Do Prime Brokers Matter in the Search for Informed Hedge Fund Managers?

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Abstract

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Keywords: Hedge funds; prime brokers; search frictions; due diligence; funds of funds.
JEL Codes: G11, G14, G23, G24

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Abstract

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1 Introduction

Hedge fund managers play an important role in financial markets since their trading activities can bring asset prices closer to fundamental values. However, due to a lack of regulatory oversight and public disclosure about manager quality, investors who allocate their capital to hedge funds face severe information frictions in identifying informed versus uninformed managers. A better understanding of whether and how investors overcome these frictions is crucial for our understanding of the efficiency of this $3 trillion asset management market as well as underlying securities markets where hedge fund managers trade (Gârleanu and Pedersen 2018).

In this paper, we posit that prime brokers (PBs) can be a valuable source of hedge fund information that can lower the cost of finding and vetting informed hedge fund managers. PBs are essential to hedge fund operations, as they provide a range of services to hedge funds, from securities lending and debt financing to global custody and clearing. The provision of these services gives PBs substantial insights about their hedge fund clients, putting PBs in a unique informational position in the secretive hedge fund marketplace. Using a major class of hedge fund investors, namely funds of hedge funds (FoFs), we ask if investors recognize and benefit from this potential source of hedge fund information in their search for informed hedge fund managers.

A key consideration in our empirical strategy is that some PBs may be easier to reach out to than other PBs. For each FoF, we identify such PBs ("connected" PBs) as those from which the FoF's management firm purchases prime brokerage services for its member funds. This means that PB connections can be identified when other funds in the same family subscribe to prime brokerage services, even if the FoF does not. We then test if FoFs have an advantage in searching for informed managers among the connected PBs' hedge fund clients. In doing so, we posit that PBs serve as a (segmented) source of hedge fund information for FoFs connected to them, in exchange for prime brokerage fees from FoFs' management firms.

We begin our empirical analysis by examining whether FoFs exhibit "PB bias," that is, disproportionate preference for hedge funds serviced by their connected PBs. Since the cost of hedge fund due diligence is high relative to FoFs' capital (e.g., Brown, Fraser, and Liang 2008; Brown, Gregoriou, and Pascalau 2012), this would be a natural outcome if FoFs are able to gather and vet information about their connected PBs' hedge fund clients (henceforth PB hedge funds) at a lower cost than they could about other hedge funds (henceforth OPB hedge funds). In our main analysis, we use 1,071 FoFs for which we were able to identify PB connections among those that report monthly returns to the Lipper TASS database. The availability of FoF returns, along with the returns of PB and OPB hedge funds, permits a return-based inference about the FoF's preference, similar to Sialm, Sun, and Zheng (2019). Our baseline results show that the average FoF's weight on its PB hedge funds is 39.14%, which is disproportionately high given that its PB hedge funds comprise only 25.84% of the aggregate portfolio of FoFs. We also perform a holding-based analysis using a smaller sample of registered FoFs that publicly disclose quarterly portfolio holdings to the Securities and Exchange Commission (SEC). As pointed out by Aiken, Clifford, and Ellis (2013, 2015a, 2015b), registered FoFs represent some of the largest money managers and financial institutions, with presumably less need to economize on the cost of hedge fund due diligence. Despite this, our holding-based analysis also reveals a significant tilt in the portfolios of registered FoFs, by 5.14% on average, toward their respective PB hedge funds.[1]

Our finding that FoFs exhibit PB bias is robust not only to the use of holdings data but also to various perturbations in our return-based approach. In particular, PB bias is not just a repackaging of Sialm, Sun, and Zheng's (2019) finding of a local bias in FoF portfolios, as we continue to find a strong preference for PB hedge funds even when there are no local hedge funds among them. Similarly, PB bias is also not merely a manifestation

[1] In Section 3.4, we predict and find that FoFs' preference for PB hedge funds increases with their need to economize on the cost of finding and vetting informed hedge fund managers. Smaller PB bias for registered FoFs is also consistent with this prediction.

of FoFs' style focus or internal investments in sibling hedge funds (Bhattacharya, Lee, and Pool 2013; Elton, Gruber, and de Souza 2018). In fact, PB bias is stronger among hedge funds that are outside the FoF's local area and style expertise, where information frictions are likely to be greater. We also run a placebo test where we replace a FoF's connections to PBs with its connection to hedge fund auditors. Unlike PBs, auditors are less likely to gain and share special insights about the day-to-day trading and operations of hedge funds. Consistent with this idea, we find no evidence of an "auditor bias."

PB bias is also related to several FoF- and PB-specific characteristics in a plausible way. For example, we find that PB bias is stronger among FoFs with less resources for hedge fund due diligence (such as FoFs belonging to management firms with smaller FoF assets), and when FoF managers have greater incentives to perform (as in FoFs with higher incentive fees and managers' personal capital invested in the FoF). This is consistent with information-hungry FoFs tapping PBs for hedge fund information. We also find stronger PB bias among FoFs with larger and older hedge fund siblings, consistent with PBs being more forthcoming with information when the FoF's management firm generates higher prime brokerage fees, longer. Finally, PB bias is also stronger for PBs serving a greater number of hedge fund clients but connected to a smaller number of other FoFs, consistent with the FoF's benefit from PB connections being greatest when the PB possesses a greater breath of knowledge about the hedge fund marketplace that is shared with fewer competitors.

A prominent noninformation story for local bias is that investors prefer local stocks simply because they are familiar with them (e.g., Huberman 2001). In our context, such a story would posit that PBs provide the opportunity for FoFs to simply become familiar with PB hedge funds—for example, through occasional PB-hosted events, such as capital introduction conferences and seminars—though not necessarily particularly informed about PB hedge funds. Another alternative story—based on the view that fund families' aim is to maximize overall family profits rather than the performance of an individual fund (e.g., Gaspar, Massa, and Matos 2006; Bhattacharya, Lee, and Pool 2013)—is that fund families use their (low-fee) FoFs to facilitate capital introduction to PB hedge funds, in order to cultivate PB ties and relationships that benefit their (high-fee) hedge funds but not necessarily, or at the cost of, the FoFs' performance. In addition to our findings above, we have additional pieces of evidence that go against these alternative possibilities.

First, we find that FoFs exhibit a strong propensity to overweight PB hedge funds that subsequently perform well, and underweight those that subsequently perform poorly. Among PB hedge funds, FoFs' (beginning-of-month) weight on the (end-of-month) top-25-percentile hedge funds is 16.33 percentage points higher than the market's weight on the same hedge funds. The corresponding number for the bottom-25 percentile is 11.02 percentage points lower than the market's weight. This suggests that FoFs select PB hedge funds at an information advantage. The evidence that FoFs select OPB hedge funds at an information advantage, however, is mixed. In particular, FoFs' propensity to underweight the bottom-25-percentile hedge funds is no longer observed (or, in fact, reversed) among OPB hedge funds. To the extent that PB connections facilitate due diligence on PB hedge funds, these results are consistent with the notion that the value of hedge fund due diligence lies more in detecting and avoiding hedge funds that will underperform than it does in selecting top-performing hedge funds (Brown, Fraser, and Liang 2008).

Next, we find that PB bias positively predicts FoF performance. When we sort FoFs into quartile portfolios based on their PB bias and hold them for three months, for example, the highest PB-bias quartile outperforms the lowest quartile (bottom three quartiles) by 2.89% (2.77%) per annum, using the Fung and Hsieh (2004) alphas. The highest PB-bias quartile portfolio generates an economically large and statistically significant alpha across all holding horizons considered, but none of the other quartile portfolios do so over any holding horizon. This is similar to Fung, Hsieh, Naik, and Ramadorai's (2008) finding that only 22% of FoFs deliver a positive and statistically significant alpha, whereas the average FoF does not. We also use multivariate regressions to show that the positive relation between PB bias and FoF performance is robust to other known predictors of FoF performance. In any case, the relation between PB bias and FoF performance only becomes statistically stronger when we use performance measures that penalize less diversified (more concentrated) FoFs, such as Sharpe ratio and information ratio.

In addition, using our sample of quarterly portfolio holdings disclosed by registered FoFs, we find that PB hedge funds added to a FoF's portfolio outperform OPB hedge funds added to the FoF's portfolio, by 0.90%–0.94% per quarter on average, though no significant difference is found between PB and OPB hedge funds dropped from the FoF's portfolio. This is consistent with FoFs having a search advantage among PB hedge funds relative to among OPB hedge funds, when the cost of finding and vetting informed hedge fund managers is high. Selling decisions are less costly in this regard, since there are fewer funds to choose from and incumbent investors face less frictions in monitoring funds than prospective investors (Hochberg, Ljungqvist, and Vissing-Jørgensen 2014; Aiken, Clifford, and Ellis 2015b).

Overall, our results suggest that FoFs benefit from their connections to PBs in selecting informed hedge funds managers. In this regard, our results relate to existing findings that institutional investors' connections to investment banks inform their trading activities in securities markets.[2] Of course, FoFs' informational gains from their PB connections do not necessarily mean that PBs divulge sensitive information about their hedge fund clients. It could be that (1) PBs make informed introductions, (2) help cross-verify information that FoFs gather through their own due diligence,[3] or (3) share immaterial information that inadvertently becomes material when combined with other information that FoFs possess. It is also worth noting that PBs could help FoFs get access to informed hedge funds that are otherwise closed to new investors or selective of their investors.[4] In any case, our results point

[2]See, e.g., Massa and Rehman (2008), Bodnaruk, Massa, and Simonov (2009), Jegadeesh and Tang (2010), Ivashina and Sun (2011), and Kedia and Zhou (2014).

[3]As illustrated by Brown, Gredil, and Kantak (2016), for example, FoFs often seek to assess how consistent the manager is with her investment approach (i.e., "Do managers do what they say they do?"). PBs, who routinely observe the trading and holdings of their hedge fund clients, are in a good position to help verify this consistency.

[4]However, it is unlikely that this occurs without PBs also serving an information role. For example, if FoFs identify informed managers among PB hedge funds totally on their own but use their PB connections only to get access to them, then we should find stronger PB bias among FoFs with *greater* resources to

to a valuable function that PBs perform in facilitating informed hedge fund investments.

Earlier studies on PBs focus on funding liquidity shocks that PBs can spread to hedge funds and the resulting contagion consequences (e.g., Klaus and Rzepkowski 2009; Boyson, Stahel, and Stulz 2010; Aragon and Strahan 2012), while more recent studies highlight that PBs can also provide (or leak) valuable information to hedge fund managers (e.g., Chung and Kang 2016; Qian and Zhong 2018; Kumar, Mullally, Ray, and Tang 2020). Our paper extends this recent development in the studies of PBs, by considering (1) the role of PBs in hedge fund manager selection and (2) prime brokerage activities (as opposed to investment banking or corporate lending activities) as the source of information that allows PBs to play an information role. In a contemporaneous working paper, Sinclair (2019) shows that PBs increase the flow-performance sensitivity of their client hedge funds, that is, return-chasing behavior of hedge fund investors.[5] Our results paint a different picture of the role of PBs for hedge fund investors, by showing that PBs affect the portfolio decisions of FoFs and this occurs in a way that benefits FoF performance.

Our paper is also related to studies of information frictions in the search for informed asset managers. Gârleanu and Pedersen (2018) predict that investors for whom the cost of finding and vetting an informed asset manager is low relative to their capital are expected to earn higher returns after fees. Consistent with this prediction, Brown, Fraser, and Liang (2008) find significant economies of scale in FoF performance and attribute this to larger FoFs having more resources to perform necessary, but expensive, hedge fund due diligence. Sialm, Sun, and Zheng (2019) show that FoFs tend to overinvest in local hedge funds, where information frictions are lower, and that this local bias predicts greater FoF performance. We build on these studies and show that tapping into PB connections is a valuable way of economizing on search and due diligence costs when information frictions are high.

perform hedge fund due diligence. In addition, our finding that PBs benefit FoFs particularly in avoiding "problem" funds is also inconsistent with the possibility that PBs merely serve to provide access to some highly sought-after "star" funds that are otherwise closed to or selective of new investors.

[5]Since Sinclair (2019) uses fund-level flow data and fund–PB relationships, his results reflect the behavior of aggregate investors in a hedge fund and do not account for investors' relationships with the fund's PB.

Finally, we add to prior studies of portfolio holdings disclosed by SEC-registered FoFs.[6] Aiken, Clifford, and Ellis (2015b) and Gao, Haight, and Yin (2020) show that registered FoFs exhibit skill in making "firing" and rebalancing (additional purchase or partial redemption) decisions, respectively, that is, in assessing the prospects of the funds that they already own. Our analysis of holdings shows that PBs benefit FoFs in making "hiring" decisions, that is, in assessing the prospects of new hedge funds.

2 Data and Descriptive Statistics

2.1 Lipper TASS database

Our main sample of FoFs and hedge funds, as well as their PBs, come from Chung and Kang (2016), who combine multiple downloads of the Lipper TASS database to construct a panel of broker–client relationships. The data cover 2,799 FoFs and 7,215 hedge funds, which represent all live and graveyard funds in TASS that report monthly net-of-fee U.S. dollar returns. We follow the literature and exclude the first 18 months of returns for each fund to mitigate backfill bias, exclude all observations before 1994 to mitigate survivorship bias, and correct for master-feeder duplicates as in Aggarwal and Jorion (2010). The resulting sample includes 2,167 FoFs and 5,404 hedge funds.

Chung and Kang (2016) assume that the first PB a fund reports to TASS was the fund's PB since its inception, and update the PB information as each new download becomes available. We adopt this algorithm to match the most accurate PB information possible with each fund in each month, while also accounting for PB mergers and other data issues with PBs' CompanyID in TASS.[7] As a result, we identify 295 unique PBs by their cleaned

[6] See, e.g., Aiken, Clifford, and Ellis (2013, 2015a, 2015b), Agarwal, Aragon, and Shi (2019), Sialm, Sun, and Zheng (2019), and Gao, Haight, and Yin (2020).

[7] See Section 1 of Chung and Kang (2016) for a detailed discussion. To clean PBs' CompanyID, we rely on the PBLINK and PBMERGER tables from Chung and Kang (2016), who manually clean the data—within and across downloads made in 2007 (March 5), 2009 (May 6, July 28, and October 2), and 2010 (July 26) and multiple times in 2011 and 2012 (until July 27)—so that each investment bank (including its subsidiaries) is given one ID, and, when PBs merge, a separate ID is given for the acquirer before and after the merger.

ID across our sample of 2,167 FoFs and 5,404 hedge funds from January 1994 to June 2012. Following Chung and Kang (2016), we then require PBs to service at least five funds (whether FoFs or hedge funds), leaving us with a final sample of 79 unique PBs. We identify a FoF's PB connections at the management firm level, meaning that a FoF can be identified as connected to a PB even if the FoF does not use the PB. In our sample, there are a total of 1,071 FoFs identified as connected to 79 PBs, either as a client (493 FoFs) or as a client's sibling (951 FoFs) or both. In any case, we use all 2,167 FoFs and 5,404 hedge funds in the sample to proxy for the aggregate portfolio of FoFs and the universe of hedge funds in which FoFs could invest, respectively.[8]

Table 1 summarizes our sample FoFs, hedge funds, and PBs at the beginning, middle, and end of the sample period. Panel A provides the total number of FoFs, hedge funds, and PBs in the sample, as well as the distribution of the number of FoFs and hedge funds serviced by a PB. The total number of funds varies over time: At the beginning of the sample period, there are 119 FoFs and 281 hedge funds while at the middle of the sample period, there are 615 FoFs and 1,553 hedge funds. The numbers drops to 490 FoFs and 1,324 hedge funds in 2012, mainly because of the financial crisis in 2008. The number of PBs averages about 27 per month, ranging from a low of 14 in January and February 1994 to a high of 37 in July 2007. The average (median) PB services 4.81 (3.30) FoFs per month and 34.38 (10.38) hedge funds per month, on average. Since PBs enter the sample as long as they service five or more hedge funds or FoFs, the minimum number of FoFs per PB or hedge funds per PB can be zero.

Panel B of Table 1 presents the number of FoFs for which we identify PB connections, as well as the distribution of the number of connected PBs per FoF. FoFs have fairly concentrated PB connections, if at all: Taking into account all PBs that service either the FoF

Although Chung and Kang (2016) exclude FoFs from their analysis, their cleaning procedure is conducted on a larger sample that includes FoFs, which constitutes our initial sample of 2,799 FoFs and 7,215 hedge funds.

[8]Another form of FoF–PB connections can arise when a FoF and a PB belong to the same financial conglomerate. For robustness, we repeat our analysis after dropping 176 FoFs that are affiliated with a PB in this way and find qualitatively similar results.

or any other fund managed under the same roof with the FoF, the average (median) FoF is connected to 1.27 (one) sample PBs, on average. To see what this means in terms of the number of hedge funds the FoF can potentially learn about via PB connections, Panel B also reports the distribution of the number of unique hedge funds serviced by the connected PBs per FoF (i.e., the distribution of the number of PB hedge funds per FoF). The monthly statistics suggest that the average (median) FoF can gain a potential information advantage about 78.19 (29.78) hedge funds, on average, via its PB connections. These numbers are by no means small, considering that FoFs typically hold tens rather than hundreds of hedge funds in their portfolios (see, e.g., Brown, Gregoriou, and Pascalau 2012; Aiken, Clifford, and Ellis 2013). Of course, whether FoFs indeed exploit such an advantage remains to be seen.

2.2 Registered FoFs

Our holding-based analysis uses a sample of registered FoFs that publicly disclose their portfolio holdings in quarterly filings of Forms N-CSR, N-CSRS, and N-Q. We identify 127 registered FoFs using the search algorithm of Aiken, Clifford, and Ellis (2013), as modified by Gao, Haight, and Yin (2020). The sample period begins in 2004Q3 when FoFs started disclosing their holdings on a quarterly basis, and ends in 2016Q4.

For the purpose of our analysis, we have two main tasks: (1) identifying registered FoFs' PB connections (including those arising via sibling funds) and (2) finding PB information for portfolio hedge funds held by registered FoFs. First, to identify registered FoFs' PB connections, we search TASS for the names of each registered FoF and its adviser (obtained from Form N-SAR item 8) to see if they show up in TASS—because if they do, we can also identify the registered FoF's sibling funds that report to TASS. For registered FoFs and their sibling funds that report to TASS, we employ the data and PB matching algorithm of Chung and Kang (2016) and then aggregate the funds' PBs at the family level to create a list of connected PBs for each registered FoF in each quarter. This way, we identify PB connections for 23 registered FoFs over the period from 2004Q3 to 2012Q2 (279 FoF-quarter observations). Further, we make use of historical Form ADVs filed by registered FoFs' advisers since 2012Q1, because item 7.B therein provides us with a list of private funds under their management and the funds' service provider information.[9] This allows us to expand the number of observations for which we identify PB connections to a total of 45 registered FoFs from 2004Q3 to 2016Q4 (716 FoF-quarter observations).

Next, to find PB information for portfolio hedge funds held by registered FoFs, we search for the name of each portfolio hedge fund in an expanded panel of broker–client relationships constructed by augmenting the data from Chung and Kang (2016) with item 7.B of all historical Form ADV filings. This is to ensure that we use more updated PB information to match with quarters after 2012Q2 (or after the fund stopped reporting to TASS), and that we have PB information to match with portfolio hedge funds that never report to TASS. Nevertheless, some FoF-quarter observations still have less than a representative number of portfolio hedge funds matched with PB information. For example, among 716 FoF-quarter observations above, 97 (236) observations have less than half (two thirds) of the FoF's assets matched with PB information. This paucity of the data means that our use of holdings data is limited to a relatively small set of analyses, which we defer to Section 5.

3 PB Connections and the Preferences of FoFs

3.1 Definition of PB bias

To set the stage, we begin by writing the period t return of FoF i as

$$R_{i,t}^{FOF} = \sum_{j=0}^{J} x_{i,j,t} \, R_{j,t}, \tag{1}$$

[9] Since private funds' inception date information is not available in Form ADV, the registered FoF's sibling funds identified in this way are allowed to add to the list of connected PBs for the FoF only from 2012Q1 (or from the execution date of the first Form ADV filing that includes the fund in item 7.B.)

where $x_{i,j,t}$ is FoF i's beginning-of-period weight on hedge fund j, $R_{j,t}$ is the end-of-period return on hedge fund j, and $\sum x_{i,j,t} = 1$. The subscript $j = 0$ denotes a portfolio of any non–hedge fund securities, such as cash, and J denotes the number of all hedge funds in existence at the beginning of period t.[10] We denote the set of hedge funds that are clients of FoF i's connected PBs (as of the beginning of period t) by $\mathcal{I}_{PB}$ and the remaining set of hedge funds by $\mathcal{I}_{OPB}$.[11] For brevity, we suppress the time subscript on J, $\mathcal{I}_{PB}$, and $\mathcal{I}_{OPB}$. Using these notations, we can rewrite the FoF return as

$$\begin{aligned} R_{i,t}^{FOF} &= \sum_{j \in \mathcal{I}_{PB}} x_{i,j,t}\, R_{j,t} + \sum_{j \in \mathcal{I}_{OPB}} x_{i,j,t}\, R_{j,t} + x_{i,0,t}\, R_{0,t}, \\ &= w_{i,t}^{PB}\, R_{i,t}^{PB} + w_{i,t}^{OPB}\, R_{i,t}^{OPB} + \epsilon_{i,t}, \end{aligned} \tag{2}$$

where

$$\begin{aligned} w_{i,t}^{PB} &= \sum_{j \in \mathcal{I}_{PB}} x_{i,j,t} \ \geq 0, & R_{i,t}^{PB} &= \sum_{j \in \mathcal{I}_{PB}} \frac{x_{i,j,t}}{w_{i,t}^{PB}}\, R_{j,t}, \\ w_{i,t}^{OPB} &= \sum_{j \in \mathcal{I}_{OPB}} x_{i,j,t} \ \geq 0, & R_{i,t}^{OPB} &= \sum_{j \in \mathcal{I}_{OPB}} \frac{x_{i,j,t}}{w_{i,t}^{OPB}}\, R_{j,t}, \text{ and} \\ \epsilon_{i,t} &= x_{i,0,t}\, R_{0,t}. \end{aligned} \tag{3}$$

The terms $w_{i,t}^{PB}$ and $w_{i,t}^{OPB}$ represent FoF i's weights on hedge funds within $\mathcal{I}_{PB}$ and $\mathcal{I}_{OPB}$, respectively; $R_{i,t}^{PB}$ and $R_{i,t}^{OPB}$ represent the returns on FoF i's hedge fund portfolio within $\mathcal{I}_{PB}$ and $\mathcal{I}_{OPB}$, respectively. Note that $w_{i,t}^{PB} + w_{i,t}^{OPB} \neq 1$ unless $x_{i,0,t} = 0$. In fact, the sum $w_{i,t}^{PB} + w_{i,t}^{OPB}$ can be even greater than one, if the FoF holds short positions in non–hedge fund securities. In what follows, therefore, we work with

$$W_{i,t}^{PB} = \frac{w_{i,t}^{PB}}{w_{i,t}^{PB} + w_{i,t}^{OPB}}, \tag{4}$$

[10] This means that $x_{i,j,t}$ will be zero for many js that are not held by FoF i.

[11] That is, $\mathcal{I}_{PB}$ and $\mathcal{I}_{OPB}$ represent the set of PB and OPB hedge funds, respectively, for FoF i. Our use of the notation $\mathcal{I}$ is intentional to highlight that the sets are specific to FoF i.

rather than $w_{i,t}^{PB}$, so that we capture FoF i's relative preference among hedge funds, irrespective of how leveraged (or unleveraged) the FoF's total investment in hedge funds is.[12] The term $W_{i,t}^{PB}$ represents the fraction of FoF i's hedge fund portfolio allocated to hedge funds in $\mathcal{I}_{PB}$.

Note that $W_{i,t}^{PB}$ can be mechanically large when $\mathcal{I}_{PB}$ is large, even if the FoF has no particular preference for those in $\mathcal{I}_{PB}$. Therefore, before declaring a significant bias, one must adjust $W_{i,t}^{PB}$ for the size of hedge fund clienteles of the FoF's connected PBs. To this end, we follow the local bias literature (e.g., Coval and Moskowitz 2001) and benchmark $W_{i,t}^{PB}$ against the fraction of all FoFs' holdings allocated to hedge funds in $\mathcal{I}_{PB}$. In this way, we avoid declaring a bias when the FoF is in fact investing in PB and OPB hedge funds in proportion to the amount held by the universe of FoFs. Denoting such a FoF by m or "market" FoF, we can write its return as

$$\begin{aligned} R_{m,t}^{FOF} &= \sum_{j \in \mathcal{I}_{PB}} x_{m,j,t}\, R_{j,t} + \sum_{j \in \mathcal{I}_{OPB}} x_{m,j,t}\, R_{j,t} + x_{m,0,t}\, R_{0,t}, \\ &= w_{m,t}^{PB}\, R_{m,t}^{PB} + w_{m,t}^{OPB}\, R_{m,t}^{OPB} + \epsilon_{m,t}, \end{aligned} \tag{5}$$

where $w_{m,t}^{PB}$, $R_{m,t}^{PB}$, $w_{m,t}^{OPB}$, $R_{m,t}^{OPB}$, and $\epsilon_{m,t}$ are defined analogously as in Equation (3) with i replaced by m, except that $\mathcal{I}_{PB}$ and $\mathcal{I}_{OPB}$ (and hence the superscripts PB and OPB) are still defined in reference to FoF i. The benchmark weight is then given by

$$W_{m,t}^{PB} = \frac{w_{m,t}^{PB}}{w_{m,t}^{PB} + w_{m,t}^{OPB}}, \tag{6}$$

representing the fraction of the market FoF's hedge fund portfolio (that is, the aggregate hedge fund portfolio of all FoFs) allocated to hedge funds in $\mathcal{I}_{PB}$. We define the PB bias of FoF i as $W_{i,t}^{PB} - W_{m,t}^{PB}$—that is, the degree to which FoF i holds hedge funds within $\mathcal{I}_{PB}$ in

[12]It is commonplace in the literature to employ scaled weights rather than actual weights. For example, Coval and Moskowitz (2001), who examine CRSP-listed equities among other holdings of U.S. mutual funds, "recompute the weights on each holding as though the true portfolio consisted of CRSP-listed equities only ... to ensure that the portfolio weights of each fund sum to one" (p. 815).

excess of what the FoF would hold within $\mathcal{I}_{PB}$ if the FoF held the market FoF's portfolio.

3.2 PB bias: Return-based analysis

While it is possible to determine a FoF's PB bias from an analysis of the FoF's holdings, a return-based approach of the sort proposed by Sialm, Sun, and Zheng (2019) provides a useful alternative, especially given the paucity of holdings data. An inspection of Equations (2) and (5) suggests a procedure that can be used in this connection: using only realized fund returns, one could simply run a regression analysis with FoF returns as the dependent variable and hedge fund portfolio returns as the independent variables. The resulting slope coefficients could then be interpreted as the FoF's *average* weights over time (thus denoted without the subscript t below) on the corresponding sets of hedge funds.

More specifically, given the nonnegativity constraints in Equation (3), we estimate the slope coefficients via the following quadratic programming problem:

$$\begin{gathered}\min_{w_i^{PB},\, w_i^{OPB}} \left[\mathrm{var}\left(R_{i,t}^{FOF} - w_i^{PB} R_t^{PB} - w_i^{OPB} R_t^{OPB} \right) \right] \\ \text{subject to } \; w_i^{PB},\, w_i^{OPB} \geq 0, \end{gathered} \tag{7}$$

where R_t^{PB} and R_t^{OPB} are the returns on indexes of hedge funds from $\mathcal{I}_{PB}$ and $\mathcal{I}_{OPB}$, respectively. These "PB index" and "OPB index" are defined in the same way as $R_{i,t}^{PB}$ and $R_{i,t}^{OPB}$ in Equation (3), except that their portfolio compositions will inevitably differ from those described by $\frac{x_{i,j,t}}{w_{i,t}^{PB}}$ and $\frac{x_{i,j,t}}{w_{i,t}^{OPB}}$, $j = 1, \cdots, J$, which are after all unavailable to researchers. This return-based procedure shares the essence of Sharpe's (1992) style analysis in that it allows us to abstract from the FoF's (unknown) portfolio composition *within* each set (i.e., $\frac{x_{i,j,t}}{w_{i,t}^{PB}}$ and $\frac{x_{i,j,t}}{w_{i,t}^{OPB}}$) and infer the FoF's allocation *across* the sets of hedge funds considered (i.e., $w_{i,t}^{PB}$ and $w_{i,t}^{OPB}$), so long as hedge funds in each set are reasonably well correlated in their returns. For our application, such a basis is provided by Chung and Kang (2016), who report a strong degree of PB-level comovement in hedge fund returns.[13] Throughout, we construct the PB and OPB indexes by averaging the returns of all sample hedge funds within $\mathcal{I}_{PB}$ and $\mathcal{I}_{OPB}$, respectively.[14]

To obtain the benchmark weight, we solve a parallel quadratic programming problem for the market FoF, using the same PB and OPB indexes that we use for FoF i:

$$\begin{gathered}\min_{w_m^{PB},\, w_m^{OPB}} \left[\operatorname{var}\left(R_{m,t}^{FOF} - w_m^{PB} R_t^{PB} - w_m^{OPB} R_t^{OPB}\right)\right] \\ \text{subject to } \; w_m^{PB},\, w_m^{OPB} \geq 0.\end{gathered} \tag{8}$$

Following Sialm, Sun, and Zheng (2019), we proxy the market FoF's return, $R_{m,t}^{FOF}$, by averaging the month t returns of all FoFs in the sample. As outlined in Section 3.1, the benchmark weight with which to compare $W_i^{PB} = \frac{w_i^{PB}}{w_i^{PB}+w_i^{OPB}}$ is then given by $W_m^{PB} = \frac{w_m^{PB}}{w_m^{PB}+w_m^{OPB}}$, and the corresponding PB bias measure is given by $W_i^{PB} - W_m^{PB}$.

We solve Equations (7) and (8) for each sample FoF that allows at least a 24-month estimation period. The cross-sectional averages of W_i^{PB} and W_m^{PB}, as well as their difference, are presented in the first two rows of Table 2, along with the average R^2 from each equation (in brackets) and the t-statistic for the difference (in parentheses).[15] Our baseline results show that FoFs exhibit a strong bias in favor of hedge funds serviced by their connected PBs: The average FoF allocates 39.14% of its hedge fund portfolio to those serviced by its connected PBs, while only 25.84% is allocated to them by the market FoF. The PB bias, on average, is 13.30% and is highly statistically significant.

[13] Blake, Elton, and Gruber (1993) show that estimated weights from quadratic programming solution closely match actual portfolio weights. For more applications of Sharpe's (1992) style analysis and quadratic programming procedure, see, e.g., Busse (1999), Kallberg, Liu, and Trzcinka (2000), Chan, Chen, and Lakonishok (2002), Comer (2006), Chan, Dimmock, and Lakonishok (2009), Comer, Larrymore, and Rodriguez (2009), and Green, Hand, and Soliman (2011).

[14] Our choice is dictated by the fact that, on average, about 32.55% (32.76%) of the hedge funds included in the equally weighted PB (OPB) index are excluded from the asset-weighted PB (OPB) index because of missing lagged assets under management (AUM). However, our baseline results are qualitatively similar when we use asset-weighted indexes.

[15] Using the traditional definition, the expressions for R^2 in Equations (7) and (8) are given by $1 - \frac{\operatorname{var}\left(R_{i,t}^{FOF} - \hat{w}_i^{PB} R_t^{PB} - \hat{w}_i^{OPB} R_t^{OPB}\right)}{\operatorname{var}\left(R_{i,t}^{FOF}\right)}$ and $1 - \frac{\operatorname{var}\left(R_{m,t}^{FOF} - \hat{w}_m^{PB} R_t^{PB} - \hat{w}_m^{OPB} R_t^{OPB}\right)}{\operatorname{var}\left(R_{m,t}^{FOF}\right)}$, respectively.

It should be pointed out that FoF return in Equation (1) is gross of fees, whereas we use net-of-fee returns that FoFs report to commercial databases. However, we do not expect this to materially impact our estimates, given that the solutions to Equations (7) and (8) are concerned with the covariance, rather than the average level, of FoF returns. In the third and fourth rows of Table 2, we confirm this by using the gross-of-fee FoF returns computed following the methodology detailed in Agarwal, Daniel, and Naik (2009).[16]

Note that we do not constrain the w terms to sum to one when solving Equations (7) and (8) because, as discussed above, we allow for FoFs' holdings of non–hedge fund securities. That is, we allow $x_{i,0,t}$ and $x_{m,0,t}$ to be nonzero in Equations (2) and (5), respectively. Under the assumption that FoFs' non–hedge fund portfolio consists only of cash or cash equivalents, however, we can also formulate quadratic programming problems featuring both the nonnegativity and sum-to-one constraints as follows:

$$\begin{aligned} \min_{w_i^{PB}, w_i^{OPB}, x_{i,0}} & \left[\operatorname{var}\left(R_{i,t}^{FOF} - w_i^{PB} R_t^{PB} - w_i^{OPB} R_t^{OPB} - x_{i,0}\, LIBOR_t \right) \right] \\ \text{subject to } & w_i^{PB},\, w_i^{OPB} \geq 0, \\ & w_i^{PB} + w_i^{OPB} + x_{i,0} = 1, \end{aligned} \tag{9}$$

and

$$\begin{aligned} \min_{w_m^{PB}, w_m^{OPB}, x_{m,0}} & \left[\operatorname{var}\left(R_{m,t}^{FOF} - w_m^{PB} R_t^{PB} - w_m^{OPB} R_t^{OPB} - x_{m,0}\, LIBOR_t \right) \right] \\ \text{subject to } & w_m^{PB},\, w_m^{OPB} \geq 0, \\ & w_m^{PB} + w_m^{OPB} + x_{m,0} = 1, \end{aligned} \tag{10}$$

where $LIBOR_t$ is the borrowing/lending rate. Nevertheless, the fifth and sixth rows of Table 2 show that W_i^{PB} and W_m^{PB} obtained from Equations (9) and (10) are very similar to those

[16] While useful, this methodology suffers from the frequent occurrence of discontinuities in the historical series of AUM, especially when applied to monthly series, making it difficult for us to base our main analyses on the gross-of-fee FoF returns computed from this methodology.

obtained from Equations (7) and (8). For brevity, we present our remaining results based on the latter.

Finally, in case FoFs' non–hedge fund portfolio contains assets other than cash or cash equivalents, our estimates from Equations (7) and (8) can be subject to omitted variable bias, to the extent that the return on omitted assets is correlated with the returns of PB or OPB hedge funds. To assess the impact of this possibility, we follow Sialm, Sun, and Zheng (2019) and include the Fung and Hsieh (2004) seven factors in Equations (7) and (8), on the basis that omitted assets, if any, are correlated with PB or OPB hedge funds through their exposure to common risk factors. The results are reported in the seventh and eighth rows of Table 2 and show that PB bias remains largely unchanged.[17]

3.3 PB bias: Additional results

3.3.1 Indirect connections

So far, we have defined a FoF as connected to a PB if the FoF uses the PB (direct connection) or if the FoF has a sibling fund that uses the PB (indirect connection). The motivation for considering indirect connections, as well as direct connections, is that if a PB values its relationship with the management firm to which a FoF belongs, the FoF may still have a comparative advantage in gathering information about the PB's hedge fund clients, even if the FoF does not use the PB itself. Importantly, indirect connections are also less likely to be driven by the needs of the FoF, and so are useful in alleviating the concern that the FoF's preference for PB hedge funds is driven by some unobserved characteristics that also drive the FoF's PB selection.[18] To show that our results hold even when we focus solely on indirect connections, we repeat our baseline analysis after reconstructing the PB and OPB indexes, so that the PB index does not include hedge funds serviced by directly connected

[17]This also addresses a similar concern that the error term from Equations (7) and (8) may capture hedge funds that are not included in our sample, and so may be correlated with the PB or OPB indexes.

[18]In this connection, we also considered using PB mergers as an exogenous change to a FoF's PB connections, but only 21 FoFs remain after imposing a set of requirements similar to those listed in Chung and Kang's (2016) analysis of PB mergers, precluding any meaningful statistical analysis.

PBs. The results, reported in the ninth and tenth rows of Table 2, confirm that PB bias is not specific to direct connections, as indirect connections alone also work. In untabulated results, we also repeat the baseline analysis after dropping FoF-month observations where the FoF is directly connected to a PB, and obtain similar results.

3.3.2 Auditor connections

At this stage, it may be instructive to perform a "placebo"-type analysis, to ensure that we are not falsely declaring a significant effect. For this purpose, we consider an alternative set of hedge funds that are expected *not* to be preferred by the FoF over the remaining set of hedge funds, to see if our analysis indeed picks up no effect. Specifically, we make use of information on hedge fund auditor—another important type of hedge fund service provider in the literature (e.g., Liang 2003; Bollen and Pool 2008, 2009; Cassar and Gerakos 2011)—and repeat the baseline analysis using a pair of hedge fund indexes constructed in the same way as the PB and OPB indexes, except that they are based on auditors. Unlike PBs, auditors do not observe day-to-day hedge fund operations and trading, and gain little from facilitating investors' search among their hedge fund clients.[19] As expected, the results reported in the eleventh and twelfth rows of Table 2 show that there is no significant bias, reassuring that our results above are unlikely false positive.

3.3.3 Excluding top PBs

One could argue that "high-quality" FoFs and hedge funds are likely to be sorted into the same PBs (i.e., top PBs), so PB bias might just be a consequence of high-quality FoFs investing in high-quality hedge funds that the FoFs identify by themselves. Note that such a sorting restricts PB bias to top PBs: FoFs connected to nontop PBs ("low-quality" FoFs) would make random allocations to high- and low-quality hedge funds and thus exhibit no PB bias. To see if this is the case, we repeat our baseline analysis after dropping FoF-month

[19] For example, auditors gain little from additional capital invested in their hedge fund clients.

observations where the FoF is connected to one of the top 5 PBs, based on the number of hedge fund clients. The results are reported in the bottom two rows of Table 2 and show that PB bias is not restricted to a few top PBs. FoFs connected to the other PBs also exhibit a strong degree of PB bias.[20]

3.3.4 Purging the effect of other known preferences

Sialm, Sun, and Zheng (2019) find that FoFs tilt their portfolios toward local hedge funds. To show that we are not simply picking up the effect of FoFs' local preference, we repeat our baseline analysis using the PB and OPB indexes purged of local hedge funds. That is, we solve quadratic programming problems based on an expanded representation of the FoF return:

$$R_{i,t}^{FOF} = w_{i,t}^{PB}\, R_{i,t}^{PB} + w_{i,t}^{OPB}\, R_{i,t}^{OPB} + w_{i,t}^{L}\, R_{i,t}^{L} + \epsilon_{i,t}, \tag{11}$$

where

$$\begin{aligned}
w_{i,t}^{PB} &= \sum_{j \in \mathcal{I}_{PB} \setminus \mathcal{I}_L} x_{i,j,t} \;\geq 0, & R_{i,t}^{PB} &= \sum_{j \in \mathcal{I}_{PB} \setminus \mathcal{I}_L} \frac{x_{i,j,t}}{w_{i,t}^{PB}}\, R_{j,t}, \\
w_{i,t}^{OPB} &= \sum_{j \in \mathcal{I}_{OPB} \setminus \mathcal{I}_L} x_{i,j,t} \;\geq 0, & R_{i,t}^{OPB} &= \sum_{j \in \mathcal{I}_{OPB} \setminus \mathcal{I}_L} \frac{x_{i,j,t}}{w_{i,t}^{OPB}}\, R_{j,t}, \\
w_{i,t}^{L} &= \sum_{j \in \mathcal{I}_L} x_{i,j,t} \;\geq 0, & R_{i,t}^{L} &= \sum_{j \in \mathcal{I}_L} \frac{x_{i,j,t}}{w_{i,t}^{L}}\, R_{j,t},
\end{aligned} \tag{12}$$

and $\mathcal{I}_L$ is the set of hedge funds located in the same geographical area as the FoF. The idea is that if our results are just an artifact of $\mathcal{I}_{PB}$ overlapping more than $\mathcal{I}_{OPB}$ does with $\mathcal{I}_L$, that is, a concentration of local hedge funds among PB hedge funds, then a FoF's allocation between $\mathcal{I}_{PB}$ and $\mathcal{I}_{OPB}$ should converge to that of the market FoF once local hedge funds are removed from both sets. However, the results reported in Panel A of Table 3 show that the PB bias measure does not get any smaller, even without any local hedge funds in the

[20] Note from the outset that the sorting story is also inconsistent with our other findings. For example, it cannot explain why (1) a *given* FoF makes superior selection among PB hedge funds than among OPB hedge funds (see Section 5.2) and (2) FoFs that are more likely to be able to identify high-quality hedge funds by themselves exhibit *smaller* PB bias (see Section 3.4).

PB and OPB indexes—regardless of whether we define local hedge funds as those located in the same country (the first two rows), the same state (the next two rows), or the same MSA (the bottom two rows) as the FoF—suggesting that PB bias is not just a repackaging of the local bias effect.[21]

Note that $\mathcal{I}_L$ encompasses all hedge funds managed under the same roof with the FoF. Thus, the results here also assure that PB bias is not driven by FoFs investing internally in their sibling hedge funds (Bhattacharya, Lee, and Pool 2013; Elton, Gruber, and de Souza 2018). The inference does not change when we purge the PB and OPB indexes only of the FoF's sibling hedge funds, if any, or when we repeat the baseline analysis after excluding from the PB index (including in the OPB index) the FoF's sibling hedge funds, if any (unreported).

While many FoFs are diversified across multiple hedge fund styles, some may be more concentrated on a certain style of hedge funds.[22] To ensure that we are not attributing FoFs' style preference (or style focus) to PB bias, we conduct the same analysis as in Panel A of Table 3, but by purging the PB and OPB indexes of the FoF's preferred style of hedge funds. Again, the idea is that if a FoF appears to prefer PB hedge funds only because of the FoF's preferred style of hedge funds among them, then we should not see a significant PB bias once the corresponding style of hedge funds are removed from $\mathcal{I}_{PB}$ and $\mathcal{I}_{OPB}$. However, the results presented in Panel B of Table 3 continue to show a significant PB bias even after purging the effect of style focus.

Overall, the results in Table 3 show that PB bias is not merely a manifestation of FoFs' local preference and style focus. In fact, compared to our baseline results (13.30%), the magnitude of PB bias is larger when we purge the PB and OPB indexes of in-state (25.00%)

[21] Only U.S. FoFs are included in the analysis when we define local hedge funds as those located in the same state or MSA as the FoF.

[22] Using a proprietary data obtained from TASS, we identify 303 such FoFs (among 708 in the baseline analysis) with the following breakdown of focus style: convertible arbitrage (2), emerging markets (40), equity market neutral (10), event driven (14), fixed-income arbitrage (3), global macro (20), long/short equity hedge (94), managed futures (49), options strategy (4), and other (67; dropped).

and in-MSA (23.28%) hedge funds and of hedge funds within the FoF's focus style (17.50%), that is, PB bias is stronger among out-of-state and out-of-MSA hedge funds and hedge funds from outside the FoF's focus style. This makes sense if FoFs rely more on PB connections when investing outside their geographical area or style expertise. To strengthen this point, we report the results when we purge the PB and OPB indexes of nonlocal hedge funds and hedge funds from outside the FoF's focus style, to capture PB bias *within* the FoF's geographical area and style expertise. Panel A of Table 4 shows that PB bias almost halves in magnitude among in-state (12.03%) and in-MSA (14.75%) hedge funds, as compared with out-of-state and out-of-MSA hedge funds. Strikingly, FoFs no longer exhibit a significant PB bias among hedge funds within their focus style (Panel B). Overall, this shows that PB connections matter more when information frictions are greater: when searching among nearby hedge funds or hedge funds within their style expertise, FoFs rely less on their PB connections and exhibit a smaller PB bias.

3.4 Determinants of PB bias

We now explore whether the degree of PB bias is related to FoF and PB characteristics in a way that is consistent with the information story. As discussed in the introduction, we posit that FoFs prefer PB hedge funds because it is less costly for FoFs to search for informed hedge fund managers among PB hedge funds than among OPB hedge funds. This means that FoFs' preference for PB hedge funds can increase with their need to economize on the cost of finding and vetting informed managers. Thus, our first prediction is that PB bias is stronger among FoFs with less resources for hedge fund due diligence, such as smaller FoFs or FoFs belonging to smaller management firms, especially those managing smaller FoF assets.[23] In addition, if PB bias is indeed is a result of FoFs searching for informed managers (as opposed to random managers) among PB hedge funds, we would expect PB bias to be

[23]Since FoFs may benefit from the due diligence work performed by other FoFs in the same fund family, we focus more on the size of the fund family's FoF business than on the size of the FoF itself to capture the FoF's need to economize on the cost of hedge fund due diligence.

stronger when the rewards for identifying informed managers are greater, as in FoFs with higher incentive fees and FoFs with managers' personal capital invested in the FoF.

We posit that PBs serve an information role for FoFs connected to them, in exchange for (or in anticipation of) prime brokerage fees from the FoFs' management firms. Thus, our next prediction is that PB bias is stronger among FoFs whose management firms are likely to generate higher prime brokerage fees, such as larger management firms, especially those running a larger hedge fund business. Note that hedge fund AUM, compared with FoF AUM of an equal size, would contribute more to generating prime brokerage fees, while FoF AUM would contribute more to covering the expense of a FoF business, such as due diligence cost. Thus, we use the management firm's hedge fund AUM, rather than the total AUM, to more cleanly capture PBs' incentive to cater to FoFs. Conversely, we use the management firm's FoF AUM, rather than the total AUM, to more cleanly capture the FoF's need to economize on the cost of necessary due diligence.

Finally, we ask if PB bias is stronger among FoFs connected to larger PBs, especially those serving a larger number of hedge fund clients—on the basis that FoFs may be more keen to tap into PB connections when doing so can lead to an information advantage about a larger number of hedge funds. However, if this advantage erodes as more competitors exploit the same connections, then we would expect PB bias to be weaker among PBs with a larger number of connected FoFs.

To test these predictions, we regress PB bias estimated over 24-month rolling windows on lagged characteristic variables in a panel regression that controls for FoF-level clustering and time fixed effects. The results are summarized in Table 5 and are largely consistent with our predictions above. Specifically, PB bias—while only insignificantly related to FoF size (AUM) and fund family size (FamAUM)—is significantly negatively related to the size of the fund family's FoF business (FamFoFAUM), a cleaner (inverse) measure of the FoF's need to economize on the cost of hedge fund due diligence, as discussed above. PB bias is also positively and statistically strongly related to incentive fee rates (IncentiveFee) and, to a lesser degree, to whether or not the managers have personal capital invested in the FoF (PersonalCapital). Meanwhile, PB bias increases significantly with the size of the fund family's hedge fund business (FamHFAUM), confirming that the family's hedge fund AUM and FoF AUM have opposing effects on PB bias.[24] Similarly, when we use age as an alternative measure of PBs' incentive to cater to FoFs—on the basis that older funds or fund families may have more established PB ties and relationships (Chung and Kang 2016)—we find that the age of the fund family's hedge fund business (FamHFAge) has a positive effect on PB bias, whereas that of FoF business (FamFoFAge) has a negative effect, consistent with fund families with more experience in hedge fund due diligence relying less on PB connections. Finally, these results do not change much in the presence of other FoF characteristics or when we add PB characteristics in the regression. Likewise, PB bias is also positively related to the number of hedge fund clients (NumHFClients) and negatively related to the number of connected FoFs (NumConnFoFs), as predicted, with or without FoF characteristics in the regression.[25] Overall, the evidence supports an information rationale for PB bias: FoFs rely more on PB connections when they are more resource-constrained and information-hungry, when PBs have a greater incentive to cater to FoFs, and when information gained from such channels has greater investment value.

4 PB Connections and Performance

In this section, we undertake two additional sets of analyses to give further credence to the information story. In Section 4.1, we investigate whether FoFs select PB hedge funds at an information advantage; in Section 4.2, we test whether PB bias is related to future FoF

[24]The (unreported) results show that the inferences are robust to the use of the number of hedge funds (FoFs) in the family or simply the indicator variable for whether the FoF has a hedge fund (FoF) sibling—in place of the size of the family's hedge fund (FoF) assets. In addition, the results are virtually unchanged when we use PB bias estimated after excluding from the PB index (including in the OPB index) the FoF's sibling hedge funds, if any.

[25]In case the FoF is connected to multiple PBs, we use the average number of hedge fund clients (connected FoFs) across the PBs.

performance.

4.1 Are FoFs successful at selecting PB hedge funds?

If FoFs have an information advantage in selecting hedge funds among those serviced by their connected PBs, then we would expect FoFs to overweight PB hedge funds that subsequently perform well, and underweight those that subsequently perform poorly. To see if this is the case, we divide hedge funds in the PB index based on whether their end-of-month returns are above (PB^{above}) or below (PB^{below}) a threshold. We then solve Equations (7) and (8) after replacing the PB index with the PB^{above} and PB^{below} indexes, and measure the FoF's relative allocation between them by $W_i^{PB^{above}} = \frac{w_i^{PB^{above}}}{w_i^{PB^{above}}+w_i^{PB^{below}}}$, where $w_i^{PB^{above}}$ and $w_i^{PB^{below}}$ represent the FoF's average beginning-of-month weight on the PB^{above} and PB^{below} indexes, respectively. As before, we benchmark the FoF's allocation against the market's allocation across the same set of hedge fund indexes, denoted by $W_m^{PB^{above}} = \frac{w_m^{PB^{above}}}{w_m^{PB^{above}}+w_m^{PB^{below}}}$.

Table 6 reports the results based on whether the PB^{above} index includes PB hedge funds whose end-of-the-month returns are in the top 25 (the first two rows), top 50 (the next two rows), or top 75 (the bottom two rows) percentile of returns across all sample hedge funds. The results show that as the PB^{above} index contains more and more hedge funds, both $W_i^{PB^{above}}$ and $W_m^{PB^{above}}$ become larger (mechanically). More importantly, regardless of which threshold is used, the difference between $W_i^{PB^{above}}$ and $W_m^{PB^{above}}$ is invariably positive and statistically significant. For example, a FoF's weight on the top-25-percentile hedge funds averages 16.33 percentage points higher than the market's weight on the same hedge funds, and a FoF's weight on the *bottom*-25-percentile hedge funds averages 11.02 percentage points *lower* than the market benchmark. These results suggest that PB bias is unlikely due to FoFs making random allocations to PB hedge funds. Rather, FoFs' selection among PB hedge funds reflects an information advantage in assessing the future prospects of PB hedge funds.[26]

[26]In our full analysis, we split the PB index based on returns that are going to be realized over the next k

Table 7 reports the results when we split the OPB index into the OPB^{above} and OPB^{below} indexes in the same way we split the PB index in Table 6. The results show that the differences between $W_i^{OPB^{above}}$ and $W_m^{OPB^{above}}$ are smaller in magnitude than the corresponding differences in Table 6. In particular, a FoF's weight on the *bottom*-25-percentile hedge funds now averages 4.17 percentage points *higher* than the market benchmark, highlighting that FoFs' tendency to underweight the bottom-25-percentile hedge funds is only observed among PB hedge funds. Overall, these results suggest that PBs benefit FoFs particularly in avoiding "problem" funds as opposed to selecting "star" funds: Given that PBs finance hedge funds as creditors, who are likely to be more concerned with the ability of hedge funds to survive than to thrive, this may be a natural consequence if FoFs exploit information advantage gained from PB connections.

4.2 Does PB bias predict FoF performance?

In a recent theoretical work, Gârleanu and Pedersen (2018) show that investors for whom the cost of finding and vetting an informed asset manager is low relative to their capital have a greater incentive to become "searching investors" (as opposed to "noise allocators") and hence are expected to earn higher returns. If PB connections serve to lower the cost of finding and vetting informed hedge fund managers, and if PB bias captures the extent to which FoFs lower such cost via PB connections, we would expect FoFs with higher PB bias to earn higher returns, *ceteris paribus*. In this subsection, we probe the relation between PB bias and FoF performance, using a portfolio-sorting approach in Section 4.2.1 and a multivariate regression approach in Section 4.2.2.

months (from the beginning of month t), where $k \in \{1, 3, 6, 12, 24\}$. Because the results are very similar, we only tabulate the results when $k = 1$, for brevity. In any case, hedge funds that are going to exit from the database over the k-month period ($k > 1$) are included in the PB^{below} index.

4.2.1 Portfolios of high- and low-PB-bias FoFs

Each month, we sort FoFs into quartile portfolios according to their PB bias measured over the previous 24 months. We then compute the equal-weighted average return of FoFs in each portfolio for the subsequent 1, 3, 6, 12, and 24 months. We follow Titman and Tiu (2011) and revise the portfolio every month so that for the three-month holding period, for example, one-third of the portfolio is revised in each month. The portfolios run from January 1996 to June 2012, and their performance is measured using the Fung and Hsieh (2004) seven-factor adjusted alpha and the corresponding information ratio (defined as a FoF's alpha divided by its residual standard deviation), as well as the raw excess return and the Sharpe ratio.

Recall that our PB bias measure is designed to be invariant to FoF leverage and cash holdings, as well as other holdings of non–hedge fund securities, if any. For example, a FoF with 50% of its assets invested in a hedge fund portfolio and the remaining in cash would have the same PB bias even if the FoF were fully invested (or more than fully invested) in the same hedge fund portfolio. In this regard, the Sharpe ratio and information ratio have an advantage because they are also invariant to FoF leverage and cash holdings. These features of the Sharpe ratio and information ratio are useful for the purpose of revealing the relationship between PB bias and FoF performance, thus making them our preferred measures of FoF performance.

The results, summarized in Table 8, reveal that high-PB-bias FoFs outperform low-PB-bias FoFs for all holding horizons. The differences between the Sharpe ratios of the high- and low-PB-bias portfolios are quite large, ranging from 0.07 to 0.10. After adjusting for the factors from the Fung and Hsieh (2004) model, the differences further increase to 0.10 to 0.17. The statistical significance of the differences between Sharpe ratios and information ratios is tested, as in Titman and Tiu (2011) and Chung and Kang (2016), based on the distribution of these differences simulated under the null of no difference. The distribution is constructed by a 5,000-times repetition of essentially our sample portfolio analysis, except that we randomly sort FoFs rather than sorting based on their PB bias. The resulting p-values show that the differences between Sharpe ratios and information ratios of quartiles 4 and 1 are statistically significant.

The table also shows that high-PB-bias FoFs deliver positive and statistically significant alpha, ranging from 0.21% to 0.29% per month (2.54% to 3.42% per annum). In contrast, none of the other quartile portfolios deliver significant alpha over any holding horizon. This is consistent with the cross-sectional variation in FoF alpha documented in Fung, Hsieh, Naik, and Ramadorai (2008), who show that about one-quarter of FoFs deliver significant alpha, whereas the average FoF does not. The differences between quartiles 4 and 1 are only marginally significant at best, perhaps because of the imprecisely estimated alphas of the low-PB-bias portfolio: although of a similar magnitude, the differences between quartile 4 and a composite portfolio consisting of all FoFs from quartiles 1 to 3 (denoted by Q1:3) show up strongly significant with t-statistics no smaller than 2.

4.2.2 Multivariate regression analyses

We extend our analysis of FoF performance using multivariate regressions to control for other characteristics known to affect FoF performance. Similar to the empirical design of Titman and Tiu (2011), Sun, Wang, and Zheng (2012), and Chung and Kang (2016), we estimate the following regression:

$$\text{Performance}_{i,t+1:t+12} = b_0 + b_1 \, \text{PB bias}_{i,t-23:t} + \mathbf{b}_2' \, \mathbf{Controls}_{i,t} + \varepsilon_{i,t}, \tag{13}$$

where $\text{Performance}_{i,t+1:t+12}$ measures the performance of FoF i during the year after month t, and $\text{PB bias}_{i,t-23:t}$ is the PB bias of FoF i calculated using the past two years of the FoF's history. $\mathbf{Controls}_{i,t}$ include the standard deviation of FoF i's monthly excess returns over the past two years ($\text{Vol}_{i,t-23:t}$); redemption notice period, measured in units of 30 days ($\text{RedemptionNotice}_i$); lockup period ($\text{Lockup}_i$); management fee ($\text{MgmtFee}_i$); incentive fee

(IncentiveFee$_i$); the log of the FoF's age at month t ($\log(\text{Age}_{i,t})$); the log of AUM at month t ($\log(\text{AUM}_{i,t})$); monthly money flows, as a percentage of AUM, averaged over the past two years ($\text{Flow}_{i,t-23:t}$); monthly excess return averaged over the past two years ($R_{i,t-23:t}$); the log of one plus minimum investment ($\log(1 + \text{MinInvestment}_i)$); indicator variables for whether personal capital is committed (PersonalCapital$_i$), whether there is a high watermark provision (HighWaterMark$_i$), whether the FoF uses leverage (Leveraged$_i$), and, finally, whether the FoF is offshore (Offshore$_i$).

Table 9 reports results from the Fama–MacBeth (1973) and panel regressions; in all regressions, we standardize PB bias so that the estimated coefficients can be interpreted as the effect of a one-standard-deviation change in PB bias on performance. Consistent with the information story, we find a significant positive relationship between PB bias and FoF performance, even after controlling for other FoF characteristics. The Fama–MacBeth regressions in Panel A show that a one-standard-deviation increase in PB bias is associated with a 0.03 increase in Sharpe ratio, a 0.13 increase in information ratio, a 0.63 percentage point increase in annualized excess return, and a 0.94 percentage point increase in annualized alpha over the subsequent year. The panel regressions in Panel B yield similar conclusions. In any case, the relationship between PB bias and FoF performance is statistically stronger when using the Sharpe ratio and information ratio than when using the excess return and alpha, as expected. Moreover, consistent with our portfolio results, the relationship becomes economically and statistically more significant after adjusting for the Fung and Hsieh (2004) seven factors. Overall, these results suggest that PB bias arises in a way that benefits FoF performance. These results, while in support of the information story, are difficult to explain by alternative possibilities, such as that PB bias is induced by familiarity (e.g., Huberman 2001; Pool, Stoffman, and Yonker 2012) or by FoFs being used to prop up PB hedge funds as a part of family-level profit maximization (e.g., Gaspar, Massa, and Matos 2006; Bhattacharya, Lee, and Pool 2013).[27]

[27] In untabulated results, we also control for a local bias measure (constructed in the same way as our PB bias measure, but using local and nonlocal indexes), and obtain similar results.

5 Holding-based Analysis

In this section, we revisit our analysis of whether FoFs exhibit PB bias, using the quarterly portfolio holdings of registered FoFs. We also further investigate whether FoFs have a search advantage among PB hedge funds relative to among OPB hedge funds, by comparing postdecision (in particular posthired) returns of PB and OPB hedge funds. If FoFs learn more about a hedge fund after investing in the fund (Aiken, Clifford, and Ellis 2015b), the benefit from PB connections should be easier to detect *before* FoFs own the fund, that is, when FoFs make hiring decisions than when making rebalancing or firing decisions.

5.1 PB bias

With holdings data, we can now compute PB bias, as well as $W_{i,t}^{PB}$ and $W_{m,t}^{PB}$, for each FoF-quarter observation—as long as PB connections are identified for the FoF and PB information is available for a representative portion of the FoF's assets. Our sample contains 480 such FoF-quarter observations, after requiring PB information for at least two-thirds of the FoF's assets. The benchmark weight $W_{m,t}^{PB}$, with which to compare $W_{i,t}^{PB}$, is computed based on the aggregate portfolio of all hedge funds held by the universe of registered FoFs (defined as encompassing all 127 registered FoFs for which we could or could not identify PB connections).

Panel A of Table 10 reports the pooled averages of $W_{i,t}^{PB}$, $W_{m,t}^{PB}$, and their difference across 480 FoF-quarter observations, along with the t-statistic for the difference (in parenthesis) adjusted for time-series dependence in the data. The results show that despite comprising fewer, presumably less resource-constrained FoFs (Aiken, Clifford, and Ellis 2013, 2015a, 2015b), the sample yields fairly strong evidence of PB bias: The average FoF in the sample allocates 55.28% of its assets to PB hedge funds, even though its PB hedge funds comprise only 50.14% of the aggregate hedge fund portfolio of registered FoFs. On average, the difference is 5.14%, and is statistically significant with a t-statistic greater than 2.[28]

5.2 Postdecision returns of PB and OPB hedge funds

The data also allow us to compute quarterly returns on portfolio hedge funds, via the following formula given by Aiken, Clifford, and Ellis (2013):

$$R_{j,t+1} = \frac{\text{Value}_{j,t+1} - \left(\text{Cost}_{j,t+1} - \text{Cost}_{j,t}\right)}{\text{Value}_{j,t}} - 1, \tag{14}$$

where $R_{j,t+1}$ is the return on portfolio hedge fund j in quarter $t+1$, and $\text{Value}_{j,t}$ and $\text{Cost}_{j,t}$ are the dollar value and cost basis, respectively, of the FoF's position in hedge fund j as of the end of quarter t.[29] To see if PBs benefit FoFs' hiring decisions, we compare postdecision returns of PB and OPB hedge funds. That is, for each FoF-quarter observation, we form portfolios of PB and OPB hedge funds hired by the FoF and compare their returns in the subsequent quarter. Following Aiken, Clifford, and Ellis (2015b), newly hired funds are identified as those added to the FoF's portfolio in the recent k quarters, where $k \in \{4, 8, 12\}$, among other hedge funds held by the FoF.[30] We compute value-weighted returns on these subsets of PB and OPB holdings and denote them by $R^{PBh}_{i,t+1}$ and $R^{OPBh}_{i,t+1}$, respectively.

Panel B of Table 10 reports the pooled averages of $R^{PBh}_{i,t+1}$ and $R^{OPBh}_{i,t+1}$, as well as their difference, across FoF-quarter observations where we have at least one newly hired PB and OPB hedge fund with nonmissing return in the subsequent quarter. The results show that the average FoF earns 1.22%–1.60% per quarter from the PB hedge funds it recently hires and

[28] $W^{PB}_{i,t}$ and $W^{PB}_{m,t}$ here are larger than those in the return-based analysis simply because the set of PB hedge funds, $\mathcal{I}_{PB}$, is larger. For example, the average (median) number of connected PBs across 480 FoF-quarter observations here is 2.85 (2.00), whereas the corresponding number across 52,224 FoF-month observations used in the baseline analysis is 1.52 (1.00).

[29] As discussed in Aiken, Clifford, and Ellis (2013), however, there are issues with computing hedge fund returns in this way when cost basis changes from quarter t to quarter $t+1$. In this case, and when the formula yields a missing return value, we replace the return with the median return computed using other FoFs holding the same hedge fund during the quarter (without changing cost basis). Following Aiken, Clifford, and Ellis (2013), returns are trimmed at the 0.5% and 99.5% levels before use.

[30] That is, we rebalance these FoF-level portfolios every quarter to include newly hired hedge funds and remove funds that have stayed in the portfolio longer than k quarters and funds that are no longer held by the FoF.

0.31%–0.68% per quarter from its other new hires. The difference, 0.90%–0.94% per quarter, is statistically significant after correcting for time-series and cross-sectional dependence in the data, suggesting that PBs benefit FoFs in making hiring decisions.

In Panel C of Table 10, we repeat the analysis in Panel B, by forming portfolios of PB and OPB hedge funds *fired* by the FoF. Similar to above, newly fired funds are those dropped from the FoF's portfolio in the recent k quarters, where $k \in \{4, 8, 12\}$, among other hedge funds no longer held by the FoF. Since the dollar value of the FoF's positions in these funds is zero by design, we compute equal-weighted (rather than value-weighted) returns, denoted by $R_{i,t+1}^{PBf}$ and $R_{i,t+1}^{OPBf}$, for each FoF-quarter observation. The results show that the average return differential—although negative when we allow longer holding periods (i.e., $k = 8$ or 12)—is smaller in magnitude and statistically insignificant.

Overall, our finding of a significant difference in posthired returns but not in postfired returns between PB and OPB hedge funds is consistent with the notion that PB connections matter more when information frictions are greater: since incumbent investors face less frictions in assessing the fund's prospects compared with prospective investors (Hochberg, Ljungqvist, and Vissing-Jørgensen 2014; Aiken, Clifford, and Ellis 2015b), PB connections drive only an insignificant wedge between postdecision returns of PB and OPB hedge funds that FoFs already own.[31] This finding is also consistent with PBs' incentive to play an information role: PBs may be less incentivized to play an information role that leads to informed *divestment* from their hedge fund clients.

[31] In unreported results, we repeat the analysis in Panels B and C, by computing equal-weighted posthired returns and value-weighted postfired returns (using the last dollar value observed before termination as the weight), respectively, and continue to find a significant difference in posthired returns but not in postfired returns between PB and OPB hedge funds. We also repeat the analysis in Panel B, by including the remaining, long-held PB and OPB hedge funds (not just newly hired PB and OPB hedge funds), and find mixed results, depending on whether we value weight (insignificant) or equal weight (significant) PB and OPB holdings.

6 Conclusion

PBs are uniquely informed about the opaque and highly secretive hedge fund marketplace. We find that FoFs use their connections to PBs to facilitate their search for informed hedge fund managers. FoFs exhibit a disproportionate preference for hedge funds serviced by their connected PBs, and this PB bias is stronger when search costs or information frictions are larger relative to capital and when the FoF belongs to the family that generates higher prime brokerage fees. PB bias is unlikely due to random allocations to PB hedge funds, as FoFs tend to overweight ex-post winners among PB hedge funds, while underweighting ex-post losers. Moreover, FoFs with higher PB bias tend to perform better subsequently, suggesting that PB bias arises in a way that benefits FoF performance.

Our results echo the insight from Sialm, Sun, and Zheng (2019) that FoFs benefit from searching among hedge funds where it is less costly for them to identify informed hedge fund managers. More broadly, to the extent that fewer information frictions in the search for informed asset managers make underlying securities markets more efficient (Gârleanu and Pedersen 2018), our results also suggest that PBs play a bigger role in shaping price efficiency than previously understood: PBs contribute to price efficiency not only by facilitating arbitrage activities via securities lending and debt financing (e.g., Aragon and Strahan 2012; Cao, Liang, Lo, and Petrasek 2018), but also by reducing investors' costs of finding and vetting informed arbitrageurs.

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TABLE 1: **Summary statistics**

Panel A

				Number of FoFs per PB				Number of hedge funds per PB			
Month	Number of FoFs	Number of hedge funds	Number of PBs	Mean	Median	Max.	Min.	Mean	Median	Max.	Min.
1994	119.00	281.00	14.00	2.29	1.00	7.00	0.00	11.36	7.50	36.00	0.00
2003	615.00	1553.00	31.00	3.90	3.00	13.00	0.00	36.26	7.00	259.00	0.00
2012	490.00	1324.00	24.00	5.17	3.00	18.00	0.00	37.83	12.50	168.00	1.00
Ave.	630.90	1431.69	27.09	4.81	3.30	20.72	0.09	34.38	10.38	219.44	0.39

Panel B

		Number of connected PBs per FoF				Number of PB hedge funds per FoF			
Month	Number of FoFs with PB connections	Mean	Median	Max.	Min.	Mean	Median	Max.	Min.
1994	39.00	1.00	1.00	1.00	1.00	14.87	8.00	36.00	0.00
2003	224.00	1.30	1.00	3.00	1.00	98.32	31.00	426.00	0.00
2012	252.00	1.28	1.00	4.00	1.00	63.98	54.00	374.00	1.00
Ave.	263.33	1.27	1.00	3.68	1.00	78.19	29.78	451.47	0.46

Panel A of the table provides the total number of FoFs, hedge funds, and PBs in the sample, as well as the distribution of the number of FoFs and hedge funds serviced by a PB for January 1994, March 2003, and June 2012. Panel B of the table reports the total number of FoFs for which we identify PB connections, as well as the distribution of the number of connected PB per FoF and the distribution of the number of hedge funds serviced by the connected PBs (i.e., PB hedge funds) per FoF, both across the FoFs with identified PB connections. The last row of each panel reports time-series averages of the corresponding monthly statistics across the entire sample months.

TABLE 2: **PB bias**

	W_i^{PB} (%)	W_m^{PB} (%)	Difference	N
Baseline	39.14	25.84	13.30	708
	[48.72]	[87.76]	(10.29)	
Gross-of-fee FoF returns	39.41	23.32	16.09	274
	[49.40]	[87.91]	(7.49)	
Eqs. (9) and (10)	39.25	26.05	13.20	704
	[49.10]	[87.81]	(10.20)	
Fung–Hsieh factors	38.26	25.53	12.74	706
	[63.17]	[91.81]	(11.07)	
Indirect	36.83	26.93	9.90	423
	[50.96]	[88.14]	(6.16)	
Auditors	60.29	59.47	0.82	1348
	[49.60]	[90.18]	(0.80)	
Excluding top 5 PBs	31.71	19.19	12.52	487
	[48.47]	[87.15]	(8.67)	

This table reports the results of our baseline analysis and some of its variations. In our baseline analysis, we solve Equations (7) and (8) for each sample FoF that allows at least a 24-month estimation period. W_i^{PB} is given by $w_i^{PB}/\left(w_i^{PB}+w_i^{OPB}\right)$, where w_i^{PB} and w_i^{OPB} represent the FoF's average weight over time on the PB and OPB indexes, respectively; W_m^{PB} is given by $w_m^{PB}/\left(w_m^{PB}+w_m^{OPB}\right)$, where w_m^{PB} and w_m^{OPB} represent the market FoF's average weight over time on the PB and OPB indexes, respectively. Cross-sectional averages of W_i^{PB} and W_m^{PB} and the difference between them are presented in the first two rows of the table, along with the average R^2 from each equation (in brackets) and the t-statistic for the difference (in parentheses). In the next two rows, we repeat the baseline analysis by using the gross-of-fee returns (instead of net-of-fee returns) for FoFs, computed following the methodology detailed in Agarwal, Daniel, and Naik (2009). In the fifth and sixth rows, we solve Equations (9) and (10), which are formulated under the assumption that FoFs' non–hedge fund portfolio consists only of cash or cash equivalents and that the borrowing and lending rates are the same and equal the LIBOR rate. In the seventh and eighth rows, we include the Fung and Hsieh (2004) seven factors in Equations (7) and (8), without requiring their coefficients to be nonnegative. In the ninth and tenth rows, we repeat the baseline analysis after reconstructing the PB and OPB indexes, so that the PB index does not include hedge funds serviced by directly connected PBs. In the eleventh and twelfth rows, we repeat the baseline analysis using a pair of hedge fund indexes constructed in the same way as the PB and OPB indexes, except that they are based on auditors. In the bottom two rows, we exclude FoF-month observations where the FoF is connected to a top 5 PB, defined based on the number of hedge fund clients each month.

TABLE 3: **PB bias purged of the effect of other known preferences**

	W_i^{PB} (%)	W_m^{PB} (%)	Difference	N
Panel A: Purged of local preference				
Country	46.25	31.94	14.31	678
	[51.51]	[90.28]	(8.94)	
State	48.12	23.11	25.00	212
	[49.55]	[90.15]	(8.57)	
MSA	48.81	25.53	23.28	198
	[49.06]	[90.23]	(7.77)	
Panel B: Purged of style preference				
Focus style	42.18	24.69	17.50	234
	[54.81]	[88.99]	(7.05)	

In Panel A of the table, we repeat the baseline analysis using the PB and OPB indexes purged of the FoF's local hedge funds. Local hedge funds are defined as hedge funds located within the FoF's local area, defined alternatingly as the country (the first two rows), state (the next two rows), or metropolitan statistical area (MSA) (the bottom two rows) in which the FoF is located. Only U.S. FoFs are included in the analysis when the FoF's local area is defined as its state or MSA. In Panel B, we repeat the baseline analysis using the PB and OPB indexes purged of hedge funds within the FoF's focus style, which we identify using a proprietary data obtained from TASS. W_i^{PB} is given by $w_i^{PB}/\left(w_i^{PB}+w_i^{OPB}\right)$, where w_i^{PB} and w_i^{OPB} represent the FoF's average weight over time on the purged PB and OPB indexes, respectively; W_m^{PB} is given by $w_m^{PB}/\left(w_m^{PB}+w_m^{OPB}\right)$, where w_m^{PB} and w_m^{OPB} represent the market FoF's average weight over time on the purged PB and OPB indexes, respectively. Cross-sectional averages of W_i^{PB} and W_m^{PB} and the difference between them are presented in the table, along with the average R^2 from each equation (in brackets) and the t-statistic for the difference (in parentheses).

TABLE 4: **PB bias within local area or focus style**

	W_i^{PB} (%)	W_m^{PB} (%)	Difference	N
Panel A: Within local area				
Country	43.20	24.25	18.95	548
	[50.77]	[90.28]	(11.39)	
State	48.97	36.94	12.03	180
	[50.55]	[89.65]	(3.37)	
MSA	47.16	32.41	14.75	171
	[48.60]	[89.68]	(4.05)	
Panel B: Within focus style				
Focus style	40.70	41.76	-1.06	183
	[56.21]	[89.05]	(-0.33)	

In Panel A of the table, we repeat the baseline analysis using the PB and OPB indexes purged of the FoF's nonlocal hedge funds. Nonlocal hedge funds are defined as hedge funds located outside the FoF's local area, defined alternatingly as the country (the first two rows), state (the next two rows), or metropolitan statistical area (MSA) (the bottom two rows) in which the FoF is located. Only U.S. FoFs are included in the analysis when the FoF's local area is defined as its state or MSA. In Panel B, we repeat the baseline analysis using the PB and OPB indexes purged of hedge funds outside the FoF's focus style, which we identify using a proprietary data obtained from TASS. W_i^{PB} is given by $w_i^{PB}/\left(w_i^{PB}+w_i^{OPB}\right)$, where w_i^{PB} and w_i^{OPB} represent the FoF's average weight over time on the purged PB and OPB indexes, respectively; W_m^{PB} is given by $w_m^{PB}/\left(w_m^{PB}+w_m^{OPB}\right)$, where w_m^{PB} and w_m^{OPB} represent the market FoF's average weight over time on the purged PB and OPB indexes, respectively. Cross-sectional averages of W_i^{PB} and W_m^{PB} and the difference between them are presented in the table, along with the average R^2 from each equation (in brackets) and the t-statistic for the difference (in parentheses).

TABLE 5: **Determinants of PB bias**

	Dependent variable: PB bias$_{t+1:t+24}$ (%)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
log(AUM$_t$)	-0.61									
	(-0.74)									
log(FamAUM$_t$)		-0.68								
		(-1.03)								
log(FamFoFAUM$_t$)			-1.70							
			(-2.53)							
log(1 + FamHFAUM$_t$)			0.49							
			(3.49)							
MgmtFee (%)				1.19						
				(0.52)						
IncentiveFee (%)					0.43					
					(2.33)					
PersonalCapital						4.60				
						(1.65)				
log(Age$_t$)							-2.21			
							(-1.40)			
log(FamAge$_t$)								-3.29		
								(-1.87)		
log(FamFoFAge$_t$)									-6.04	
									(-3.61)	
log(1 + FamHFAge$_t$)									1.07	
									(2.40)	
log(NumHFClients$_t$)										2.71
										(4.47)
log(NumConnFoFs$_t$)										-2.86
										(-2.65)
Adjusted R^2 (%)	8.48	9.83	10.50	9.57	10.34	9.80	9.41	9.54	10.38	11.22
Observations	21,537	27,483	23,945	40,590	40,405	40,590	36,815	36,815	36,815	34,872

(continued)

TABLE 5 (Continued): **Determinants of PB bias**

	Dependent variable: PB bias$_{t+1:t+24}$ (%)					
	(11)	(12)	(13)	(14)	(15)	(16)
log(AUM$_t$)	-0.06	0.62	0.02			
	(-0.06)	(0.55)	(0.02)			
log(FamAUM$_t$)	-0.81					
	(-0.89)					
log(FamFoFAUM$_t$)		-1.95	-1.38			
		(-2.03)	(-1.41)			
log($1+$FamHFAUM$_t$)		0.48	0.30			
		(3.19)	(1.96)			
MgmtFee (%)	0.19	0.06	0.76	1.64	2.04	2.24
	(0.09)	(0.03)	(0.31)	(0.67)	(0.83)	(0.87)
IncentiveFee (%)	0.60	0.54	0.58	0.41	0.37	0.35
	(2.99)	(2.65)	(2.92)	(1.98)	(1.81)	(1.67)
PersonalCapital	1.86	2.80	1.93	5.28	6.04	4.70
	(0.61)	(0.93)	(0.64)	(1.84)	(2.12)	(1.63)
log(Age$_t$)				-1.75	0.29	0.21
				(-0.90)	(0.15)	(0.10)
log(FamAge$_t$)				-2.17		
				(-0.98)		
log(FamFoFAge$_t$)					-6.59	-5.86
					(-2.78)	(-2.36)
log($1+$FamHFAge$_t$)					1.21	0.92
					(2.71)	(1.98)
log(NumHFClients$_t$)			2.75			1.94
			(3.05)			(3.12)
log(NumConnFoFs$_t$)			-1.29			-2.51
			(-1.05)			(-2.27)
Adjusted R^2 (%)	10.18	11.66	13.22	10.80	11.70	12.94
Observations	21,500	20,596	19,387	36,644	36,644	34,708

This table reports the panel regression results for PB bias on lagged FoF and PB characteristics. PB bias is estimated via Eqs. (7) and (8) for FoFs that allow at least 18-month estimation period within each 24-month window. AUM$_t$ denotes FoF size; FamAUM$_t$ denotes fund family size; FamFoFAUM$_t$ denotes the size of the fund family's FoF business (defined as the total AUM of all the individual FoFs belonging to the fund family); FamHFAUM$_t$ denotes the size of fund family's hedge fund business (defined as the total AUM of all the individual hedge funds belonging to the fund family; 0 if the fund family has no hedge funds as of month t); MgmtFee denotes management fee; IncentiveFee denotes incentive fee; PersonalCapital denotes an indicator variable for whether personal capital is committed; Age$_t$ denotes FoF age; FamAge$_t$ denotes fund family age; FamFoFAge$_t$ denotes the age of the fund family's FoF business (defined as the number of months since the inception of the first FoF of the fund family); FamHFAge$_t$ denotes the age of the fund family's hedge fund business (defined as the number of months since the inception of the first hedge fund of the fund family; 0 if the fund family has never had a hedge fund as of month t); NumHFClients$_t$ denotes PB size (defined as the number of hedge fund clients); and NumConnFoFs$_t$ denotes the number of FoFs connected to the PB. In case the FoF is connected to multiple PBs, the PB characteristic variables are computed as the average across the PBs. The table reports the results when month fixed effects are included in the regressions, while standard errors are clustered by FoF. The extreme 1% of all variables are winsorized. The t-statistics are reported in parentheses.

TABLE 6: **Selection among PB hedge funds**

	$W_i^{PB^{above}}$ (%)	$W_m^{PB^{above}}$ (%)	Difference	N
$\geq$ top 25th percentile	26.99	10.66	16.33	596
	[49.87]	[90.43]	(11.44)	
$\geq$ top 50th percentile	36.58	19.48	17.11	624
	[49.79]	[90.24]	(11.82)	
$\geq$ top 75th percentile	54.90	43.89	11.02	588
	[50.18]	[90.52]	(6.78)	

We solve, for each sample FoF that allows at least a 24-month estimation period, a variant of Equations (7) and (8) where the PB index is replaced by its two subindexes, namely the PB^{above} and PB^{below} indexes. $W_i^{PB^{above}}$ is given by $w_i^{PB^{above}}/\left(w_i^{PB^{above}}+w_i^{PB^{below}}\right)$, where $w_i^{PB^{above}}$ and $w_i^{PB^{below}}$ represent the FoF's average weight over time on the PB^{above} and PB^{below} indexes, respectively; $W_m^{PB^{above}}$ is given by $w_m^{PB^{above}}/\left(w_m^{PB^{above}}+w_m^{PB^{below}}\right)$, where $w_m^{PB^{above}}$ and $w_m^{PB^{below}}$ represent the market FoF's average weight over time on the PB^{above} and PB^{below} indexes, respectively. Cross-sectional averages of $W_i^{PB^{above}}$ and $W_m^{PB^{above}}$ and the difference between them are reported in the table, along with the average R^2 from each equation (in brackets) and the t-statistic for the difference (in parentheses). The PB^{above} index consists of hedge funds in the PB index that are going to realize above-threshold returns at the end of the corresponding month; the PB^{below} index consists of the remaining hedge funds in the PB index. The first two rows of the table contain the results where we use the top-25th-percentile return of all sample hedge funds in the corresponding month as the threshold for inclusion in the PB^{above} index; the next two rows contain the results where we use the median return of all sample hedge funds in the corresponding month as the threshold for inclusion in the PB^{above} index; the bottom two rows contain the results where we use the bottom-25th-percentile return of all sample hedge funds in the corresponding month as the threshold for inclusion in the PB^{above} index.

TABLE 7: **Selection among OPB hedge funds**

	$W_i^{OPB^{above}}$ (%)	$W_m^{OPB^{above}}$ (%)	Difference	N
$\geq$ top 25th percentile	22.57	11.04	11.53	706
	[52.97]	[92.78]	(10.52)	
$\geq$ top 50th percentile	34.39	29.87	4.52	703
	[52.90]	[92.38]	(4.00)	
$\geq$ top 75th percentile	49.32	53.49	-4.17	702
	[52.83]	[91.97]	(-3.53)	

We solve, for each sample FoF that allows at least a 24-month estimation period, a variant of Equations (7) and (8) where the OPB index is replaced by its two subindexes, namely the OPB^{above} and OPB^{below} indexes. $W_i^{OPB^{above}}$ is given by $w_i^{OPB^{above}}/\left(w_i^{OPB^{above}}+w_i^{OPB^{below}}\right)$, where $w_i^{OPB^{above}}$ and $w_i^{OPB^{below}}$ represent the FoF's average weight over time on the OPB^{above} and OPB^{below} indexes, respectively; $W_m^{OPB^{above}}$ is given by $w_m^{OPB^{above}}/\left(w_m^{OPB^{above}}+w_m^{OPB^{below}}\right)$, where $w_m^{OPB^{above}}$ and $w_m^{OPB^{below}}$ represent the market FoF's average weight over time on the OPB^{above} and OPB^{below} indexes, respectively. Cross-sectional averages of $W_i^{OPB^{above}}$ and $W_m^{OPB^{above}}$ and the difference between them are reported in the table, along with the average R^2 from each equation (in brackets) and the t-statistic for the difference (in parentheses). The OPB^{above} index consists of hedge funds in the OPB index that are going to realize above-threshold returns at the end of the corresponding month; the OPB^{below} index consists of the remaining hedge funds in the OPB index. The first two rows of the table contain the results where we use the top-25th-percentile return of all sample hedge funds in the corresponding month as the threshold for inclusion in the OPB^{above} index; the next two rows contain the results where we use the median return of all sample hedge funds in the corresponding month as the threshold for inclusion in the OPB^{above} index; the bottom two rows contain the results where we use the bottom-25th-percentile return of all sample hedge funds in the corresponding month as the threshold for inclusion in the OPB^{above} index.

TABLE 8: **Portfolio performance based on PB bias**

	Sharpe ratio					Information ratio				
	1m	3m	6m	12m	24m	1m	3m	6m	12m	24m
Q1 (low)	0.10	0.10	0.10	0.11	0.10	0.04	0.03	0.04	0.05	0.05
Q2	0.12	0.13	0.12	0.12	0.11	0.08	0.10	0.07	0.08	0.07
Q3	0.06	0.05	0.06	0.07	0.09	0.01	-0.01	0.01	0.01	0.05
Q4 (high)	0.18	0.19	0.18	0.18	0.17	0.18	0.20	0.18	0.17	0.16
Q4 - Q1	0.08	0.10	0.08	0.07	0.07	0.14	0.17	0.15	0.11	0.10
p-value	0.04	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00

	Excess return (% per month)					Alpha (% per month)				
	1m	3m	6m	12m	24m	1m	3m	6m	12m	24m
Q1 (low)	0.21	0.20	0.20	0.21	0.20	0.07	0.04	0.06	0.08	0.08
t-stat	(1.31)	(1.19)	(1.24)	(1.33)	(1.30)	(0.57)	(0.34)	(0.45)	(0.69)	(0.73)
Q2	0.22	0.23	0.21	0.21	0.20	0.11	0.13	0.10	0.10	0.10
t-stat	(1.39)	(1.53)	(1.39)	(1.41)	(1.36)	(0.97)	(1.29)	(0.98)	(1.05)	(1.02)
Q3	0.12	0.10	0.12	0.13	0.18	0.01	-0.01	0.02	0.02	0.06
t-stat	(0.70)	(0.56)	(0.74)	(0.81)	(1.12)	(0.07)	(-0.10)	(0.18)	(0.19)	(0.63)
Q4 (high)	0.34	0.35	0.33	0.30	0.30	0.27	0.29	0.26	0.23	0.21
t-stat	(2.13)	(2.29)	(2.19)	(2.15)	(2.12)	(2.24)	(2.45)	(2.31)	(2.20)	(2.00)
Q4 - Q1	0.12	0.15	0.13	0.09	0.10	0.20	0.24	0.20	0.14	0.13
t-stat	(1.24)	(1.47)	(1.32)	(1.09)	(1.26)	(1.79)	(1.95)	(1.84)	(1.57)	(1.52)
Q4 - Q1:3	0.15	0.18	0.15	0.12	0.10	0.21	0.23	0.20	0.16	0.13
t-stat	(2.02)	(2.47)	(2.09)	(1.97)	(1.68)	(2.49)	(2.97)	(2.60)	(2.49)	(2.00)

We sort FoFs into quartiles based on their PB bias measured over the previous 24 months. PB bias is estimated via Equations (7) and (8) for FoFs that allow at least 18-month estimation period within each 24-month window. Portfolios are rebalanced every month and held for 1, 3, 6, 12, or 24 months. For the three-month holding period, for example, one-third of the portfolio is revised in each month. The top panel reports the monthly Sharpe ratio and information ratio of these portfolios; the bottom panel reports the monthly excess returns and Fung and Hsieh (2004) seven-factor adjusted alphas. The p-values are derived from 5,000 bootstrap simulations under the null of no difference between the corresponding performance measures for the low- and high-PB-bias portfolios. The t-statistics are derived from Newey–West standard errors with three lags. Q1:3 denotes a composite portfolio consisting of all FoFs from the first three quartiles.

TABLE 9: **Regressions of FoF performance on PB bias**

Panel A: Fama–MacBeth regressions

	Dependent variable: Performance$_{t+1:t+12}$			
	SR	IR	Ex. ret. (% p.m.)	Alpha (% p.m.)
PB bias$_{t-23:t}$ (%)	0.03	0.13	0.05	0.08
	(3.86)	(4.57)	(1.85)	(2.39)
Vol$_{t-23:t}$ (% p.m.)	-0.03	-0.08	0.04	-0.01
	(-5.37)	(-5.69)	(2.32)	(-0.64)
RedemptionNotice	-0.02	-0.02	-0.05	-0.04
	(-1.81)	(-0.58)	(-1.73)	(-0.79)
Lockup	-0.01	-0.02	-0.01	-0.01
	(-3.52)	(-2.72)	(-2.00)	(-1.99)
MgmtFee (%)	0.01	0.01	-0.07	-0.11
	(1.00)	(0.43)	(-2.76)	(-3.43)
IncentiveFee (%)	0.00	-0.01	0.00	-0.01
	(-2.56)	(-1.89)	(-1.11)	(-1.30)
log(Age$_t$)	0.01	-0.07	0.13	0.09
	(0.68)	(-1.51)	(2.38)	(1.28)
log(AUM$_t$)	0.03	0.04	0.01	-0.03
	(3.85)	(2.29)	(0.73)	(-1.09)
Flow$_{t-23:t}$ (%)	0.00	0.00	0.01	0.01
	(-0.68)	(-0.08)	(1.40)	(1.55)
$R_{t-23:t}$ (% p.m.)	0.03	0.14	0.08	0.17
	(2.03)	(2.85)	(1.48)	(2.79)
log(1 + MinInvestment)	0.03	0.09	0.05	0.06
	(2.73)	(2.98)	(2.47)	(2.00)
PersonalCapital	0.05	0.06	-0.01	0.06
	(2.23)	(0.85)	(-0.25)	(0.81)
HighWaterMark	0.14	0.18	0.34	0.27
	(4.27)	(2.35)	(4.34)	(3.16)
Leveraged	0.00	0.06	-0.01	-0.02
	(0.10)	(0.74)	(-0.25)	(-0.27)
Offshore	-0.04	-0.10	-0.03	0.07
	(-2.20)	(-1.98)	(-0.48)	(1.20)
Adjusted R^2 (%)	24.48	15.69	19.60	16.52
Observations	19,695	19,695	19,695	19,695

(continued)

TABLE 9 (Continued): **Regressions of FoF performance on PB bias**

Panel B: Panel regressions

	Dependent variable: Performance$_{t+1:t+12}$			
	SR	IR	Ex. ret. (% p.m.)	Alpha (% p.m.)
PB bias$_{t-23:t}$ (%)	0.02	0.10	0.03	0.05
	(1.81)	(3.39)	(1.13)	(2.00)
Vol$_{t-23:t}$ (% p.m.)	-0.03	-0.07	0.04	-0.01
	(-4.06)	(-3.65)	(1.90)	(-0.29)
RedemptionNotice	0.00	0.02	-0.01	0.02
	(-0.01)	(0.57)	(-0.34)	(0.82)
Lockup	0.00	-0.01	0.00	0.00
	(-1.59)	(-2.08)	(-0.43)	(-0.10)
MgmtFee (%)	-0.02	-0.05	-0.09	-0.09
	(-1.49)	(-1.28)	(-2.72)	(-2.69)
IncentiveFee (%)	0.00	-0.01	0.00	-0.01
	(-1.68)	(-1.36)	(-0.45)	(-2.07)
log(Age$_t$)	0.01	-0.04	0.12	0.07
	(0.28)	(-0.63)	(2.69)	(1.45)
log(AUM$_t$)	0.02	0.03	0.02	0.00
	(2.49)	(1.65)	(1.17)	(-0.15)
Flow$_{t-23:t}$ (%)	0.00	0.00	0.00	0.00
	(-0.29)	(1.27)	(-0.28)	(0.69)
$R_{t-23:t}$ (% p.m.)	0.01	0.07	-0.09	0.05
	(0.83)	(1.76)	(-1.92)	(0.94)
log(1 + MinInvestment)	0.01	0.03	0.02	0.01
	(2.17)	(1.78)	(1.61)	(1.55)
PersonalCapital	0.03	0.11	-0.01	0.07
	(1.42)	(1.58)	(-0.21)	(1.31)
HighWaterMark	0.08	0.16	0.23	0.22
	(3.46)	(2.20)	(4.28)	(3.96)
Leveraged	0.02	0.03	0.06	0.07
	(0.90)	(0.44)	(1.48)	(1.52)
Offshore	-0.05	-0.05	-0.11	0.02
	(-1.93)	(-0.70)	(-1.84)	(0.35)
Adjusted R^2 (%)	42.81	25.57	31.72	15.80
Observations	19,695	19,695	19,695	19,695

This table reports Fama–MacBeth and panel regression results for FoF performance on PB bias. Performance measures considered include Sharpe ratio (SR), information ratio (IR), average excess return (Ex. Ret.), and Fung and Hsieh (2004) alpha, estimated over the 12-month period after PB bias is calculated. PB bias is calculated as in Table 8. Panel A reports Fama–MacBeth regression results where t-statistics are derived from Newey–West standard errors with three lags; Panel B reports panel regression results with month fixed effects and standard errors are clustered by FoF. We standardize PB bias by subtracting the mean and dividing by the standard deviation. The extreme 1% of all variables are winsorized. The t-statistics are reported in parentheses.

TABLE 10: **Holding-based analysis**

Panel A: PB bias

	$W_{i,t}^{PB}$ (%)	$W_{m,t}^{PB}$ (%)	Difference	N
Estimate	55.36	50.14	5.21	480
			(2.30)	

Panel B: Posthired returns

	$R_{i,t+1}^{PBh}$ (%)	$R_{i,t+1}^{OPBh}$ (%)	Difference	N
$k=4$	1.22	0.31	0.90	94
	(2.03)	(0.58)	(2.02)	
$k=8$	1.46	0.51	0.94	115
	(2.70)	(1.16)	(2.58)	
$k=12$	1.60	0.68	0.92	119
	(2.84)	(1.50)	(2.22)	

Panel C: Postfired returns

	$R_{i,t+1}^{PBf}$ (%)	$R_{i,t+1}^{OPBf}$ (%)	Difference	N
$k=4$	0.36	0.20	0.16	78
	(0.37)	(0.29)	(0.19)	
$k=8$	0.09	0.50	-0.41	120
	(0.13)	(0.90)	(-0.49)	
$k=12$	-0.03	0.26	-0.29	131
	(-0.04)	(0.44)	(-0.34)	

This table reports the results of our holding-based analyses using the data from registered FoFs. In Panel A, we estimate PB bias for a sample of registered FoFs for which we identify PB connections. We compute $W_{i,t}^{PB}$, as defined in Equation (4), for each FoF-quarter observation with at least two-thirds of the FoF's assets matched with PB information. The benchmark weight $W_{m,t}^{PB}$, with which to compare $W_{i,t}^{PB}$, is computed based on the aggregate portfolio of all hedge funds held by the universe of registered FoFs. Pooled averages of $W_{i,t}^{PB}$ and $W_{m,t}^{PB}$, as well as the difference between them, are reported in the first three columns of the panel, along with the t-statistic for the difference (in parenthesis) adjusted for time-series dependence in the data. In Panel B, we form quarterly portfolios of PB and OPB hedge funds "hired" by each registered FoF, defined as those added to the FoF's portfolio in the recent k quarters, where $k \in \{4, 8, 12\}$. We then compute their value-weighted returns over the subsequent quarter, denoted by $R_{i,t+1}^{PBh}$ and $R_{i,t+1}^{OPBh}$, respectively. $R_{i,t+1}^{PBh}$ and $R_{i,t+1}^{OPBh}$, as well as the difference between them, are computed for each FoF-quarter observation where PB information is available for at least two-thirds of the FoF's newly hired positions (in assets) and we have at least one PB and OPB hedge fund among them with nonmissing return in the subsequent quarter. Pooled averages are reported in the first three columns of the panel, along with t-statistic for the difference (in parenthesis) adjusted for time-series and cross-sectional dependence in the data. In Panel C, we repeat the analysis in Panel B, by forming equal-weighted portfolios of PB and OPB hedge funds "fired" by each registered FoF, defined as those dropped from the FoF's portfolio in the recent k quarters, where $k \in \{4, 8, 12\}$. Quarterly returns on individual hedge funds hired or fired by registered FoFs are computed via Equation (14).