered at the hedge fund level. Z-statistics are in brackets.

$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

3.1. Determinants

In Table 3, we present multivariate logit (Models 1 and 2) and Tobit (Model 3) regressions modeling the probability that a hedge fund in the universe is hired by an FoF each quarter. In particular, we test how fund characteristics such as performance, flows, risk, and liquidity are associated with the FoF's hiring decision.

[8] Because many hedge funds report to multiple databases, we eliminate duplicate observations following steps similar to those in Joenväärä et al. (2012). Specifically, we match fund names using a standard name-matching algorithm and determine funds to be duplicates if their returns have a correlation greater than 0.99. We exclude funds with missing styles, FoFs, commodity trading advisors, and hedge fund indices from our analysis.

[9] When AUM is missing in time t, we impute it from its last reported AUM, if available. If not, we use the cross-sectional average AUM in time t.

We define the hiring choice three ways. In Model 1, the dependent variable equals 1 in each quarter that a registered FoF hires a hedge fund and 0 otherwise. The dependent variable is the same in Model 2, yet we remove all subsequent fund observations after the first instance when the hedge fund was hired by any of the FoFs in our sample.[10] In Model 3 (Tobit specification), the dependent variable is the percentage of FoFs that purchased the hedge fund in the quarter, conditional on the fact that they do not already own the fund. This measures the relative intensity of FoF hiring for a particular hedge fund. In all three models, the unit of observation is a hedge fund/quarter. The coefficients in Models 1 and 2 are presented as odds ratios. All independent variables (defined in the appendix) are lagged one quarter and standardized with zero mean and unit variance. To control for unobserved heterogeneity, we include both time and style fixed effects. Finally, our standard errors are clustered at the hedge fund level.[11]

In each of the three models, we find that higher style-adjusted performance is associated with being hired by registered FoFs. These results are robust to alternative measures of performance, such as raw returns, Fung and Hsieh (2004) seven-factor alphas, and Sharpe ratios (unreported). Coupled with the fact that hedge funds with higher net flows are more likely to be hired, this suggests that FoFs chase performance and follow other investors when they initially allocate capital to hedge funds. This could be good for investors if hedge funds exhibit performance persistence (Jagannathan et al. 2010). On the other hand, if hedge funds face capacity constraints, then performance-based inflows could lead to lower future fund returns (Boyson 2008, Joenväärä et al. 2014).

We find that FoFs hire funds with lower volatility and lower operational risk. Brown et al. (2008b, 2012b) find that funds with higher operational risk have poor future performance and are more likely to fail, but they find little evidence that exposure to operational risk influences investor capital allocations. This suggests that FoFs may be more sensitive to mitigating operational risk exposure than investors on average, which could be a source of value for FoF clients.

Furthermore, FoFs are more likely to hire hedge funds that have higher minimum investments and place more restrictions on investor withdrawals (higher *Share illiquidity*). Funds with high minimum investments and/or illiquid redemption rights could be prohibitively costly for small investors to invest in directly. By pooling investor capital, FoFs could add value by accessing funds that are difficult for smaller investors to access on their own.

The hiring determinants suggest that FoFs select funds with some characteristics that the literature has shown to predict better future performance (e.g., higher share illiquidity and lower operational risk). However, FoFs also select larger funds with high recent inflows—characteristics that, because of capacity constraints, are associated with lower future performance. In the next section, we test whether these decisions reflect FoF selection skill.

3.2. Performance

To test whether FoFs exhibit skill in their selection decisions, we measure the relative performance of the hired funds using a calendar-time portfolio approach similar to Goyal and Wahal (2008). We form monthly calendar-time portfolios based on three event windows (12, 24, and 36 months) relative to the month the fund was hired. We rebalance portfolios monthly to include newly hired funds and remove fired funds. For each calendar month, we calculate equal- and value-weighted event portfolios of FoF holdings.[12] The posthired windows begin the month after the hiring date, and our sample comprises 93 monthly observations from April 2002 through December 2009.[13]

To measure abnormal performance, we regress the time series of posthired portfolio excess returns ($ExcessRet_t$) on the excess returns of a hedge fund benchmark created from the entire hedge fund universe

[10] We do this because in Model 1, the dependent variable equals 0 for a fund that is held (but not contemporaneously hired) by an FoF. This could potentially reduce the power to detect differences between the universe and the FoF holdings sample.

[11] In unreported results, we estimate the determinants of hedge fund hiring but constrain the sample to only include fund families that allowed at least one registered FoF to invest in at least one of their hedge funds at some point in time. The interpretation of this model is the determinants of hedge fund hiring within families that allow registered FoFs access. Our results are similar. Also, our inferences remain essentially unchanged if we cluster the standard errors by both time and hedge fund.

[12] Portfolios are formed at the holdings level, and we value-weight the portfolios using the holding's portfolio weight from the perspective of the hiring FoF. Event windows represent a maximum membership period, and funds that exit the event window early (as a result of the fund delisting from the database or being fired from an FoF) are not replaced. Also, it is possible for a hedge fund to appear in the portfolio multiple times if it was hired by more than one FoF. For robustness, we eliminate duplicate positions in the portfolio, such that each hedge fund can only be present once in the monthly posthired portfolio. We also examine net hiring and firing decisions for each hedge fund/quarter. For example, if a hedge fund is hired by two FoFs and fired by another FoF, it receives one observation in the hiring portfolio but is absent from the firing portfolio. In both cases, our results are similar.

[13] For example, assume XYZ fund was purchased by an FoF in September 2007 and sold in March 2009 (assume 36-month event windows). XYZ's monthly return is included in posthired portfolios from October 2007 through March 2009.

Table 4 Posthired Performance

Panel A: Posthired alpha

	12 months		24 months		36 months	
	EW portfolio	VW portfolio	EW portfolio	VW portfolio	EW portfolio	VW portfolio
Equal-weighted HF index	−0.02	0.02	0.03	0.08	0.02	0.03
	[−0.21]	[0.19]	[0.47]	[1.04]	[0.22]	[0.45]
Value-weighted HF index	0.00	0.03	0.05	0.09	0.03	0.05
	[−0.06]	[0.41]	[0.97]	[1.63]	[0.67]	[0.91]

Panel B: Sharpe ratios (annualized)

	12 months		24 months		36 months	
	EW portfolio	VW portfolio	EW portfolio	VW portfolio	EW portfolio	VW portfolio
(1) Posthired portfolio	0.85	0.90	0.98	1.07	0.95	0.97
(2) Equal-weighted HF index	0.99	0.99	0.99	0.99	0.99	0.99
(3) Value-weighted HF index	0.91	0.91	0.91	0.91	0.91	0.91
(1) − (2)	−0.14	−0.09	−0.01	0.08	−0.04	−0.01
F-statistic for difference in Sharpe ratios	1.52	0.71	0.01	0.59	0.16	0.03
(1) − (3)	−0.06	−0.01	0.07	0.08*	0.04	0.07
F-statistic for difference in Sharpe ratios	0.34	0.01	0.63	2.93	0.18	0.69

Notes. The table presents the performance of hedge funds after they are hired by FoFs. Each calendar month, we form monthly posthired portfolios based on three event windows (12, 24, and 36 months) relative to the month the fund was hired. The event windows begin the month after the hiring date, and our sample comprises 93 monthly observations from April 2002 through December 2009. We present results for both equal-weighted (EW) and value-weighted (VW) calendar-time portfolios. Portfolios are formed at the holdings level, and we value-weight the portfolios using the holding's portfolio weight from the perspective of the hiring FoF. In panel A, we present alphas (percentage per month) estimated from time-series regressions of posthired portfolio excess returns on the excess returns of equal-weighted and value-weighted benchmark indices formed from the hedge fund universe. Robust t-statistics are in brackets. In panel B, we compare the annualized Sharpe ratios of the posthired portfolios to those of the hedge fund benchmarks and test their equality using the time-series F-test developed in Leung and Wong (2008).

($HFBI_{k,t}$).[14] Specifically, we estimate the following specification:

$$ExcessRet_t = \alpha + \beta_k \times HFBI_{k,t} + \varepsilon_t,$$

where alpha (α) is the benchmark-adjusted abnormal return for the posthired hedge fund portfolio. We interpret alpha as a measure of the average FoF hiring skill. Because of the preponderance of small hedge funds in the universe, we use both value-weighted and equal-weighted *HFBI* in our performance tests. The equal-weighted index reflects the performance of an average hedge fund selection by an investor, whereas the value-weighted index reduces the weight of smaller hedge funds and reflects the performance of the average dollar in the hedge fund industry.

In Table 4, panel A we present 12 estimates of FoF hiring skill (equal- and value-weighted indices and portfolios, across three different event windows). The alpha estimates range from −0.02% to 0.09% per month. The alpha estimates tend to increase as we value-weight event portfolios and compare them to a value-weighted index. However, none of the alpha estimates is statistically significant at conventional levels (t-statistics range from −0.21 to 1.63). In panel B, we also compare the posthired portfolio Sharpe ratio (annualized) to that of the hedge fund benchmarks, and test the equality of Sharpe ratios using the time-series F-test developed in Leung and Wong (2008). The annualized Sharpe ratios of hired funds range from 0.85 to 1.07, compared to 0.99 (0.91) for the equal-weighted (value-weighted) hedge fund indices. Only 1 of the 12 Sharpe ratio differences is different from zero at the 10% level of significance.

Collectively, these results suggest that, despite being among the best performers before they are hired, FoF selections perform no better than the average hedge fund after they are hired. As such, we lack evidence to support the hypothesis that FoF managers can skillfully select superior hedge funds. We argue, however, that this lack of evidence should not convict FoFs of not adding value for their investors. It could be that we lack power to detect abnormal performance. For instance, if the majority of hedge funds in the benchmark are held by other (unobservable) FoFs, this could add noise to our estimates and reduce our ability to detect abnormal performance. Furthermore, as argued above, simply

[14] Some studies of hedge fund performance estimate abnormal returns using a factor model such as Fung and Hsieh (2004) and find that the average hedge fund from a commercial database exhibits positive and significant seven-factor alpha (e.g., Chen et al. 2011). Because our primary research question is whether FoFs have skill to select funds that are better than average, we argue that relative performance is the most appropriate metric for measuring the selection and termination skill of FoF managers.

investing in and monitoring an average portfolio of hedge funds is a nontrivial task for most investors, suggesting that FoFs may be adding value through other channels.

4. Firing Decisions

The complexity of hedge fund trading strategies, combined with the opacity of hedge fund disclosure, can make it difficult for investors to skillfully monitor and time their exit from hedge funds. FoF managers argue that one particular source of the value they provide is continued monitoring efforts after they hire a hedge fund, implying that FoFs are adept at identifying and exiting "problem" funds before their performance worsens. In this section, we study the determinants of an FoF's decision to fire its portfolio funds and track the posttermination performance of the fired funds to test whether FoF firing predicts poor future performance.

4.1. Determinants

In Table 5, we study the determinants of FoF firing decisions using logit and multinomial logit regressions. The sample is restricted to FoF holdings only, and the unit of observation is the FoF holding/quarter.[15] In Model 1, we estimate a logit regression where the dependent variable is equal to 1 if the FoF fires a fund next quarter and 0 otherwise. We use the same independent variables that we used in the hiring logit regressions in Table 3.

FoFs are more likely to fire hedge funds with lower trailing performance and larger net outflows. Poor performance could be persistent, which could be exacerbated by outflow-induced fire sales (Coval and Stafford 2007). FoFs are less likely to fire large funds, which are also less likely to subsequently fail (Liang and Park 2010). FoFs are more likely to fire hedge funds with high operational risk, which has been shown to predict poor future performance (Brown et al. 2009). Funds with illiquid share classes are less likely to be fired, although this could simply be mechanical, as a result of restrictions on withdrawals. Taken together, our evidence suggests that FoFs are more likely to fire funds that have characteristics related to poor future performance, consistent with the idea that they could be skillful monitors.

We note that firing is not the only option for an FoF that has received a negative signal about the quality of a holding in its portfolio. An FoF could also react to a negative signal about a portfolio hedge fund by reducing capital from the fund. In Model 2, we estimate a multinomial logit to compare the determinants of firing to reducing or adding capital. Holdings with no change in capital are the omitted reference group.

The inferences related to firing from the multinomial regressions are similar to those from the logit regression in Model 1. For example, poorly performing funds are significantly more likely to be fired. However, past performance has no relationship with the decision to reduce capital from a fund and is only modestly related to capital additions. This is consistent with evidence in the mutual fund literature, whereby when a mutual fund completely divests from a stock, it is more likely to reflect negative information about the stock than when it only sells a partial stake (Pool et al. 2014). For example, a fund may reduce capital for reasons unrelated to hedge fund fundamentals, such as to move toward target portfolio weights after realizing capital appreciation.

In Model 3, we more fully explore this issue by including the holding's portfolio weight (*Portfolio weight* (%)) as an additional explanatory variable. Consistent with target-weight rebalancing, FoFs are more likely to reduce capital from and less likely to add capital to funds with larger portfolio weights. Interestingly, however, FoFs are less likely to fire their larger holdings. If FoFs allocate more money when they have stronger beliefs about the future prospects of a fund, then FoFs should be less likely to fire their largest holdings. This further supports the idea that FoF firing decisions are likely to be driven by information and reflect active monitoring by FoFs.

4.2. Performance

In this section, we test whether FoFs correctly assess the prospects of the funds they fire. We define a firing decision as being skillful if the fired fund *underperforms* the hedge fund universe benchmarks after it is fired. To test for firing skill, we use the same calendar-time methodology as in §3.2. In Table 6, we present alphas from time-series regressions in panel A and (annualized) Sharpe ratios in panel B.

We find convincing evidence that, after a fund is terminated by an FoF, its performance is significantly worse than the performance of the hedge fund universe. The alpha estimates range from −0.24% to −0.53% per month, and each is statistically significant at conventional levels (t-statistics range from −3.38 to −5.09). Similarly, the annualized Sharpe ratios of fired funds range from only 0.04 to 0.40, compared with 0.99 (0.91) for the equal-weighted (value-weighted) hedge fund indices, and each difference is statistically significant. Collectively, we interpret these results as evidence that FoFs skillfully forecast and avoid poor performance, indicating that they have firing skill.

However, an alternative story is that being fired by an FoF could cause a hedge fund to have poor performance. A sizeable withdrawal from an FoF

[15] We find similar results when we use the hedge fund/quarter as the unit of observation and define our dependent variable as the average firing intensity by FoFs in each quarter.

Table 5 Determinants of Firing Decisions

	Model 1	Model 2			Model 3		
	Fire	Fire	Reduce capital	Add capital	Fire	Reduce capital	Add capital
Style-adjusted return	0.69***	0.70***	1.01	1.13*	0.71***	1.00	1.14*
	[−3.95]	[−3.71]	[0.12]	[1.79]	[−3.55]	[−0.02]	[1.90]
Standard deviation	1.12	1.13	1.13	0.87	1.10	1.14	0.86
	[1.23]	[1.21]	[1.34]	[−1.42]	[0.98]	[1.45]	[−1.54]
Operational risk	1.87***	1.91***	1.25**	0.98	1.88***	1.26**	0.97
	[5.81]	[5.68]	[2.12]	[−0.18]	[5.55]	[2.18]	[−0.25]
Quarterly flow	0.76**	0.81*	0.94	1.31***	0.82	0.94	1.31***
	[−2.25]	[−1.67]	[−0.77]	[4.60]	[−1.58]	[−0.81]	[4.60]
Share illiquidity	0.88***	0.86***	0.92*	0.94	0.85***	0.92	0.93
	[−2.69]	[−3.04]	[−1.69]	[−1.52]	[−3.20]	[−1.59]	[−1.59]
AUM missing (0 | 1)	0.96	0.94	1.08	0.85	0.93	1.07	0.85
	[−0.33]	[−0.51]	[0.59]	[−1.53]	[−0.53]	[0.55]	[−1.54]
AUM (ln)	0.81**	0.77***	0.91	0.81***	0.78***	0.90	0.81***
	[−2.50]	[−2.90]	[−1.33]	[−2.97]	[−2.76]	[−1.51]	[−2.83]
Age (ln) (years)	0.97	0.97	1.09	0.93	0.98	1.08	0.93
	[−0.45]	[−0.49]	[1.28]	[−1.38]	[−0.32]	[1.14]	[−1.30]
Minimum investment (ln)	0.93	0.93	0.97	1.02	0.93	0.96	1.02
	[−1.23]	[−1.30]	[−0.80]	[0.49]	[−1.18]	[−0.94]	[0.62]
Management fee (%)	1.01	1.00	1.04	0.93	0.97	1.06	0.91
	[0.15]	[−0.00]	[0.70]	[−1.22]	[−0.40]	[0.92]	[−1.46]
Incentive fee (%)	0.97	0.97	0.93	1.07	1.00	0.92	1.08
	[−0.40]	[−0.29]	[−0.49]	[0.59]	[−0.03]	[−0.56]	[0.71]
Big 4 accounting (0 | 1)	0.95	0.95	0.94	1.07	0.96	0.94	1.08
	[−0.54]	[−0.46]	[−0.59]	[0.74]	[−0.38]	[−0.57]	[0.80]
Highwater mark (0 | 1)	1.49	1.57*	1.29*	1.09	1.54	1.29*	1.07
	[1.51]	[1.71]	[1.73]	[0.60]	[1.62]	[1.74]	[0.45]
Portfolio weight (%)					0.75***	1.11***	0.88**
					[−4.91]	[2.59]	[−2.54]
Style FE	Yes		Yes			Yes	
Time FE	Yes		Yes			Yes	
Observations	9,285		9,285			9,285	
Pseudo R-squared	0.06		0.06			0.06	

Notes. In the table, we model the FoF's decision to fire a hedge fund. The sample is restricted to FoF holdings only, and the unit of observation is the FoF holding/quarter. In Model 1, we estimate a logit regression where the dependent variable is equal to 1 if the FoF fires a fund and 0 otherwise. In Models 2 and 3, we estimate a multinomial logit regression where the dependent variable can take on multiple outcomes depending on whether the FoF fires, reduces capital, or adds capital to the holding. Holdings with no change in capital are the omitted reference group. *Portfolio weight* (%) is the holding's fraction of total FoF portfolio value. All other variable definitions can be found in the appendix. All continuous, independent variables in the model have been standardized with mean zero and unit variance and lagged one quarter. To control for unobserved heterogeneity, we include both time and style fixed effects (FE). Our standard errors are clustered at the hedge fund level. Z-statistics are in brackets.

$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

investor could force the hedge fund to liquidate portfolio assets at unfavorable prices (e.g., see Coval and Stafford 2007, Chen et al. 2010), leading to the underperformance we observe. We note that in our sample, the typical FoF's ownership stake is small from the perspective of the hedge fund (the median FoF holding represents 1% of *hedge fund* assets at the time of the firing decision). We believe that withdrawals below 1% would be unlikely to cause fire sales. Thus, to alleviate the concern that firing simply causes fire sales, we reestimate the tests (unreported) but only include firing decisions when the FoF's withdrawal is below 1% of hedge fund assets. We continue to find negative and significant firing skill across all specifications, suggesting that FoFs predict poor future performance rather than cause it.

Finally, it is important to note that we are only able to calculate alphas of fired funds as long as they remain in the database. Funds that perform poorly are more likely to delist from databases, continue to perform poorly after delisting, and subsequently fail, resulting in large unmeasured losses for investors (Grecu et al. 2007, Agarwal et al. 2013). If it were the case that fired funds subsequently delist from a database at a high rate, then the negative postfired performance we document would be a lower bound of firing skill. We investigate whether fired funds are more likely to fail in §5.

Table 6 Postfired Performance

Panel A: Postfired alpha

	12 months		24 months		36 months	
	EW portfolio	VW portfolio	EW portfolio	VW portfolio	EW portfolio	VW portfolio
Equal-weighted HF index	−0.53***	−0.41***	−0.41***	−0.34***	−0.35***	−0.28***
	[−5.09]	[−5.03]	[−4.24]	[−4.61]	[−3.73]	[−4.10]
Value-weighted HF index	−0.48***	−0.37***	−0.36***	−0.29***	−0.30***	−0.24***
	[−4.61]	[−4.72]	[−3.63]	[−3.94]	[−3.19]	[−3.38]

Panel B: Sharpe ratios (annualized)

	12 months		24 months		36 months	
	EW portfolio	VW portfolio	EW portfolio	VW portfolio	EW portfolio	VW portfolio
(1) Postfired portfolio	0.04	0.19	0.22	0.32	0.28	0.40
(2) Equal-weighted HF index	0.99	0.99	0.99	0.99	0.99	0.99
(3) Value-weighted HF index	0.91	0.91	0.91	0.91	0.91	0.91
(1) − (2)	−0.95***	−0.80***	−0.77***	−0.66***	−0.71**	−0.59***
F-statistic for difference in Sharpe ratios	13.29	25.45	6.98	16.51	5.26	11.72
(1) − (3)	−0.87***	−0.72***	−0.69**	−0.58***	−0.63*	−0.51***
F-statistic for difference in Sharpe ratios	9.56	15.48	4.93	10.13	3.66	7.03

Notes. The table presents the performance of hedge funds after they are fired by FoFs. Each calendar month, we form monthly postfired portfolios based on three event windows (12, 24, and 36 months) relative to the month the fund was fired. The event windows begin the month after the firing date, and our sample comprises 93 monthly observations from April 2002 through December 2009. We present results for both equal-weighted (EW) and value-weighted (VW) calendar-time portfolios. Portfolios are formed at the holdings level, and we value-weight the portfolios using the holding's portfolio weight from the perspective of the firing FoF. In panel A, we present alphas (percentage per month) estimated from time-series regressions of postfired portfolio excess returns on the excess returns of equal-weighted and value-weighted benchmark indices formed from the hedge fund universe. Robust t-statistics are in brackets. In panel B, we compare the annualized Sharpe ratios of the postfired portfolios to those of the hedge fund benchmarks and test their equality using the time-series F-test developed in Leung and Wong (2008).

$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

4.3. Discussion

Why do FoF managers exhibit skill in their firing decisions but not in their hiring decisions? Although a lack of statistical power could explain a lack of evidence of hiring skill, it should also bias against finding evidence of firing skill. This suggests that, at a minimum, there is an asymmetry between FoF hiring and firing skill. We posit that asymmetric skill can be explained by a model of investor learning that assumes asymmetric information between prospective and incumbent investors.

Hochberg et al. (2014) develop such a model of investor learning in the context of hiring venture capital fund managers. In their model, incumbent investors have an informational edge over prospective investors, as the latter observe only public (hard) information such as past fund returns, whereas the former can also observe private (soft) information about the fund manager and his future prospects. Thus, one learns more about the true skill of the fund manager after investing in the fund. We believe that this model fits the institutional realities of hedge fund investing. Because hedge funds disclose only a limited amount of information publicly, prospective investors receive a limited number of signals from which they can form their prior assessments of manager skill. However, incumbent investors receive more hard information (a larger and potentially more informative set of fund disclosures) and more soft information (greater access to discussions with fund management), increasing the precision of their skill estimates. Thus, it could be that FoF firing decisions are more skillful than their hiring decisions because, after a fund is hired, monitoring and due diligence yield more information about the fund's prospects than they do before hiring.

5. Learning

Our results thus far suggest that learning plays an important role in the outcomes of FoF portfolio decisions. The fact that FoFs make more skillful decisions when they fire funds than when they hire funds suggests that FoFs learn fund-specific knowledge after investing, consistent with the idea that opacity creates informational advantages for incumbent investors as compared to prospective investors (Hochberg et al. 2014). In this section, we examine a related question: Does the knowledge that FoFs gain through experience help them to make better subsequent decisions over time?

We hypothesize that experienced hedge fund investors have an advantage over inexperienced investors when it comes to evaluating and monitoring hedge funds, particularly because of the informational asymmetry between funds and prospective investors. Prior to investing, an inexperienced investor not only has limited information about each fund but also has a limited set of data from which to draw prior beliefs *across* hedge funds; this reduces the precision of the updating process as the investor learns about each fund (i.e., due diligence and monitoring). After investing, an investor not only acquires specific knowledge about the quality of those portfolio funds (allowing for skillful firing decisions) but may also acquire general knowledge or expertise that can be used to improve monitoring and due diligence technologies.

For example, acquiring more general experience may help an FoF to extract more precise signals from prospective disclosures and manager interviews. Furthermore, by interacting with more hedge funds over time, experienced FoFs can build a more comprehensive proprietary database of hedge fund characteristics that improves their ability to make comparisons across funds. This "learning-by-doing" hypothesis predicts that experienced FoFs should make more skillful hiring and firing decisions than inexperienced FoFs.

In Table 7, we test this hypothesis using the age of the FoF as proxy for experience, within the same calendar-time regression framework used above. Specifically, in each calendar month, we classify an FoF as being young (old) if its age is below (above) the median FoF age measured in that month. We form event portfolios over a 24-month holding period and estimate separate calendar-time regressions for the hiring (panel A) and firing (panel B) decisions of old FoFs, young FoFs, and a long/short portfolio (old minus young).

The general pattern of results suggests that FoF decisions get better with age. As before, the young FoFs do not have a significant alpha in the posthiring regressions, but they do have a significant alpha in the postfiring regressions. However, there is clear evidence that old FoFs make better hiring and firing decisions than their younger counterparts. Funds hired by old FoFs significantly outperform those hired by young FoFs in each model by an average of 13 basis points (bps) per month (more hiring skill), whereas the funds fired by old FoFs significantly underperform those fired by young FoFs by an average of 81 bps/month (more firing skill). In fact, old FoFs have a significant posthiring alpha in three of four models, with alpha estimates ranging from 12 to 19 bps/month (t-statistics range from 1.94 to 2.64), suggesting that older FoFs have an ability to select hedge funds that are better than average. These results support the learning-by-doing hypothesis and indicate that as FoFs learn more about the hedge fund selection and termination process over time, their hiring and firing decisions become more skillful.

To quantify the joint effect of fund-level learning and learning-by-doing, we perform a placebo test that compares the performance of an actual FoF to the performance of a hypothetical placebo FoF that keeps only its *initial* investments and does not hire, fire, or rebalance over time (results unreported). We form placebo portfolios for each FoF using the hedge funds it owned in its first year of operation. We assign that placebo fund its original portfolio weights and do not rebalance (other than forced rebalancing as a result of delisting from the database) and compare its value-weighted returns to the realized returns of the actual FoF portfolios (including all rebalancing effects). We find the actual FoF portfolios significantly

Table 7 Performance and FoF Age

Panel A: Posthired alpha

	Equal-weighted portfolio			Value-weighted portfolio		
	Young FoF	Old FoF	Old − Young	Young FoF	Old FoF	Old − Young
Equal-weighted HF index	−0.01	0.11	0.12**	0.04	0.18*	0.14**
	[−0.12]	[1.34]	[2.16]	[0.60]	[1.94]	[2.20]
Value-weighted HF index	0.01	0.12*	0.11**	0.06	0.19***	0.13**
	[0.22]	[1.95]	[1.99]	[1.05]	[2.64]	[2.14]

Panel B: Postfired alpha

	Equal-weighted portfolio			Value-weighted portfolio		
	Young FoF	Old FoF	Old − Young	Young FoF	Old FoF	Old − Young
Equal-weighted HF index	−0.18***	−1.04***	−0.86**	−0.20***	−0.98***	−0.78**
	[−2.94]	[−2.92]	[−2.42]	[−3.23]	[−2.77]	[−2.20]
Value-weighted HF index	−0.13**	−0.98***	−0.84**	−0.16**	−0.92**	−0.77**
	[−2.17]	[−2.74]	[−2.38]	[−2.53]	[−2.62]	[−2.17]

Notes. The table examines the relationship between FoF age and hiring and firing skill. We use the same calendar-time benchmark methodology from Tables 4 and 6. In each calendar month, we classify an FoF as being young (old) if its age is below (above) the median FoF age measured in that month. In panel A, we estimate posthired alphas (percentage per month) for young FoFs, old FoFs, and a long/short portfolio using the 24-month posthired event window. In panel B, we repeat this process for hedge funds that were fired by an FoF. Robust t-statistics are in brackets.

$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 8 Performance Assuming a Constrained Opportunity Set

Panel A: Posthired alpha

	Constrained benchmark		Constrained benchmark (excludes funds closed to new investors)	
	Equal-weighted portfolio	Value-weighted portfolio	Equal-weighted portfolio	Value-weighted portfolio
Equal-weighted HF index	0.05	0.08	0.06	0.10
	[0.81]	[1.58]	[0.94]	[1.54]
Value-weighted HF index	0.09	0.12**	0.12**	0.16***
	[1.40]	[2.18]	[2.12]	[2.65]

Panel B: Postfired alpha

	Constrained benchmark		Constrained benchmark (excludes funds closed to new investors)	
	Equal-weighted portfolio	Value-weighted portfolio	Equal-weighted portfolio	Value-weighted portfolio
Equal-weighted HF index	−0.37***	−0.31***	−0.36***	−0.29***
	[−3.99]	[−3.08]	[−3.71]	[−3.99]
Value-weighted HF index	−0.31***	−0.25***	−0.26**	−0.20**
	[−4.39]	[−3.22]	[−2.24]	[−2.18]

Notes. The table presents estimates of the skill of FoF hiring and firing decisions, conditional on facing a set of assumed investment constraints. We use the same calendar-time benchmark methodology from Tables 4 and 6. However, we generate our hedge fund benchmark from a constrained set of hedge funds from the universe. We create this benchmark by drawing a random sample of funds that match the size and age characteristics of the FoF holdings population through time. In the last two columns, we repeat the process but exclude hedge funds that are closed to new investors. We estimate posthired and postfired alphas (percentage per month) using the 24-month event window. Robust t-statistics are in brackets.

*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

outperform the placebo portfolios by 93 bps/year (t-statistic $= 2.13$).

6. Performance Assuming a Constrained Opportunity Set

In our primary analysis, we evaluate the posthired and postfired performance of FoF holdings relative to the performance of the hedge fund universe. This framework for relative performance evaluation defines the benchmark cost of capital using an unconstrained opportunity set of hedge funds. This benchmark may obscure the skills of FoFs if they, or their investors, face investment constraints that limit their access to some funds. In this section, we construct a constrained benchmark and reevaluate FoF skill. To the extent that FoFs (or their clients) actually face the constraints we model, the alpha estimates derived in this framework can be interpreted as the FoF's *conditional* skill within a constrained investment opportunity set.

Hedge funds can be closed to new investment, perhaps because of perceived diminishing returns to capital. Furthermore, some hedge funds may not be closed in a discrete sense but may have characteristics that effectively limit their capacity to add capital. As noted in Table 1, the average FoF allocation is $10.06 million, or 18% of the median hedge fund size. This could preclude many hedge funds from an FoF's opportunity set if, as discussed in Joenväärä et al. (2014), institutional investors are often unwilling to account for a large fraction of a fund's AUM. Furthermore, frictions and diminishing returns could make it difficult for small and/or young funds to accommodate these relatively large allocations in the first place.[16] To test whether FoFs have conditional selection ability in the presence of potential investment constraints, we create benchmarks from a sample whose distribution of fund size and age closely matches that of the FoF holdings sample.[17]

In Table 8, we repeat our performance tests using equal- and value-weighted (constrained) benchmark

[16] Small and/or young hedge funds may utilize investment strategies that are not completely scalable, and thus they may be unable to profitably manage very large allocations of capital (Boyson 2008). Additionally, these funds may not have a sufficient marketing and compliance infrastructure in place to attract money from large institutional investors. Moreover, relative to older, more established managers, young fund managers have stronger incentives to build their reputations (Aggarwal and Jorion 2010) and may be more concerned that excessive asset growth could erode their performance, thereby damaging their limited track record.

[17] We create the constrained benchmark using the following procedure. In each month t, we measure quintile breakpoints for size and age from the FoF holdings distribution. We then form 25 size–age portfolios from the intersection of the size and age quintiles and measure the sampling frequency distribution of FoF holdings across each of the 25 portfolios. Next, for each portfolio j, we draw a random sample (with replacement) of size ($n_{jt} = p_{jt} \times k_t$) from the hedge fund universe, where p_{jt} is the proportion of FoF holdings in portfolio j and k_t is the size of the hedge fund universe in time t. Repeating this process for each portfolio j and month t results in a "constrained set"; this constrained set has the same number of observations as the hedge fund universe, but its age–size sampling frequency matches that of the underlying distribution of FoF holdings. We also create an additional benchmark from the constrained set that excludes funds that are listed in the databases as being closed to new investment.

indices, both including and excluding funds that are listed in the databases as being closed to new investment. We focus on the 24-month holding period and estimate calendar-time regressions for both equal- and value-weighted event portfolios. We find that the equal-weighted benchmark alphas are positive but not significant in any of the four models. Interestingly, when using a value-weighted benchmark, we find some evidence that FoFs have conditional hiring ability. Posthired alphas are positive and significant in three of the four models. The most favorable estimate of hiring skill (0.16% per month, t-statistic = 2.65) comes when we value-weight both the event portfolios and the benchmark and exclude closed funds from the benchmark. However, we stress that this evidence of selection ability is conditional on FoFs and their investors actually facing the modeled constraints. Closed funds may reopen at any time, and FoFs may not actually be constrained but instead may select funds that are large and old to reduce their exposure to headline risk (Joenväärä et al. 2014), because small and young funds may be more likely to fail. Furthermore, the conditional selection ability we estimate may not be relevant to an investor that can access hedge funds that an FoF cannot.

Finally, we examine the robustness of our postfired performance tests using the constrained benchmarks. One concern may be that an unconstrained benchmark could overstate the relative underperformance of fired funds. Although employing the constrained benchmark reduces our estimates of underperformance in fired funds, postfired alphas remain negative and significant in each of the eight models, with alpha estimates ranging from −20 to −37 bps/month (t-statistics range from −2.18 to −4.39).

7. Extreme Returns and Hedge Fund Failure

Given that hedge funds are especially exposed to tail risk (Kelly and Jiang 2012), some investors may be less concerned with average fund performance and more concerned with extreme, negative performance. For instance, clients that are particularly sensitive to headline risk, such as public pension funds, may be willing to pay a skilled monitor to help them avoid the scrutiny that would result from directly participating in a hedge fund blowup. In this section, we investigate whether FoFs can avoid holding hedge funds that suffer extreme negative outcomes, such as a large quarterly loss or liquidation.

In Table 9, we estimate logit regressions to model the probability that a hedge fund experiences an extreme negative outcome. In Models 1 and 2, the dependent variable is *Extreme negative return*, which equals 1 if the fund's style-adjusted return ranks in the bottom 5% of the hedge fund universe in that quarter and 0 otherwise. In Models 3 and 4, the dependent variable is *Hedge fund failure*, which equals 1 if the fund delists from the hedge fund databases and lists "liquidation" as the reason and 0 otherwise.[18] The unconditional

Table 9 Extreme Negative Returns and Hedge Fund Failure

	Extreme negative return		*Hedge fund failure*	
Variable	Model 1	Model 2	Model 3	Model 4
Held	0.72***	0.97	0.31***	0.54***
	[−4.20]	[−0.37]	[−7.11]	[−3.77]
Fired	1.74***	1.48***	2.51***	1.87**
	[4.22]	[2.99]	[2.89]	[1.96]
Style-adjusted return		0.84***		0.71***
		[−11.95]		[−8.52]
Standard deviation		1.99***		0.79***
		[46.55]		[−7.83]
Operational risk		1.69***		2.10***
		[20.40]		[13.49]
Quarterly flow		1.01		0.79***
		[0.84]		[−5.65]
Share illiquidity		0.99		0.90***
		[−0.56]		[−4.02]
AUM missing (0 | 1)		0.94*		0.77***
		[−1.85]		[−4.30]
AUM (ln)		0.93***		0.60***
		[−4.89]		[−24.24]
Age (ln) (years)		0.95***		0.83***
		[−2.87]		[−7.01]
Minimum investment (ln)		0.96***		1.06**
		[−2.99]		[2.38]
Management fee (%)		1.05***		1.02
		[4.00]		[1.11]
Incentive fee (%)		1.13***		1.14***
		[7.84]		[5.73]
Big 4 accounting (0 | 1)		0.94**		1.39***
		[−2.09]		[7.21]
Highwater mark (0 | 1)		0.99		0.98
		[−0.24]		[−0.29]
Style FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	151,077	151,077	151,077	151,077
Pseudo R-squared	0.04	0.13	0.03	0.10

Notes. The table presents estimates from logit regressions of extreme negative performance and hedge fund failure. The unit of observation is a hedge fund/quarter. In Models 1 and 2, the dependent variable is *Extreme negative return*, which equals 1 if the fund's style-adjusted return ranked in the bottom 5% of the hedge fund universe in that quarter and 0 otherwise. In Models 3 and 4, the dependent variable is *Hedge fund failure*, which equals 1 if the fund delists from the hedge fund universe databases and lists "liquidation" as the reason and 0 otherwise. *Held* is an indicator variable that equals 1 if an FoF holds the hedge fund during the previous quarter and 0 otherwise. *Fired* is an indicator variable that equals 1 if an FoF fires the hedge fund during the previous quarter and 0 otherwise. All other variables are defined in the appendix. All continuous, independent variables in the model have been lagged one quarter and standardized with mean zero and unit variance. All coefficients are presented as odds ratios. To control for unobserved heterogeneity, we include both time and style fixed effects (FE). Standard errors are clustered by fund, and robust z-statistics are reported in brackets.
*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

[18] Our classification of hedge fund failure is similar to the classifications used in Liang and Park (2010) and Aragon and Strahan (2012).

probability of *Hedge fund failure* is 3.7% per quarter. If FoFs skillfully monitor their investments, we expect them to avoid both of these extreme events.

We first model the probability of extreme events as a function of whether the fund was held by an FoF in the previous quarter (*Held*) or was fired by an FoF in the previous quarter (*Fired*). In Model 1, we find that hedge funds held by FoFs are 28% less likely (z-statistic $= -4.20$) to realize extreme negative returns, whereas hedge funds fired by FoFs are 74% more likely (z-statistic $= 4.22$) to realize extreme negative returns. *Hedge fund failure* has an even stronger association with FoF ownership. In Model 3, we find that hedge funds held by FoFs are 69% less likely (z-statistic $= -7.11$) to fail, whereas hedge funds fired by FoFs are 151% more likely (z-statistic $= 2.89$) to fail. These results support the hypothesis that FoFs have monitoring skill, because the funds they fire (hold) are more (less) likely to subsequently experience extreme negative performance or fail.

To test whether this monitoring skill reflects private information on the part of the FoF, in Models 2 and 4, we include the same fund-level control variables used in the hire (and fire) logit regressions in Tables 3 and 5. In doing so, we test whether FoF ownership predicts extreme outcomes beyond what can be gleaned from observable characteristics. Including these fund characteristics reduces the magnitude of the FoF monitoring effect in all cases, yet *Fired* remains large and significant in both the *Extreme negative return* and *Hedge fund failure* regressions. *Held* loses significance in the *Extreme negative return* regressions but remains statistically and economically significant in the *Hedge fund failure* regressions. Thus, although the processing of public information plays an important role, our evidence suggests that FoFs also receive informative private signals that help them to forecast bad outcomes. Taken as a whole, the evidence in Table 9 suggests that FoFs act as capable monitors who skillfully avoid fund failures and the bad returns that accompany them, an important and previously undocumented source of value that FoFs could offer their clients.

8. Conclusion

Investing in hedge funds is costly and difficult. As such, funds of hedge funds have become a popular financial intermediary, providing investors access to a diversified portfolio of hedge funds in exchange for an additional layer of management and performance fees. Despite their prevalence, there is little empirical evidence of how FoFs form their portfolios or make investment decisions. In this paper, we utilize a unique database of registered FoF holdings that allows us to directly observe FoF investment decisions and explore several channels through which FoFs could add value for their investors.

We find only modest evidence that FoFs have selection skill: FoF selections perform comparably to the average hedge fund and slightly better than a set of funds that are less likely to face capacity constraints. However, we find that FoFs provide investors diversification and access to hedge funds with high minimum investments and illiquid redemption terms, the net result of which would be difficult for many investors to replicate on their own. Because of the significant frictions in the hedge fund market, using FoFs as an intermediary may represent a transactions-costs-minimizing solution for constrained investors. Yet FoFs are not simply middlemen between hedge funds and investors. We find evidence that FoFs are also skilled monitors that fire funds likely to have poor future performance, offering investors a valuable service beyond simply pooling and transforming their capital. These results help us to understand why FoFs play such an important role as intermediaries in the market for hedge fund capital.

Appendix. Data Definitions

Variable	Description
Annual return	12-month holding period return (in percent).
Standard deviation	Volatility of monthly performance over the trailing 12 months (in percent).
Sharpe ratio	Ratio of the fund's monthly excess return and monthly standard deviation (annualized).
Style-adjusted return	Difference between the fund's trailing 12-month return and the trailing 12-month return for the fund's Lipper TASS style (in percent).
Operational risk	Indicator variable equal to 1 if the fund's ω-score (Brown et al. 2008b) is in the top tercile for the period and equal to 0 otherwise. We estimate the ω-score by performing a canonical correlation analysis between ADV variables and the performance and contract characteristics in the hedge fund universe. We gather ADV data from the December 2009 (the end of our sample) file provided by the Electronic Data Gathering, Analysis, and Retrieval (EDGAR) system of the SEC.
Quarterly flow	Fund's implied net flows over the quarter (in percent): $\mathit{Quarterly\ flow}_{i,t} = \frac{AUM_{i,t} - AUM_{i,t-1}(1+r_{i,t})}{AUM_{i,t-1}}$.
Redemption notice	Number of days' notice an investor must provide the fund to withdraw capital.
Withdrawal frequency	Number of days between withdrawal periods for the hedge fund.
Lockup	Number of days the investor must remain in the fund before withdrawing capital.
Share illiquidity	An index of the investor share liquidity, defined as the first principal component of the variables *Redemption notice*, *Withdrawal frequency*, and *Lockup*.

Appendix. (Continued)

Variable	Description
Minimum investment	Minimum investment required to invest in the fund (in millions of dollars).
AUM	Hedge fund's assets under management (in millions of dollars). When AUM is missing in time t, we impute it from its last reported AUM, if available. If not, we use the cross-sectional average AUM in time t.
AUM missing	Indicator variable equal to 1 if the fund fails to report AUM for the quarter and equal to 0 otherwise.
Age	Number of years since the fund began reporting to a commercial database.
Management fee	Annual hedge fund fee charged to investors as a percent of AUM (in percent).
Incentive fee	Annual hedge fund performance-based fee charged to investors (in percent).
Big 4 accounting	Indicator equal to 1 if the hedge fund is audited by Ernst & Young, PricewaterhouseCoopers, Deloitte, or KPMG and equal to 0 otherwise.
Highwater mark	Indicator equal to 1 if the hedge fund has a highwater mark and equal to 0 otherwise.

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