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

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Abstract. Using the setting of funds of hedge funds (FoFs), we show that prime brokers (PBs) facilitate investors' search for informed hedge fund managers. We find that FoFs exhibit PB bias, a disproportionate preference for hedge funds serviced by their connected PBs. This PB bias is stronger when the cost of hedge fund due diligence is higher relative to capital and when the FoF's management firm generates higher prime brokerage fees. PB bias also predicts FoF performance: the highest PB-bias quartile outperforms the rest by 2.08%–2.45% per annum after adjusting for differences in their risks.

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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, because of 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.[1] 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 in which 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 provide a range of services that are essential to hedge fund operations from securities lending and debt financing to global custody and clearing and concierge services, such as risk management and capital introduction. 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. Specifically, PBs observe a hedge fund's trading activities and holdings, are incentivized (as lenders) to monitor the value of collateral and the risk of a hedge fund's portfolio, and undertake due diligence before promoting a hedge fund via capital introduction events (see, e.g., Lhabitant 2006 for more details). Given this, PBs are well placed—indeed they may be best placed among market participants—to know their clients' potential for future performance and risk of failure.[2] Using a major class of hedge fund investors, namely, funds of hedge funds (FoFs), we ask if investors recognize and, importantly, benefit from this potential source of hedge fund information in their search for informed hedge fund managers.

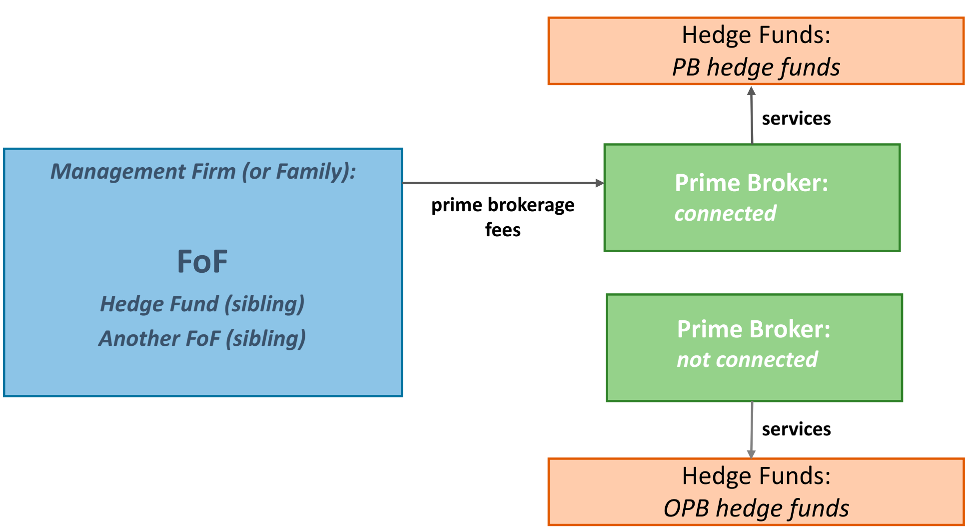
A key consideration in our empirical strategy is that some PBs may be easier to reach out to than other PBs. For each FoF, we identify such PBs ("connected" PBs) as those that do business with the FoF's management firm, that is, those that service at least one fund in the FoF's family.[3] FoFs we identify as connected to a PB are likely to be among the PB's existing contacts because PBs maintain close contacts with potential hedge fund investors in their network in assisting a hedge fund's efforts in raising capital. Such FoFs may also be important to the connected PB given the PB's incentive to retain lucrative prime brokerage business with the FoFs' management firms.[4] We then test if FoFs have an advantage in searching for informed managers among the connected PBs' hedge fund clients (henceforth, PB hedge funds) relative to among other hedge funds (henceforth, OPB hedge funds). 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 the FoFs' management firms.[5] Figure 1 illustrates the logical relationship between the terms introduced here.

We begin our empirical analysis by examining whether FoFs exhibit "PB bias," that is, disproportionate preference for hedge funds serviced by their connected PBs. Because the cost of hedge fund due diligence is high relative to FoFs' capital (e.g., Brown et al. 2008a; 2012a), this is a natural outcome if FoFs are able to gather and vet information about their PB hedge funds at a lower cost than they could about OPB hedge funds. In our main analysis, we use 1,303 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 et al. (2020). Our baseline results show that the average FoF's weight on its PB hedge funds is 35.27%, which is disproportionately high given that its PB hedge funds comprise only 21.59% 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 et al. (2013; 2015a; b), 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 4.12% on average, toward their respective PB hedge funds.[6]

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 the Sialm et al. (2020) 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 of FoFs' style focus or internal investments in sibling hedge funds (Bhattacharya et al. 2013, Elton et al. 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 in which we replace an 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 fewer 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

Figure 1. (Color online) Key Concepts and Terms



Notes. A PB is identified as connected to an FoF when the PB does business with the FoF's management firm, that is, when the PB serves at least one fund in the FoF's family. The term "management firm" refers to a firm that manages one or more FoFs and/or hedge funds and is used interchangeably with the term "family," which refers to a group of funds managed by the same management firm. The figure depicts a case in which the FoF has a hedge fund and another FoF in the same family. We use the term "sibling" to refer to other funds in the FoF's family. Though not depicted in the figure, a FoF can also have only hedge fund siblings, only FoF siblings, or no siblings. Unless an FoF has no siblings, connected PBs can be identified even when the FoF does not use prime brokerage services if the FoF has a sibling fund that does. We call the connected PBs' hedge fund clients "PB hedge funds" and all the other hedge funds in the market "OPB hedge funds." Our central question is whether an FoF has an advantage in searching for informed managers among its PB hedge funds relative to among OPB hedge funds.

with information-hungry FoFs tapping PBs for hedge fund information. We also find stronger PB bias among FoFs with larger hedge fund siblings, consistent with PBs being more forthcoming with information when the FoF's management firm generates higher prime brokerage fees. 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 breadth 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 et al. 2006, Bhattacharya et al. 2013)—is that fund families use their (low-fee) FoFs as a liquidity provider to distressed 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% hedge funds is 15.92 percentage points higher than the market's weight on the same hedge funds. The corresponding number for the bottom 25% is 11.77 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% hedge funds is no longer observed (or, in fact, reversed) among OPB hedge funds. Similarly, we also find that FoFs, while successfully underweighting PB hedge funds that are going to fail subsequently, overweight other such hedge funds. This highlights that the value of PB connections lies particularly in detecting and avoiding hedge funds that will do poorly or even fail as opposed to selecting top-performing hedge funds. According to Brown et al. (2008a), this is precisely where the value of hedge fund due diligence lies, suggesting that PB connections facilitate due diligence on PB hedge funds.

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 a year, for example, the highest PB-bias quartile outperforms the lowest quartile (bottom three quartiles) by 2.26% (2.45%) 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 the Fung et al. (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 remains strong if not stronger when we use performance measures that penalize less diversified (more concentrated) FoFs, such as information ratio.

In addition, using our sample of quarterly portfolio holdings disclosed by registered FoFs, we find that PB hedge funds added to an FoF's portfolio outperform OPB hedge funds added to the same FoF's portfolio by 0.88%–0.92% per quarter on average though no significant difference is found between PB and OPB hedge funds dropped from an 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 because there are fewer funds from which to choose, and incumbent investors face fewer frictions in monitoring funds than prospective investors (Hochberg et al. 2014, Aiken et al. 2015b).

Overall, our results suggest that FoFs benefit from their connections to PBs in selecting informed hedge fund managers. In this regard, our results relate to existing findings that institutional investors' connections to investment banks inform their trading activities in securities markets.[7] 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 PBs (1) make informed introductions, (2) help cross-verify information that FoFs gather through their own due diligence,[8] 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.[9] In any case, our results point 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 et al. 2010, Aragon and Strahan 2012), whereas 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 et al. 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 informational 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.[10] 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 in a way that benefits FoF performance.

Our paper is also related to studies of information frictions in the search for informed asset managers. Theoretically, 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 et al. (2008a) 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 et al. (2020) show that FoFs tend to overinvest in local hedge funds for which information frictions are lower and 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.

In addition, we add to prior studies of portfolio holdings disclosed by SEC-registered FoFs.[11] Aiken et al. (2015b) and Gao et al. (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 hedge funds that they already own. Our analysis of holdings shows that PB connections benefit FoFs in making "hiring" decisions, that is, in assessing the prospects of hedge funds that they do not already own.

Finally, a number of studies in the hedge fund literature aim to develop skill measures or fund characteristics that help predict hedge fund performance.[12] However, because information about hedge funds' trading activities or security holdings is scarce, assessing managerial ability is a challenging task that relies mainly on funds' historical returns or other limited public disclosures of information that is more readily and completely available to the funds' PBs.[13] We show that investors recognize and benefit from PBs' unique informational position and, thus, contribute to our understanding of how investors select informed hedge fund managers.

2. Data and Descriptive Statistics

2.1. Lipper TASS Database

We begin with the sample of FoFs and hedge funds as well as their PBs from Chung and Kang (2016), who combine multiple downloads of the Lipper TASS database to construct a panel of broker–client relationships. We extend this panel by utilizing additional 30 downloads of the same database since the last download made by Chung and Kang (2016).[14] The extended data cover 2,527 FoFs and 6,800 hedge funds, which represent all live and graveyard funds in TASS that report monthly net-of-fee U.S. dollar returns from January 1994 to December 2016 after correcting for master-feeder duplicates as in Aggarwal and Jorion (2010).

Chung and Kang (2016) assume that the first PB a fund reports to TASS is 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.[15] As a result, we identify 343 unique PBs by their cleaned ID across our sample funds and months. 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 100 unique PBs.

Our sample of 2,527 FoFs are managed by 952 management firms, of which 575 management firms simultaneously manage at least one other fund (FoF or hedge fund) in our sample. At the fund level, 1,941 FoFs have at least one other FoF in the same family, whereas 976 have at least one hedge fund in the family. We identify an FoF as connected to a PB if the PB does business with the FoF's management firm, that is, if the PB serves at least one fund in the FoF's family. In our sample, a total of 1,303 FoFs are identified as connected to 100 PBs because a PB serves the FoF itself (599 FoFs) or a PB serves the FoF's sibling fund (1,161 FoFs) or both. In any case, we use all 2,527 FoFs and 6,800 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.

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 128 FoFs and 321 hedge funds, whereas at the middle of the sample period, there are 978 FoFs and 2,072 hedge funds. The numbers drops to 397 FoFs and 727 hedge funds in 2016, mainly because of the financial crisis in 2008 and the decrease in TASS's coverage afterward (see Joenväärä et al. 2021). The number of PBs averages about 33 per month, ranging from a low of 19 in January 1994 to a high of 44 in April 2008. The average (median) PB services 5.20 (3.74) FoFs and 37.10 (10.84) hedge funds per month, on average. Because 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: taking into account all PBs that service either the FoF or any other fund managed under the same roof with the FoF, the average (median) FoF is connected to 1.33 (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 99.39 (31.18) 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 et al. 2012a, Aiken et al. 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 et al. (2013) as modified by Gao et al. (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 (which involves identifying registered FoFs' sibling funds and their PBs) and (2) finding PB information for each portfolio hedge fund held by registered FoFs. First, to identify a registered FoF's PB connections, we search TASS for the name of the registered FoF and the name of its adviser (obtained from form N-SAR, item 8). If either name shows up in TASS, then this can lead us to identify the registered FoF's sibling funds that report to TASS. For registered FoFs and their sibling funds that report to TASS, we employ our TASS sample described earlier and the 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 29 registered FoFs over the period from 2004Q3 to 2016Q4 (496 FoF–quarter observations). Further, we make use of historical form ADVs filed by registered FoFs' advisers because, since 2012Q1, item 7.B therein provides us with a list of private funds under their management and the funds' service provider information.[16] This allows us to expand the

Table 1. Summary Statistics

Panel A

Month	Number of FoFs	Number of hedge funds	Number of PBs	Number of FoFs per PB: Mean	Median	Maximum	Minimum	Number of hedge funds per PB: Mean	Median	Maximum	Minimum
1994	128.00	321.00	19.00	3.05	2.00	9.00	0.00	17.21	12.00	68.00	0.00
2005	978.00	2,072.00	39.00	6.74	4.00	36.00	0.00	50.41	10.00	414.00	0.00
2016	397.00	727.00	23.00	3.35	5.00	8.00	0.00	21.04	10.00	89.00	0.00
Average	644.64	1,450.26	32.62	5.20	3.74	22.97	0.00	37.10	10.84	260.50	0.50

Panel B

Month	Number of FoFs with PB connections	Number of connected PBs per FoF: Mean	Median	Maximum	Minimum	Number of PB hedge funds per FoF: Mean	Median	Maximum	Minimum
1994	77.00	1.03	1.00	2.00	1.00	27.65	18.00	67.00	0.00
2005	537.00	1.52	1.00	5.00	1.00	179.45	44.00	1,051.00	0.00
2016	132.00	1.07	1.00	2.00	1.00	17.24	2.00	127.00	0.00
Average	351.16	1.33	1.00	4.50	1.00	99.39	31.18	605.27	0.50

Notes. 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 for January 1994, June 2005, and December 2016. Panel B 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.

number of observations for which we identify PB connections to a total of 51 registered FoFs from 2004Q3 to 2016Q4 (927 FoF–quarter observations).

Next, to find PB information for portfolio hedge funds held by registered FoFs, we use the panel of broker–client relationships constructed earlier and further augment it 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 the fund stopped reporting to TASS and 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 927 FoF–quarter observations, 107 (258) observations have fewer than half (two thirds) of the FoF's assets matched with PB information. This paucity of 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

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

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.[17] 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 $\mathcal{I}_{OPB}$.[18] 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

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

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.[19] 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 FoF 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 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

Whereas it is possible to determine an FoF's PB bias from an analysis of the FoF's holdings, a return-based approach of the sort proposed by Sialm et al. (2020) 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 can 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 can then be interpreted as the FoF's *average* weights over time (thus, denoted without the subscript t subsequently) 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:

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

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. The "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 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.[20] 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.[21]

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:

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

Following Sialm et al. (2020), 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 $W_i^{PB} = w_i^{PB}/(w_i^{PB} + w_i^{OPB})$ is then given by $W_m^{PB} = w_m^{PB}/(w_m^{PB} + w_m^{OPB})$, 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).[22] Our baseline results show that FoFs exhibit a strong bias in favor of hedge funds serviced by their connected PBs: the average FoF allocates 35.27% of its hedge fund portfolio to those serviced by its connected PBs, whereas only 21.59% is allocated to them by the market FoF. The PB bias, on average, is 13.68% and is highly statistically significant.

It should be pointed out that the 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 et al. (2009).[23]

Table 2. PB Bias

	W_i^{PB}, %	W_m^{PB}, %	Difference	N
Baseline	35.27	21.59	13.68***	888
	[46.64]	[87.35]	(12.40)	
Gross-of-fee FoF returns	38.26	23.28	14.98***	319
	[49.51]	[89.09]	(7.81)	
Equations (9) and (10)	35.36	21.80	13.56***	884
	[46.93]	[87.36]	(12.28)	
Fung–Hsieh factors	33.85	21.90	11.95***	889
	[60.26]	[90.76]	(11.65)	
Indirect	33.68	23.80	9.88***	583
	[48.52]	[87.60]	(7.70)	
Auditors	55.74	53.70	2.04	851
	[45.96]	[89.23]	(1.54)	
Excluding top five PBs	29.14	15.12	14.02***	628
	[46.67]	[88.26]	(11.31)	

Notes. 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 $w_i^{PB}/(w_i^{PB} + w_i^{OPB})$, 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 $w_m^{PB}/(w_m^{PB} + w_m^{OPB})$, 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 et al. (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 to 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 9th and 10th 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 11th and 12th 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 in which the FoF is connected to at least one of the top five PBs, defined based on the number of hedge fund clients each month.

***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Note that we do not constrain the w terms to sum to one when solving Equations (7) and (8) because, as discussed, we allow for FoF 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:

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

and

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

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 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 et al. (2020) 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.[24] The results are reported in the seventh and eighth rows of Table 2 and show that PB bias remains largely unchanged.[25]

3.3. PB Bias: Additional Results

3.3.1. Indirect Connections. So far, we have defined an 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 an 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.[26] 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 PBs. The results, reported in the 9th and 10th 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 for which 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.[27] As expected, the results reported in the 11th and 12th rows of Table 2 show that there is no significant bias, reassuring that our results 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 observations for which the FoF is connected to one of the top 5 PBs based on the number of hedge fund clients.[28] These 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.[29]

3.3.4. Purging the Effect of Other Known Preferences. Sialm et al. (2020) 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:

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

where

$$w_{i,t}^{PB} = \sum_{j \in \mathcal{I}_{PB} \setminus \mathcal{I}_L} x_{i,j,t} \geq 0, \qquad R_{i,t}^{PB} = \sum_{j \in \mathcal{I}_{PB} \setminus \mathcal{I}_L} \frac{x_{i,j,t}}{w_{i,t}^{PB}} R_{j,t},$$

$$w_{i,t}^{OPB} = \sum_{j \in \mathcal{I}_{OPB} \setminus \mathcal{I}_L} x_{i,j,t} \geq 0, \qquad R_{i,t}^{OPB} = \sum_{j \in \mathcal{I}_{OPB} \setminus \mathcal{I}_L} \frac{x_{i,j,t}}{w_{i,t}^{OPB}} R_{j,t},$$

$$w_{i,t}^{L} = \sum_{j \in \mathcal{I}_L} x_{i,j,t} \geq 0, \qquad R_{i,t}^{L} = \sum_{j \in \mathcal{I}_L} \frac{x_{i,j,t}}{w_{i,t}^{L}} R_{j,t}, \qquad (12)$$

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 an 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 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 metropolitan statistical area (MSA) (the bottom two rows) as the FoF, suggesting that PB bias is not just a repackaging of the local bias effect.[30]

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 et al. 2013, Elton et al. 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).

Whereas many FoFs are diversified across multiple hedge fund styles, some may be more concentrated on a certain style of hedge funds.[31] To ensure that we are not attributing FoF 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 an 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.

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	43.29	27.29	16.01***	843
	[48.56]	[89.54]	(11.75)	
State	48.20	22.94	25.26***	257
	[49.35]	[89.58]	(9.98)	
MSA	49.16	25.29	23.87***	241
	[48.60]	[89.76]	(8.88)	
Panel B: Purged of style preference				
Focus style	40.26	21.04	19.22***	294
	[52.98]	[88.93]	(8.55)	

Notes. In panel A, 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 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 proprietary data obtained from TASS. W_i^{PB} is given by $w_i^{PB}/(w_i^{PB} + w_i^{OPB})$, 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 $w_m^{PB}/(w_m^{PB} + w_m^{OPB})$, 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).

***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Overall, the results in Table 3 show that PB bias is not merely a manifestation of FoF local preference and style focus. In fact, compared with our baseline results (13.68%), the magnitude of PB bias is larger when we purge the PB and OPB indexes of in-state (25.26%) and in-MSA (23.87%) hedge funds and of hedge funds within the FoF's focus style (19.22%); 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 roughly halves in magnitude among in-state (8.49%) and in-MSA (12.49%) 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

Table 4. PB Bias Within Local Area or Focus Style

	W_i^{PB}, %	W_m^{PB}, %	Difference	N
Panel A: Within local area				
Country	41.59	25.43	16.17***	679
	[50.13]	[89.89]	(10.36)	
State	49.06	40.56	8.49**	210
	[49.94]	[89.20]	(2.53)	
MSA	47.71	35.22	12.49***	203
	[48.24]	[89.13]	(3.73)	
Panel B: Within focus style				
Focus style	38.73	38.63	0.09	231
	[54.20]	[88.79]	(0.04)	

Notes. In Panel A, 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 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 proprietary data obtained from TASS. W_i^{PB} is given by $w_i^{PB}/(w_i^{PB}+w_i^{OPB})$, 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 $w_m^{PB}/(w_m^{PB}+w_m^{OPB})$, 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).

***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

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 FoF preference for PB hedge funds can increase with the 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 fewer resources for hedge fund due diligence, such as smaller FoFs or FoFs belonging to smaller management firms, especially those managing smaller FoF assets.[32] In addition, if PB bias is indeed a result of FoFs searching for informed managers (as opposed to random managers) among PB hedge funds, we would expect PB bias to be 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 informational 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. Because a hedge fund business is likely to be more lucrative for PBs than an FoF business of an equal size, we use the management firm's hedge fund assets under management (AUM) rather than total AUM to more cleanly capture PBs' incentive to cater to FoFs. Conversely, we use the management firm's FoF AUM rather than total AUM to more cleanly capture in-house resources into which the FoF could tap for hedge fund due diligence. Interestingly, a hedge fund sibling and an FoF sibling are, thus, expected to have the opposite effects on the FoF's PB bias.

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 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. Specifically, PB bias is significantly negatively related to the size of the fund family's FoF business (*FamFoFAUM*), our measure of in-house resources for hedge fund due diligence. PB bias is also positively and statistically strongly related to incentive fee rates (IncentiveFee) and, to a lesser degree, to whether 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*), consistent with an FoF standing to benefit from the importance of its hedge fund siblings.[33] 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 (albeit insignificant) effect on PB bias, whereas that of FoF business (*FamFoFAge*) has a strong negative effect, consistent with fund families with more experience in hedge fund due diligence relying less on PB connections. Finally, PB characteristics enter the regression with predicted signs: PB bias is positively related to the number of hedge fund clients (*NumHFClients*) and

Table 5. Determinants of PB Bias

	Dependent variable: PB bias$_{t+1:t+24}$, %					
	(1)	(2)	(3)	(4)	(5)	(6)
log (AUM$_t$)	−0.83	−0.05	−0.46			
	(−1.20)	(−0.07)	(−0.63)			
log (FamAUM$_t$)	−0.92					
	(−1.29)					
log (FamFoFAUM$_t$)		−2.12***	−1.73**			
		(−2.94)	(−2.41)			
log (1 + FamHFAUM$_t$)		0.31***	0.24**			
		(2.62)	(2.08)			
MgmtFee, %	1.96	2.13	2.65	2.61	2.92	2.97
	(0.92)	(0.99)	(1.16)	(1.15)	(1.26)	(1.26)
IncentiveFee, %	0.71***	0.64***	0.68***	0.52***	0.50***	0.49***
	(4.22)	(3.84)	(4.13)	(3.04)	(2.90)	(2.81)
PersonalCapital	1.82	1.90	1.32	4.42*	4.80**	3.72
	(0.72)	(0.76)	(0.53)	(1.86)	(2.02)	(1.55)
log (Age$_t$)				−1.26	0.01	−0.44
				(−0.80)	(0.01)	(−0.27)
log (FamAge$_t$)				−2.15		
				(−1.15)		
log (FamFoFAge$_t$)					−4.80**	−3.61*
					(−2.42)	(−1.76)
log (1 + FamHFAge$_t$)					0.58	0.50
					(1.57)	(1.29)
log (NumHFClients$_t$)			1.87***			1.55***
			(2.72)			(2.94)
log (NumConnFoFs$_t$)			−2.28**			−3.03***
			(−2.33)			(−3.44)
Adjusted R^2, %	8.55	9.44	10.41	7.98	8.30	9.20
Observations	32,782	31,412	30,071	54,276	54,276	51,870

Notes. This table reports the panel regression results for PB bias on lagged FoF and PB characteristics. PB bias is estimated via Equations (7) and (8) for FoFs that allow at least an 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 aggregate 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 aggregate AUM of all the individual hedge funds belonging to the fund family; zero 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; zero 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 and standard errors are clustered by FoF. The extreme 1% of all variables are winsorized. The t-statistics are reported in parentheses.

***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

negatively related to the number of connected FoFs (*NumConnFoFs*) with or without FoF characteristics in the regression.[34] 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 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 PB hedge funds that subsequently perform poorly. To see if this is the case, we divide hedge funds in the PB index into two groups 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 $W_i^{PB^{above}} = w_i^{PB^{above}}/(w_i^{PB^{above}} + w_i^{PB^{below}})$, 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 $W_m^{PB^{above}} = w_m^{PB^{above}}/(w_m^{PB^{above}} + w_m^{PB^{below}})$.

Panel A of Table 6 reports the results based on whether the PB^{above} index includes PB hedge funds whose end-of-month returns are in the top 25% (i.e., ≥75th percentile), top 50% (i.e., ≥50th percentile), or top 75% (i.e., ≥25th percentile) of returns across all sample hedge funds in that month. 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, an FoF's weight on the top 25% hedge funds averages 15.92 percentage points higher than the market's weight on the same hedge funds, and an FoF's weight on the *bottom* 25% hedge funds averages 11.77 percentage points *lower* than the market benchmark. These results suggest that PB bias is unlikely a result of FoFs making random allocations to PB hedge funds. Rather, FoF selection among PB hedge funds reflects an information advantage in assessing the future prospects of PB hedge funds.[35]

Panel A of 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, an FoF's weight on the *bottom* 25% hedge funds now averages 2.64 percentage points *higher* than the market benchmark. That is, among OPB hedge funds, FoFs no longer underweight the bottom 25% hedge funds, suggesting that FoFs may find it difficult to detect and avoid dog funds without the help of a connected PB.

To strengthen this point, in panel B of Tables 6 and 7, we consider an alternative characterization of dog funds, namely, hedge fund failure. For each hedge fund at the beginning of each month, we follow Liang and Park (2010) and construct an indicator variable, *Hedge fund failure*, which equals one if the fund is going to fail in the next 12 months and zero otherwise. Specifically, we set *Hedge fund failure* to one if the fund (i) exits from TASS in the next 12 months, (ii) reports a negative average return over the six-month period before the exit, *and* (iii) reports a drop in AUM over the 12-month period before the exit. We then repeat our analysis in panel A after reconstructing the above and below indexes such that the above index now contains hedge funds with *Hedge fund failure* = 1 (instead of those whose end-of-month return is above a certain threshold). The results show that FoFs significantly underweight among PB hedge funds (see panel B of Table 6) but overweight among OPB hedge funds (see panel B of Table 7), hedge funds that are going to fail subsequently. Clearly, FoFs have an advantage in avoiding negative outcomes when selecting among PB hedge funds relative to among OPB hedge funds.

In a series of similar analyses that are not reported for brevity but are available upon request, we find that this propensity to underweight dog funds among PB hedge funds but not among OPB hedge funds is particularly strong for FoFs with high PB bias.[36] This holds when we use various other characterizations of dog funds, such as high downside risk (Liang and Park

Table 6. Selection Among PB Hedge Funds

	$W_i^{PB^{above}}$, %	$W_m^{PB^{above}}$, %	Difference	N
Panel A: Return				
≥75th percentile	26.21	10.28	15.92***	743
	[47.88]	[90.12]	(12.46)	
≥50th percentile	36.27	18.30	17.97***	778
	[46.92]	[89.69]	(13.81)	
≥25th percentile	52.01	40.24	11.77***	745
	[47.63]	[89.95]	(8.36)	
Panel B: Hedge fund failure				
= 1	33.87	41.11	−7.24***	532
	[48.79]	[88.80]	(−4.03)	

Notes. We solve, for each sample FoF that allows at least a 24-month estimation period, a variant of Equations (7) and (8) in which the PB index is replaced by its two subindexes, namely, the PB^{above} and PB^{below} indexes. That is, we solve quadratic programming problems based on the following representation of the FoF return:

$$R_{i,t}^{FOF} = w_{i,t}^{PB^{above}} R_{i,t}^{PB^{above}} + w_{i,t}^{PB^{below}} R_{i,t}^{PB^{below}} + w_{i,t}^{OPB} R_{i,t}^{OPB} + \epsilon_{i,t}.$$

$W_i^{PB^{above}}$ is given by $w_i^{PB^{above}}/(w_i^{PB^{above}} + w_i^{PB^{below}})$, where $w_i^{PB^{above}}$ and $w_i^{PB^{below}}$ represent the FoF's average weight over time on the PB^{above} and PB^{below} indexes, respectively; $W_m^{PB^{above}}$ is given by $w_m^{PB^{above}}/(w_m^{PB^{above}} + w_m^{PB^{below}})$, 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). In panel A, 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 panel contain the results for which we use the 75th-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 for which 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 for which we use the 25th-percentile return of all sample hedge funds in the corresponding month as the threshold for inclusion in the PB^{above} index. In panel B, the PB^{above} index consists of hedge funds in the PB index that are going to fail in the next 12 months (from the beginning of the corresponding month), that is, those with *Hedge fund failure* = 1; the PB^{below} index consists of the remaining hedge funds in the PB index. For each hedge fund at the beginning of each month, *Hedge fund failure* is set to one if the fund (i) exits from TASS in the next 12 months, (ii) reports a negative average return over the six-month period before the exit, *and* (iii) reports a drop in AUM over the 12-month period before the exit and zero otherwise.

***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 7. Selection Among OPB Hedge Funds

	$W_i^{OPB^{above}}$, %	$W_m^{OPB^{above}}$, %	Difference	N
		Panel A: Return		
≥75th percentile	23.67	10.62	13.05***	887
	[50.81]	[92.19]	(12.76)	
≥50th percentile	35.97	29.84	6.13***	885
	[50.83]	[91.83]	(5.94)	
≥25th percentile	51.42	54.06	−2.64**	885
	[50.67]	[91.42]	(−2.50)	
		Panel B: Hedge fund failure		
= 1	38.15	31.86	6.29***	873
	[50.38]	[91.12]	(5.79)	

Notes. We solve, for each sample FoF that allows at least a 24-month estimation period, a variant of Equations (7) and (8) in which the OPB index is replaced by its two subindexes, namely, the OPB^{above} and OPB^{below} indexes. That is, we solve quadratic programming problems based on the following representaion of the FoF return:

$$R_{i,t}^{FOF} = w_{i,t}^{PB} R_{i,t}^{PB} + w_{i,t}^{OPB^{above}} R_{i,t}^{OPB^{above}} + w_{i,t}^{OPB^{below}} R_{i,t}^{OPB^{below}} + \epsilon_{i,t}.$$

$W_i^{OPB^{above}}$ is given by $w_i^{OPB^{above}}/(w_i^{OPB^{above}} + w_i^{OPB^{below}})$, 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 $w_m^{OPB^{above}}/(w_m^{OPB^{above}} + w_m^{OPB^{below}})$, 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). In panel A, 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 panel contain the results for which we use the 75th-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 for which 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 for which we use the 25th-percentile return of all sample hedge funds in the corresponding month as the threshold for inclusion in the OPB^{above} index. In panel B, the OPB^{above} index consists of hedge funds in the OPB index that are going to fail in the next 12 months (from the beginning of the corresponding month), that is, those with *Hedge fund failure* = 1; the OPB^{below} index consists of the remaining hedge funds in the OPB index. For each hedge fund at the beginning of each month, *Hedge fund failure* is set to one if the fund (i) exits from TASS in the next 12 months, (ii) reports a negative average return over the six-month period before the exit, *and* (iii) reports a drop in AUM over the 12-month period before the exit and zero otherwise.

***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

2010), high operational risk (Brown et al. 2008b; 2009; 2012b), and low governance score (Ozik and Sadka 2015) as well as low ex post return and ultimate failure. However, FoFs with high PB bias do not overweight star funds among PB hedge funds any more than they do among OPB hedge funds. This is true whether we use high ex post return or measures of high upside potential (Bali et al. 2019) to identify star funds. Taken together, these results show that FoFs exhibit (high) PB bias not because PB connections make it easier to select star funds but rather because PB connections facilitate hedge fund due diligence that helps screen out dog funds.[37] Given the nature of information PBs may be most concerned with as lenders and risk managers, it makes sense that PB connections benefit FoFs particularly in detecting and avoiding funds that will do poorly or even fail as opposed to selecting funds that will stand out as top performers. From the perspective that FoFs add value by providing due diligence and diversification (e.g., Brown et al. 2008a), our results suggest that the value added by FoFs derives at least in part from their PB connections that help avoid risk of extreme negative outcomes.

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 expect FoFs with higher PB bias to earn higher returns ceteris paribus. In this section, 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.

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.[38] The portfolios run from January 1996 to December 2016, and their performance is measured using the Fung and Hsieh (2004) seven-factor adjusted alpha and the corresponding information ratio (defined as an FoF's alpha divided by its residual standard deviation) as well as the raw excess return and the Sortino ratio.[39]

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, an FoF with 50% of its assets invested in a hedge fund portfolio and the remaining in cash would have the same PB bias as otherwise identical FoFs that are fully invested (or more than fully invested) in the same hedge fund portfolio. In this regard, the Sortino and information ratios have an advantage because they are also invariant to FoF leverage and cash holdings. These features of the Sortino and information ratios 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 Sharpe (unreported), Sortino, and information ratios are all higher for the high- than the low-PB-bias portfolio. The differences are quite large; for example, the differences between the Sortino ratios of the high- and low-PB-bias portfolios range from 0.12 to 0.19. The statistical significance of the differences between Sortino and information ratios is obtained from a bootstrap procedure following Titman and Tiu (2011) and Chung and Kang (2016). The resulting p-values show that the differences between Sortino 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 0.26% to 0.28% per month (3.07%–3.35% per annum). In contrast, none of the other quartile portfolios deliver significant alpha over any holding horizon—either individually or combined (denoted by Q1:3). This is consistent with the cross-sectional variation in FoF alpha documented in Fung et al. (2008), who show that about one quarter of FoFs deliver significant alpha, whereas the rest do not. The differences between the alphas of the high-PB-bias and other portfolios are statistically significant, especially for longer holding horizons.

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 et al. (2012), and Chung and Kang (2016), we estimate the following regression:

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

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. The control variables, $\mathbf{Controls}_{i,t}$, include the standard deviation of FoF i's monthly excess returns over the past two years ($\text{Vol}_{i,t-23:t}$); the

Table 8. Portfolio Performance Based on PB Bias

	Sortino ratio					Information ratio				
	1m	3m	6m	12m	24m	1m	3m	6m	12m	24m
Q1 (low)	0.20	0.18	0.17	0.18	0.20	0.08	0.07	0.06	0.07	0.09
Q2	0.19	0.20	0.18	0.17	0.15	0.07	0.08	0.06	0.05	0.04
Q3	0.12	0.12	0.15	0.16	0.19	0.04	0.03	0.05	0.06	0.09
Q4 (high)	0.32	0.33	0.33	0.36	0.35	0.19	0.20	0.20	0.22	0.21
Q4 − Q1	0.12**	0.14***	0.16***	0.19***	0.15***	0.11**	0.13***	0.14***	0.15***	0.12***
p-value	0.04	0.00	0.00	0.00	0.00	0.02	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)	0.22	0.21	0.20	0.19	0.21*	0.12	0.10	0.09	0.09	0.12
t-stat	(1.62)	(1.53)	(1.48)	(1.48)	(1.68)	(1.12)	(0.93)	(0.83)	(0.91)	(1.33)
Q2	0.20	0.20	0.18	0.16	0.15	0.09	0.09	0.07	0.06	0.04
t-stat	(1.63)	(1.64)	(1.45)	(1.35)	(1.23)	(1.03)	(1.14)	(0.89)	(0.80)	(0.54)
Q3	0.13	0.13	0.15	0.16	0.19	0.05	0.04	0.06	0.07	0.11
t-stat	(1.05)	(1.03)	(1.23)	(1.32)	(1.56)	(0.55)	(0.43)	(0.77)	(0.91)	(1.34)
Q1:3	0.18	0.18	0.18	0.17	0.18	0.08	0.08	0.07	0.08	0.09
t-stat	(1.48)	(1.44)	(1.42)	(1.41)	(1.52)	(0.99)	(0.89)	(0.88)	(0.92)	(1.14)
Q4 (high)	0.30**	0.30**	0.30**	0.32***	0.31***	0.26**	0.27***	0.27***	0.28***	0.26***
t-stat	(2.42)	(2.47)	(2.54)	(2.72)	(2.62)	(2.47)	(2.59)	(2.72)	(2.97)	(2.84)
Q4 − Q1	0.08	0.10	0.10	0.12	0.10	0.14	0.17	0.18*	0.19**	0.15**
t-stat	(0.92)	(1.05)	(1.17)	(1.50)	(1.44)	(1.34)	(1.51)	(1.66)	(2.01)	(2.05)
Q4 − Q1:3	0.12	0.12	0.13*	0.14**	0.13**	0.17**	0.19**	0.19**	0.20***	0.18***
t-stat	(1.54)	(1.63)	(1.75)	(2.22)	(2.20)	(2.10)	(2.18)	(2.33)	(3.00)	(3.14)

Notes. 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 an 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 Sortino and information ratios 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.

***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 9. Regressions of FoF Performance on PB Bias

Panel A: Fama–MacBeth regressions

	Dependent variable: $\text{Performance}_{t+1:t+12}$			
	SR	IR	Ex. ret. (% p.m.)	Alpha (% p.m.)
PB $\text{bias}_{t-23:t}$ (%)	0.07***	0.10***	0.09***	0.08***
	(5.34)	(6.02)	(4.28)	(3.22)
$\text{Vol}_{t-23:t}$ (% p.m.)	−0.07***	−0.08***	0.02	−0.04*
	(−8.59)	(−5.67)	(1.50)	(−1.75)
RedemptionNotice	0.02*	0.06**	0.02	0.03
	(1.71)	(2.27)	(1.25)	(1.19)
Lockup	−0.01***	−0.02***	−0.01**	−0.02*
	(−3.34)	(−3.14)	(−2.08)	(−1.96)
MgmtFee, %	0.05**	0.02	−0.04**	−0.11***
	(2.27)	(0.74)	(−2.17)	(−3.42)
IncentiveFee, %	−0.00	0.00	−0.00	−0.00
	(−1.53)	(0.69)	(−0.33)	(−0.54)
$\log(\text{Age}_t)$	−0.04	−0.16***	0.06	−0.03
	(−1.56)	(−3.29)	(1.38)	(−0.53)
$\log(\text{AUM}_t)$	0.05***	0.05***	0.01*	−0.02
	(5.15)	(3.66)	(1.69)	(−1.19)
$\text{Flow}_{t-23:t}$, %	0.00	0.00	0.01	0.01
	(1.52)	(0.11)	(1.31)	(1.42)
$R_{t-23:t}$, % p.m.	0.09***	0.15***	0.09**	0.11*
	(3.52)	(3.04)	(2.32)	(1.85)
log (1+ MinInvestment)	0.06***	0.07***	0.03*	0.02
	(3.83)	(2.79)	(1.95)	(1.45)
PersonalCapital	0.01	0.09*	−0.00	0.13**
	(0.26)	(1.78)	(−0.02)	(2.52)
HighWaterMark	0.13***	0.06	0.18***	0.09
	(3.32)	(1.12)	(4.79)	(1.52)
Leveraged	0.03	−0.04	0.04	−0.13
	(1.14)	(−0.53)	(1.03)	(−1.37)
Offshore	−0.14***	−0.20***	−0.10***	−0.07
	(−5.11)	(−3.67)	(−2.61)	(−1.14)
Adjusted R^2, %	29.62	27.33	32.64	31.70
Observations	31,278	31,278	31,278	31,278

Panel B: Panel regressions

	Dependent variable: $\text{Performance}_{t+1:t+12}$			
	SR	IR	Ex. ret. (% p.m.)	Alpha (% p.m.)
PB $\text{bias}_{t-23:t}$, %	0.06***	0.10***	0.06***	0.09***
	(3.10)	(4.34)	(3.36)	(3.88)
$\text{Vol}_{t-23:t}$, % p.m.	−0.06***	−0.09***	0.01	−0.07***
	(−6.15)	(−6.21)	(0.73)	(−3.11)
RedemptionNotice	0.05***	0.05**	0.02	0.02
	(2.91)	(2.11)	(1.19)	(0.82)
Lockup	−0.01*	−0.01***	−0.00	−0.00
	(−1.87)	(−2.88)	(−0.54)	(−0.29)
MgmtFee, %	−0.03	−0.01	−0.06**	−0.07*
	(−1.07)	(−0.34)	(−2.28)	(−1.74)
IncentiveFee, %	−0.01**	0.00	−0.00	0.00
	(−2.39)	(0.82)	(−0.84)	(0.04)
$\log(\text{Age}_t)$	−0.02	−0.05	0.09***	0.08
	(−0.49)	(−0.91)	(2.70)	(1.64)
$\log(\text{AUM}_t)$	0.03**	0.04***	0.01	0.02
	(2.55)	(2.85)	(1.38)	(1.45)
$\text{Flow}_{t-23:t}$, %	0.00**	0.00***	0.00**	0.00**
	(2.08)	(2.73)	(2.07)	(2.28)
$R_{t-23:t}$, % p.m.	0.05**	0.11***	−0.03	0.04
	(2.01)	(3.55)	(−0.83)	(0.89)
log (1+ MinInvestment)	0.02**	0.02*	−0.00	−0.00
	(2.36)	(1.86)	(−0.56)	(−0.30)
PersonalCapital	0.03	0.11**	0.00	0.09**
	(0.82)	(1.98)	(0.11)	(2.19)
HighWaterMark	0.07*	0.07	0.15***	0.14***
	(1.67)	(1.32)	(3.99)	(2.70)
Leveraged	0.04	0.00	0.09***	0.05
	(1.14)	(0.03)	(2.76)	(1.06)
Offshore	−0.12***	−0.12*	−0.17***	−0.08
	(−2.82)	(−1.94)	(−4.03)	(−1.51)
Adjusted R^2, %	33.63	24.76	28.04	15.94
Observations	31,278	31,278	31,278	31,278

Notes. This table reports Fama–MacBeth and panel regression results for FoF performance on PB bias. Performance measures considered include Sortino 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 for which *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.

***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

redemption notice period, measured in units of 30 days ($\text{RedemptionNotice}_i$); the lockup period ($\text{Lockup}_i$); the management fee (Mgmt Fee_i); the 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 ($\log(\text{AUM}_{i,t})$); the monthly money flows as a percentage of AUM, averaged over the past two years ($\text{Flow}_{i,t-23:t}$); the monthly excess return averaged over the past two years ($R_{i,t-23:t}$); the log of one plus minimum investment ($\log(1+\text{MinInvestment}_i)$); and indicator variables for whether personal capital is committed (PersonalCapital_i), whether there is a high watermark provision (High $\textit{WaterMark}_i$), whether the FoF uses leverage (Lever $\textit{aged}_i$), and finally whether the FoF is offshore (Offshore_i).

Table 9 reports results from Fama and 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 0.07 increase in Sortino ratio, a 0.10 increase in information ratio, a 1.09 percentage point increase in annualized excess return, and a 0.93 percentage point increase in annualized alpha over the subsequent year. The panel regressions in panel B yield similar conclusions. 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 et al. 2012) or by FoFs being used to prop up distressed PB hedge funds as a part of family-level profit maximization (e.g., Gaspar et al. 2006, Bhattacharya et al. 2013).[40]

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 face greater frictions in assessing a fund's prospects as prospective investors than as incumbent investors (Aiken et al. 2015b), the benefit from PB connections should be easier to detect *before* FoFs own the fund, that is, when FoFs make hiring decisions rather 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 669 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 669 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 et al. 2013; 2015a; b), the sample yields fairly strong evidence of PB bias: the average FoF in the sample allocates 41.92% of its assets to PB hedge funds even though its PB hedge funds comprise only 37.80% of the aggregate hedge fund portfolio of registered FoFs. On average, the difference is 4.12% and is statistically significant with a *t*-statistic greater than two.

Table 10. Holding-Based Analysis

Panel A: PB bias				
	$W_{i,t}^{PB}$, %	$W_{m,t}^{PB}$, %	Difference	N
Estimate	41.92	37.80	4.12**	669
			(2.38)	
Panel B: Posthired returns				
	$R_{i,t+1}^{PBh}$, %	$R_{i,t+1}^{OPBh}$, %	Difference	N
k = 4	1.30	0.40	0.90*	114
	(2.03)	(0.57)	(1.94)	
k = 8	1.44	0.52	0.92**	135
	(2.53)	(0.95)	(2.43)	
k = 12	1.49	0.62	0.88**	139
	(2.46)	(1.14)	(2.05)	
Panel C: Postfired returns				
	$R_{i,t+1}^{PBf}$, %	$R_{i,t+1}^{OPBf}$, %	Difference	N
k = 4	0.20	−0.65	0.85	89
	(0.22)	(−0.62)	(0.83)	
k = 8	0.00	0.21	−0.21	137
	(0.00)	(0.32)	(−0.25)	
k = 12	−0.05	0.19	−0.24	156
	(−0.07)	(0.33)	(−0.29)	

Notes. 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 for which 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 the *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).

***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

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 et al. (2013):

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

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.[41] 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 et al. (2015b), newly hired funds are identified as those added to the FoF's portfolio in the recent k quarters, in which $k \in \{4, 8, 12\}$, among other hedge funds held by the FoF.[42] 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 for which we have at least one newly hired PB and OPB hedge fund with a nonmissing return in the subsequent quarter. The results show that the average FoF earns 1.30%–1.49% per quarter from the PB hedge funds it recently hires and 0.40%–0.62% per quarter from its other new hires. The difference, 0.88%–0.92% 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.

Note that Aiken et al. (2015b) construct the aggregate portfolio of hedge funds hired by all registered FoFs and evaluate it against a broad market hedge fund index to see if registered FoFs in aggregate add value in hedge fund selection. In contrast, our analysis is concerned with evaluating PB hedge funds against OPB hedge funds that are hired by the same FoF to help pin down the relative improvement in an FoF's selection ability that is associated with its PB connections, while holding fixed an FoF's overall ability (or inability) to select hedge funds.[43] In doing so, we pose an additional challenge for alternative stories in which PBs play no information role. For example, under the sorting story, in which high-quality FoFs select high-quality hedge funds that the FoFs identify by themselves (see Section 3.3.3), it is hard to explain why a given FoF makes superior selections among its PB hedge funds than among OPB hedge funds.

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 before, newly fired funds are those dropped from the FoF's portfolio in the recent k quarters, in which $k \in \{4, 8, 12\}$ among other hedge funds no longer held by the FoF. Because 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 $R^{PBf}_{i,t+1}$ and $R^{OPBf}_{i,t+1}$, 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.[44]

Overall, we find a significant difference in posthired returns but not in postfired returns between PB and OPB hedge funds. Given greater information frictions FoFs face in making hiring decisions (as prospective investors) compared with firing decisions (as incumbent investors) (see Aiken et al. 2015b), our findings that PBs benefit FoF hiring decisions (i.e., $R^{PBh}_{i,t+1} - R^{OPBh}_{i,t+1}$ is significantly positive) but not firing decisions (i.e., $R^{PBf}_{i,t+1} - R^{OPBf}_{i,t+1}$ is insignificant) once again reiterate when PB connections matter more: PB connections matter more when information frictions are greater. The lack of evidence that PBs benefit FoFs' firing decisions is also consistent with PBs' incentive to play an informational role: PBs may be less incentivized to play an informational role that leads to informed *divestment* from their hedge fund clients.

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 because of 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 et al. (2020) 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 et al. 2018), but also by reducing investors' costs of finding and vetting informed arbitrageurs.

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Endnotes

[1] We borrow the terms "informed" and "uninformed" from Gârleanu and Pedersen (2018), who use these terms as a shorthand to describe different types of asset managers (see their figure 1).

[2] Prior evidence also shows that (1) holdings contain useful information about future fund performance (see, e.g., Kacperczyk et al. 2005; 2008; Cremers and Petajisto 2009; Agarwal et al. 2018), (2) financial and operational risks predict hedge fund performance and failure (see, e.g., Liang and Park 2010; Brown et al. 2008b; 2009; 2012b), and (3) due diligence is an important source of alpha for a portfolio of hedge funds (see, e.g., Brown et al. 2008a; 2012a). Finally, Brown et al. (2008b) also find that PBs are uniquely able to distinguish problem from nonproblem funds when extending credit.

[3] The term "management firm" refers to a firm that manages one or more FoFs and/or hedge funds and is used interchangeably with the term "family," which refers to a group of funds managed by the same management firm.

[4] Note that an FoF can have a hedge fund (as well as another FoF) in its family. This practice of simultaneously managing hedge funds and FoFs "under one roof" is quite common in practice and not new in the literature (see, e.g., Agarwal et al. 2016). Bhattacharya et al. (2013) and Elton et al. (2018) also study a similar practice in the mutual fund industry. We use the term "sibling" to refer to a hedge fund or another FoF in the FoF's family.

[5] Lhabitant (2006, p. 94) also notes that PBs "are entitled to distribute private hedge fund information to their own customers (i.e., potential hedge fund investors)."

[6] 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 consistent with this prediction.

[7] See, for example, Massa and Rehman (2008), Bodnaruk et al. (2009), Jegadeesh and Tang (2010), Ivashina and Sun (2011), and Kedia and Zhou (2014).

[8] As illustrated by Brown et al. (2016), for example, FoFs often seek to assess how consistent the manager is with the manager's 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.

[9] However, it is unlikely that this occurs without PBs also serving an informational 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 perform hedge fund due diligence. In addition, our finding that PBs benefit FoFs particularly in avoiding "dog" 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.

[10] Because 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.

[11] See, for example, Aiken et al. (2013; 2015a; b), Agarwal et al. (2019), Sialm et al. (2020), and Gao et al. (2020).

[12] See, for example, Aragon (2007), Agarwal et al. (2009), Sadka (2010), Teo (2011), Titman and Tiu (2011), Sun et al. (2012), Cao et al. (2013), and Agarwal et al. (2018).

[13] For example, 13F disclosures of holdings information are restricted to quarter-end snapshots of aggregated holdings at the management firm level and omit short positions and confidential holdings.

[14] Of these 30 downloads, the first and last were made on December 28, 2012, and February 24, 2017, respectively.

[15] See section 1 of Chung and Kang (2016) for details. As in Chung and Kang (2016), we manually clean the data within and across downloads 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.

[16] Because 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).

[17] This means that $x_{i,j,t}$ is zero for many *j*s that are not held by FoF *i*.

[18] 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*.

[19] It is commonplace in the literature to employ scaled weights rather than actual weights. For example, Coval and Moskowitz (2001, p. 815), 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."

[20] Blake et al. (1993) show that estimated weights from a quadratic programming solution closely match actual portfolio weights. For more applications of Sharpe's (1992) style analysis and quadratic programming procedure, see, for example, Busse (1999), Kallberg et al. (2000), Chan et al. (2002; 2009), Comer (2006), Comer et al. (2009), and Green et al. (2011).

[21] Our choice is dictated by the fact that, on average, about 31.72% (31.76%) 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 AUM. However, our baseline results are qualitatively similar when we use asset-weighted indexes.

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

[23] 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.

[24] Here and throughout, we follow Sadka (2010) and modify the term and credit factors to ensure that they represent traded assets.

[25] 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.

[26] In this connection, we also considered using PB mergers as an exogenous change to an FoF's PB connections. However, imposing certain sampling requirements as in Chung and Kang's (2016) analysis of PB mergers leaves us with only a few FoFs, precluding any rigorous statistical analysis. Nevertheless, in response to a referee's comment, we perform an (unreported) analysis in which we relax some sampling requirements and examine the relative allocation of an FoF between hedge funds serviced by PB_1 and those serviced by PB_2, where PB_1 denotes the FoF's connected PB and PB_2 denotes the merger partner of PB_1 that is not connected to the FoF prior to the merger. The results show that the FoF, whereas overweighting hedge funds serviced by PB_1 (underweighting hedge funds serviced by PB_2) prior to the merger, increases the relative allocation to hedge funds serviced by PB_2 after the merger.

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

[28] The results are similar when we drop observations in which the FoF is connected to one of the top 3 or top 10 PBs instead of top 5 PBs. For completeness, we also repeat the analysis using the dropped observations only and find significant PB bias.

[29] 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 a 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).

[30] 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.

[31] Using proprietary data obtained from TASS, we identify 433 such FoFs (among 1,303 for which we identify PB connections) with the following breakdown of focus style: emerging markets (66), equity market neutral (17), event-driven (27), fixed-income arbitrage (10), global macro (34), long/short equity hedge (103), managed futures (47), options strategy (1), and others (128; dropped).

[32] Because 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.

[33] 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.

[34] Results in which we include each FoF and PB characteristic variable separately are qualitatively similar and are not reported for brevity. In case the FoF is connected to multiple PBs, we use the average number of hedge fund clients (connected FoFs) across the PBs.

[35] In our full analysis, we split the PB index based on returns realized over the next k 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.

[36] Specifically, we sort FoFs in Table 2 (baseline) into quartiles according to their PB bias and repeat the analysis in Tables 6 and 7 for each quartile. We thank a referee for suggesting these additional analyses.

[37] Thus, the results also shed light on the source of alpha exhibited by high-PB-bias FoFs (see the next section). For other evidence that the ability to avoid poor investments adds value, see, for example, Cao et al. (2016).

[38] Results are qualitatively similar when we rebalance the entire portfolio every K months (as opposed to rebalancing the $1/K$ of the portfolio every month), for example, at the end of every December (for a 12-month holding period) and at the end of every other December (for a 24-month holding period).

[39] The Sortino ratio is a variant of the Sharpe ratio that only factors in downside risk. We thank a referee for suggesting that we use the Sortino ratio instead of the Sharpe ratio.

[40] 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.

[41] As discussed in Aiken et al. (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) or with the corresponding return from TASS. Following Aiken et al. (2013), returns are trimmed at the 0.5% and 99.5% levels before use.

[42] 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.

[43] Notwithstanding the difference in approach, we can still get to their results from ours by considering a portfolio of all (i.e., PB plus OPB) hedge funds hired by the FoF (we denote its return by $R^{ALLh}_{i,t+1}$) and evaluating it against a broad market hedge fund index (we denote its return by HFBI_{t+1}). In unreported results, we find that $R^{ALLh}_{i,t+1} - \mathrm{HFBI}_{t+1}$ is insignificant, suggesting that the average FoF does not earn from the hedge funds it recently hires any more than it would from investing in a simple hedge fund index—thus, little hiring skill as in Aiken et al. (2015b).

[44] 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 but not in postfired returns between PB and OPB hedge funds.

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