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ABSTRACT

This paper analyzes the geographical preferences of hedge fund investors and the implication of these preferences for hedge fund performance. We find that funds of hedge funds overweight their investments in hedge funds located in the same geographical areas and that funds of funds with a stronger local bias exhibit superior performance. However, this local bias of funds of funds adversely impacts the hedge funds by creating excess comovement and local contagion. Overall, our results suggest that while local funds of funds benefit from local performance advantages, their local bias creates market segmentation that could destabilize financial markets.

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1. Introduction

The hedge fund industry represents one of the fastest growing sectors in financial markets. According to French (2008), the total assets managed by hedge funds grew by 175% from 1994 to 2007, as compared to the 81% growth rate of mutual funds over the same period. Despite the sharp growth of hedge funds, there is relatively little understanding on how investors select hedge funds,[1] and in turn how their investment choices affect the underlying hedge funds. Our paper fills this gap by analyzing the geographical preferences of funds of hedge funds (FoFs).

Compared to investors of publicly traded securities, hedge fund investors may have stronger incentives to generate private information and to monitor their investments. Many studies show that being close to their investments may provide advantages in generating information and in providing effective monitoring (e.g., Coval and Moskowitz (1999)). Consequently, hedge fund investors may exhibit a stronger local preference. It is well known that hedge funds are opaque and risky compared to public equities. They follow complex trading strategies and often trade in illiquid assets. In addition, hedge funds are restricted from advertising publicly and face limited disclosure requirements (Agarwal, Jiang, Tang, and Yang (2013)). These properties incentivize investors to seek private information and to strengthen monitoring by locating close to their investments. For example, FoFs can use soft information generated from their local social networks to obtain information about the quality of local hedge funds. It is also possible that FoFs can use their local connections to obtain access to reputable local managers.

[1] The academic literature on this regard mainly focuses on how investors select hedge funds based on past performance. See, for example, Goetzmann, Ingersoll, and Ross (2003), Agarwal, Daniel, and Naik (2004), Fung, Hsieh, Naik, and Ramadorai (2008), Ding, Getmansky, Liang, and Wermers (2009), Getmansky (2012), and Aragon, Liang, and Park (2013).

We start by investigating whether FoFs on average overweight local hedge funds. Unfortunately, information on portfolio holdings of hedge funds is generally not available to academic researchers. We therefore propose a novel methodology to estimate FoFs' loadings on local hedge funds and non-local hedge funds based on their return information. We find that FoFs on average overweight local hedge funds to a substantial degree.

We also document a significant cross-sectional variation in the local bias, indicating that some FoFs exhibit a strong local bias while others tend to be more geographically diversified. We find that the degree of local bias is related to a number of characteristics of FoFs in an intuitive way. For example, smaller and younger FoFs invest more heavily in local hedge funds. Also, FoFs in which managers invest their personal capital are more biased toward local hedge funds, which is consistent with a stronger incentive to search for private information and exert monitoring efforts. Finally, FoFs that concentrate on local portfolios impose a longer redemption notice period to their investors, which may reflect their concerns for increased need for liquidity due to the location concentration.

We next test whether the local bias of FoFs is related to their performance. We find that FoFs that tilt their portfolios more heavily toward local hedge funds on average perform better. The result is statistically and economically significant and holds for different measures of performance and various proxies for the local bias. A one-standard deviation increase in the local bias is associated with a 35 basis points increase in the Fung-Hsieh seven-factor alpha over the next quarter. Moreover, the performance predicting power of the local bias is incremental to other fund characteristics that have been found to be important for hedge fund performance.

These results suggest that FoFs benefit from private information, improved monitoring or better access to skilled managers by investing in hedge funds located close to them.

However, we also find a negative impact of the propensity to invest locally. To determine the impact of local FoFs clienteles, we first investigate the flow comovement among local hedge funds. We find that a fund is more likely to experience large fund flows during a quarter when other funds in the same area are subject to large flows. The effect is robust to controlling for style flows. Since flows tend to chase performance, the comovement in flows may simply be due to the fact that returns are more correlated among funds in the same area. However, the flow comovement among local funds remains strong even after controlling for funds' past returns.

To understand whether the correlated flows generate additional comovement in returns beyond fundamentals, we study the extreme negative return clustering among local hedge funds. We first filter the returns by their exposure to common factors, thus any remaining correlation on the residual returns can be viewed as a phenomenon of contagion, as mentioned by Boyson, Stahel, and Stulz (2010). We find that the probability of a hedge fund suffering a return in its bottom decile is increased from 6.9% to 10.2% when 10% of other local funds fall into their bottom deciles. The effect is both economically and statistically significant. Moreover, we find that the probability of local contagion is significantly increased when the local FoFs experience large outflows during the previous quarter.

Our paper contributes to several strands of the literature. First, our paper contributes to the "home bias puzzle" initially documented by French and Poterba (1991). An important strand of literature has emphasized the informational advantage by local investors in explaining this puzzle.

In their seminal papers, Coval and Moskowitz (1999, 2001) find evidence that mutual fund managers invest more in stocks that are located closer to their funds and show that their local picks perform better than distant picks. Similar evidence was found for retail investors by Ivković and Weisbenner (2005) and for hedge fund managers by Teo (2009).[2] On the other hand, other studies find less support for superior performance of local investors.[3] One possible interpretation of the mixed findings is that investors may face various distortions forcing them to suboptimally concentrate in the local market, which would mask the effects of local informational advantages. For example, individual investors may be subject to psychological biases and institutional investors such as pension funds might face local political pressure.

Focusing on the home bias of FoFs provides an unique setting for detecting the effects of local advantages. FoFs investors are less likely to be subject to behavioral biases compared to individual investors and they also are subject to less investment constraints and political distortions like pension funds or more highly regulated institutional investors. Therefore a potential local bias is more likely to be driven by local advantages.

Second, our paper contributes to the emerging literature on hedge fund contagion. Using hedge fund index data, Boyson, Stahel, and Stulz (2010) and Dudley and Nimalendran (2011) document the existence of contagion across hedge fund styles, after controlling for

[2] Hau (2001), Choe, Kho, and Stulz (2005), Malloy (2005), Gaspar and Massa (2007), Bae, Stulz, and Tan (2008), Butler (2008), and Korniotis and Kumar (2012) provide additional evidence on informational advantages of local agents. Theoretically, Van Nieuwerburgh and Veldkamp (2009) provide a rational inattention model that generates home bias when domestic investors have an informational advantage on domestic assets.

[3] Froot, O'Connell, and Seasholes (2001), Seasholes and Zhu (2010), Ferreira, Massa, and Matos (2011), Giannetti and Laeven (2012), Hochberg and Rauh (2012), and Pool, Stoffman, and Yonker (2012) provide evidence inconsistent with the local advantage hypothesis.

autocorrelation and common risk factors. However, it is unclear what causes the simultaneous distress among these fundamentally diverse hedge funds. Klaus and Rzepkowski (2009) use individual hedge fund data and document the contagion effect within styles. Our paper focuses on the geographical component of the contagion phenomenon and finds evidence of extreme return clustering among funds located in the same area, even after controlling for fund styles. Our study also establishes a link between funds of funds' local bias and hedge funds' local contagion. We find that the probability of local contagion is significantly increased immediately after the local FoFs experience large cash withdrawals, which suggests that hedge funds located in the same areas may be inter-connected through their common local clients. Thus, our study provides a concrete mechanism for the contagion effect.

Finally, our paper provides a source of alpha for FoFs. FoFs are one of the most important players in the hedge fund industry. According to Hedgefund.net, by the end of 2009 they manage an estimated 43% of the total hedge fund assets. Like single hedge funds, FoFs are managed by professional money managers, facing incentive contracts that depend sensitively on performance. Despite the strong incentives of FoFs managers, many empirical studies find that, on average, FoFs underperform hedge funds after fees.[4] One possible hypothesis for why FoFs continue to be popular despite their average underperformance is that investors believe a subset of FoF managers do add value. Consistent with this hypothesis, Fung, Hsieh, Naik, and Ramadorai (2008) find that a subset of FoFs consistently deliver positive alphas. Using holdings data for a

[4] See, for example, Ackermann, McEnally, and Ravenscraft (1999), Lhabitant and Learned (2002), Amin and Kat (2003), Kat and Amin (2003), Brown, Goetzmann, and Liang (2004), Capocci and Hubner (2004), Fung and Hsieh (2004), Fung, Hsieh, Naik, and Ramadorai (2008), Aiken, Clifford, and Ellis (2012), and Agarwal, Lu, and Ray (2013).

small sample of FoFs, Aiken, Clifford, and Ellis (2012) show that FoFs add value primarily by skillfully monitoring their hedge fund investments. Our results suggest that examining the degree of local bias of FoFs may provide a useful way in identifying value-adding FoFs.

The rest of the paper is organized as follows: Section 2 summarizes the data and presents basic descriptive statistics. Section 3 proposes the measure for FoF's local bias and studies the properties of the local bias measure. Section 4 examines the relation between geographical preference of FoFs and their subsequent performance. Section 5 analyzes the impact of the local bias of FoFs on the underlying hedge funds. Section 6 concludes.

2. Data and Descriptive Statistics

The hedge fund data used for this study are from the Lipper TASS database, which is recognized as one of the leading sources of hedge fund information. The main data include monthly hedge fund returns, as well as fund characteristics. We include both live and graveyard funds, and our sample period ranges from 1994 to 2010. We apply several filters following the literature. Specifically, we filter out non-monthly filing funds, funds denoted in a currency other than U.S. dollars, and funds with unknown strategies. We then exclude the first 18 months of observations to control for the backfill bias. To avoid double counting, we filter out off-shore funds and multiple share classes of the same fund following Aggarwal and Jorion (2010).[5] The TASS database provides information on the location of funds' management companies. For our

[5] Another potential bias of commercial hedge fund databases is the self-reporting bias. However, Agarwal, Fos, and Jiang (2013) find that hedge funds choose not to report to databases for both positive and negative reasons. Thus, the self-reporting bias does not have a material impact on performance evaluations.

study, we only include hedge funds whose management firms are located in the continental United States, excluding firms and funds located in Alaska, Hawaii, or Puerto Rico.[6] The final sample encompasses 1905 management companies running 3111 unique funds, among which 573 are FoFs.

We visualize the geographic distribution of hedge funds in Figure 1. We find that although the locations of hedge funds spread most of the states in the U.S., they have a much higher concentration in financial centers such as New York, San Francisco, Stamford, Chicago, Boston and Los Angeles.[7] This could be due to the increased knowledge spillovers and learning in cities, which could eventually enhance fund performance (Hong, Kubik, and Stein (2005) and Christoffersen and Sarkissian (2009)). Interestingly, the locations of FoFs largely overlap with those of hedge funds. Areas that exhibit a high density of hedge funds also host a large number of FoFs. At least two interpretations could be given to the large overlap between hedge funds and FoFs. One could be that FoF managers also choose to locate in big cities to benefit from the knowledge spillovers and learning. Alternatively, it could be that FoFs choose to be close to hedge funds to facilitate information gathering, monitoring, or to exploit other local advantages. It is important to differentiate these two explanations, because the first one emphasizes the advantage of large cities in general, while the second one points to the local advantage.

[6] We exclude the three areas due to geographic distances between these three locations and the rest of the continental United States. In our sample, there are only 8 funds that are located in the three areas, including them does not change our results.

[7] To ensure that our results are not driven by the areas that host only a small number of hedge funds, we repeat the entire analysis using the top six MSAs. The results are both qualitatively and quantitatively similar.

Panel A of Table I presents the summary statistics of the performance and the characteristics for hedge funds and FoFs in the sample. On average, the number of FoFs is about 24% of that of hedge funds. They are similar in size, age, and management fees. FoFs on average charge 9.6% incentive fees on top of the 18.4% incentive fees charged by their underlying hedge funds. Consistent with the findings of Brown, Goetzmann, and Liang (2004), FoFs deliver lower returns and alphas than hedge funds, suggesting that the performance does not justify the fees on fees charged by funds of funds. On the other hand, FoFs reduce the standard deviation of net fee returns and alphas by about 40%, hence they do offer a significant diversification benefit to their investors, as indicated by the superior appraisal and Sharpe ratios.

We group hedge funds by their locations. To classify locations, we first obtain the zip code, the state, and the county associated with the management companies from TASS. Using the state/county/zip code information, we then merge the sample of management firms with the Metropolitan Areas and Components data defined by the Office of Management and Budget (OMB) as of 2003.[8] We define a hedge fund's location as the Metropolitan Statistical Area (MSA) of its management company. According to the OMB, an MSA consists of "a core area containing a substantial population nucleus, together with adjacent communities having a high degree of economic and social integration with that core."

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[8] One potential problem with the TASS data is that it only reports the current location of management companies. To see how representative the current location information is with respect to historical information, we compare our data with a version of TASS data downloaded in 2003. Among the 803 companies that exist in both versions of the datasets, we find that 5.4% of them (i.e. 43 companies) moved to a different area over the 8-year period. Thus, the location information for hedge funds is quite stable.

Panel B of Table I presents summary statistics for the funds and MSAs in our sample at the beginning, middle, and end of the sample period. Both the number of funds and the number of MSAs that host hedge funds increased dramatically during the first half of the sample period. The number of MSAs remains stable during the second half, but the number of funds drops by 20% from 2002 to 2010. The drop in the number of hedge funds is mainly due to the recent financial crisis that started in 2008, when we see the number decreases from 1028 to 855 during the year. There are some further drops in 2009 and 2010.

On average there are around 13 hedge funds per MSA. However the geographical representation is quite unbalanced. While half of the MSAs host one or two hedge funds, there are a few MSAs with a large number of funds.

Panel C of Table I presents the number of styles per MSA. On average, the MSAs are well diversified across styles. The average number of styles per area is three. For areas with over six hedge funds, they host at least three different styles. To obtain a concrete idea of how styles are geographically distributed within the U.S., in Panel A of Table II, we report the percentage of funds that reside in the each of the top six MSAs for each hedge fund style. Overall, we see a balanced distribution of styles among different areas, with a few exceptions. Managed futures funds have a high representation in Chicago, dedicated short bias funds have a high representation in San Francisco, and global macro funds are concentrated in Stamford. Funds of the same styles are likely to exhibit a high return correlation. To mitigate the potential confounding effects from styles, we directly control for the style effect when studying the return and flow comovements among local hedge funds.

3. Geographical Preference by Funds of Funds

In this section, we study whether FoFs exhibit local bias by tilting their portfolios toward local hedge funds. Unfortunately, information on portfolio holdings of hedge funds is generally not available to academic researchers. We therefore propose a novel methodology to estimate FoFs' return exposure to local and non-local hedge funds.

3.1. Measuring FoFs' Local Preferences

3.1.1. Base Measure: A Difference-in-Differences Measure

To quantify FoF's local bias using return information, we consider that a FoF is a portfolio of hedge funds, so its return is a weighted average return of the hedge funds it invests in. Assuming FoF *i* invests $W_{i,L}$ in hedge funds located in its local area, $W_{i,NL}$ in hedge funds located in other areas in the U.S., and the rest in other assets such as cash, private equity, or international hedge funds, then the return of the FoF can be expressed as:

$$R_{i,t}^{FOF} = W_{i,L} \times R_{i,t}^{LHF} + W_{i,NL} \times R_{i,t}^{NHF} + e_{i,t}, \quad (1)$$

where $R_{i,t}^{FOF}$ is the return for FoF *i* at time *t*, $R_{i,t}^{LHF}$ and $R_{i,t}^{NHF}$ are the returns for its local hedge funds and nonlocal U.S. hedge funds, respectively. The error term $e_{i,t}$ includes the returns of other assets, it also captures the residual component of returns due to selection within an area.

To adjust for the uneven density of hedge funds in different locations, we benchmark each FoF's local investment against the investment made by the market FoFs to its local area. In particular, for FoF *i*, we have:

$$R_t^{MKT\ FOF} = MW_{i,L} \times R_{i,t}^{LHF} + MW_{i,NL} \times R_{i,t}^{NHF} + e_t, \tag{2}$$

where R_t^{MKTFOF} is the average return for all FoFs in the market at time t, $R_{i,t}^{LHF}$ and $R_{i,t}^{NHF}$ are defined the same as in equation (1), $MW_{i,L}$ and $MW_{i,NL}$ are the fractional allocations of the market FoF in FoF i's local and nonlocal areas, respectively.[9]

A FoF's portfolio weight deviation from the market is given by subtracting Equation (2) from Equation (1):

$$R_{i,t}^{FOF} - R_t^{MKT\ FOF} = (W_{i,L} - MW_{i,L}) \times R_{i,t}^{LHF} + (W_{i,NL} - MW_{i,NL}) \times R_{i,t}^{NHF} + \tilde{e}_{i,t} \tag{3}$$

Since a FoF can underinvest in both local and non local U.S. hedge funds as compared with the market FoF, yet still tilting its portfolio toward local hedge funds, we define the local bias of FoF i as $(W_{i,L} - MW_{i,L}) - (W_{i,NL} - MW_{i,NL})$.

Based on Equation (3), we estimate the local bias for FoF i by conducting a time-series regression of its returns in excess of the market FoF's returns on its local and nonlocal hedge funds' returns:

$$R_{it}^{FOF} - R_t^{MKT\ FOF} = \alpha_i + \beta_{i,DL} \times R_{i,t}^{LHF} + \beta_{i,DNL} \times R_{i,t}^{NHF} + \varepsilon_{i,t}. \tag{4}$$

The estimated coefficients $\hat{\beta}_{i,DL}$ and $\hat{\beta}_{i,DNL}$ are the proxies for the weight deviations of a FoF's portfolio from the market FoF's portfolio, ie. $(W_{i,L} - MW_{i,L})$ and $(W_{i,NL} - MW_{i,NL})$.[10] The local bias is then computed as ($\hat{\beta}_{i,DL}$ - $\hat{\beta}_{i,DNL}$).

[9] Note that *MW* has a subscript *i* even though the dependent variable is the market FoF because *MW* is defined with respect to the specific FoF which benchmarks against the market FoF. For example, for a New York FoF, *MW* measures how much the market FoF invests in the New York area, whereas for a Boston FoF, *MW* measures how much the market FoF invests in the Boston area.

Since we use a regression method to back out FoFs' local biases, it is also important to examine how critical our regression specification is to the local bias measure. We construct two alternative local bias proxies based on different regression specifications, and study the robustness of our results.

3.1.2. Alternative Measure 1: A Measure Based on Nonnegative Weights

Although equation (4) is transformed from equation (1) and (2), one identification restriction is lost while doing the transformation. Since a FoF cannot short a hedge fund, the portfolio weights in equation (1) and (2) should be nonnegative. Therefore, we separately estimate equation (1) and (2) as follows:

$$R_{it}^{FOF} = \alpha_i + \beta_{i,L} \times R_{i,t}^{LHF} + \beta_{i,NL} \times R_{i,t}^{NHF} + \varepsilon_{i,t}, \tag{5}$$

$$R_t^{MKTFOF} = \alpha_i + \beta_{i,L}^{MKT} \times R_{i,t}^{LHF} + \beta_{i,NL}^{MKT} \times R_{i,t}^{NHF} + \varepsilon_t, \tag{6}$$

where $R_{i,t}^{FOF}$ is the return for FoF *i* at time *t*, $R_{i,t}^{LHF}$ and $R_{i,t}^{NHF}$ are the returns for its local hedge funds and nonlocal U.S. hedge funds, and R_t^{MKTFOF} is the average return for all FoFs in the market. We estimate equation (5) and (6) by restricting the coefficients $\hat{\beta}_{i,L}, \hat{\beta}_{i,NL}, \hat{\beta}_{i,L}^{MKT}, \hat{\beta}_{i,NL}^{MKT}$ to be nonnegative.[11] We then define the local bias as $\left(\frac{\hat{\beta}_{i,L}}{(\hat{\beta}_{i,L} + \hat{\beta}_{i,NL})} - \frac{\hat{\beta}_{i,L}^{MKT}}{(\hat{\beta}_{i,L}^{MKT} + \hat{\beta}_{i,NL}^{MKT})} \right)$.

[10] FOFs' portfolio weights toward local and nonlocal hedge funds are likely to be time-varying, so the coefficients estimated from the return regressions can be viewed as the historical averages of the weight deviations.

[11] This methodology is similar to the one proposed by Sharpe (1992) for mutual funds, except that FoFs can take leverage, therefore the regression coefficients do not need to add up to one.

3.1.3. Alternative Measure 2: A Measure Based on a Long-Short Local Factor

Factor models are commonly used in investment analyses. To measure the degree of local bias, we can also adapt a factor model approach. Specifically, for each FoF, we construct its "local" factor by longing the portfolio of local hedge funds, and shorting the portfolio of non-local hedge funds. FoFs can choose to invest more or less in local assets simply by combining this zero-cost portfolio with the market portfolio. We thus regress the excess return of FoFs on the excess return of the market FoFs and the returns of the local factor:

$$R_{i,t}^{FOF} - R_t^{TBill} = \alpha_i^{'} + \beta_{i,MKT} \times (R_t^{MKTFOF} - R_t^{TBill}) + \beta_{i,DL} \times (R_{i,t}^{LHF} - R_{i,t}^{NHF}) + \varepsilon_{i,t}. \quad (7)$$

where R_{it}^{FOF} and R_t^{MKTFOF} are returns for FoF *i* and the market FoFs, respectively. R_{it}^{LHF} and R_{it}^{NHF} are the average returns of the local and nonlocal hedge funds for FoF *i*. Coefficient $\hat{\beta}_{i,DL}$ measures the degree of FoF *i*'s local bias.

3.2. Properties of the Local Bias Measures

We start by investigating whether FoFs exhibit local preferences in picking hedge funds. In Panel A of Table III, we present the estimation results for our base measure. For each FoF that has at least 24 months of observations, we conduct a time-series regression of its return in excess of the market FoF's return on the average returns of its local hedge funds and nonlocal hedge funds. We report the cross-sectional averages of the estimated coefficients. FoFs on average overinvest in hedge funds located in their local area by 15%. The effect is both statistically and economically significant.

Several robustness checks are in order. First, one component of the error term in the regression specification (4) may be the return on other assets. If the return on other assets is correlated with the returns of local or nonlocal U.S. hedge funds, the estimated regression coefficients will be biased. To the extent that the other assets may include non-U.S. hedge funds, they could be correlated with the U.S. hedge funds due to their exposure to common risk factors. To mitigate the potential concern, we report in column (2) the results for which Fung-Hsieh seven factors are included in each FoF's time-series regressions. FoFs still exhibit significant local bias after controlling for the Fung-Hsieh seven factors.

Second, FoFs may also differ in their preference for hedge fund styles. For example, some FoFs may focus on investing in managed futures funds, which have a higher concentration in Chicago. It should be noted, however, that the preference for certain styles should not generate local bias unless FoFs choose to locate near their preferred investment styles. Therefore, it is not the style preference per se but the *local* style preference that matters. In column (3) we examine to what extent FoFs' preferences for local hedge funds can be attributed to their preferences for local hedge fund styles. In each FoF's time series regression, we include the returns for the ten hedge fund styles defined by TASS. After controlling for different style exposures, FoFs' local bias decreases, suggesting that a portion of the local bias is due to preferences for local styles. However, the coefficient for the local return remains positive and significant, implying a local preference within styles.

Third, we use non-parametric tests to examine whether FoFs exhibit local bias. For each fund, we calculate their local bias as ($\hat{\beta}_{i,DL}$ - $\hat{\beta}_{i,DNL}$), with $\hat{\beta}_{i,DL}$ and $\hat{\beta}_{i,DNL}$ estimated from their individual regressions. We find that 67.35% of FoFs have positive local bias measures. The percentage is significantly higher than the 50% under the null hypothesis of no local bias. Furthermore, there are about 37% of the FoFs with estimated local biases that are positive and significant at a 5% level.

Finally, we examine FoF's local bias using the two alternative measures. Consistent with the base measure, both alternative measures show that FoFs tend to tilt their investments toward local hedge funds. The three measures are also highly correlated. The base measure has a rank correlation of 0.88 with the measure based on nonnegative weights, and 0.95 with the measure based on the local factor.

To study whether the local bias is a persistent characteristic of FoFs, we estimate the local bias over two non-overlapping 24-month periods. For every other year starting from December of 1996, we sort all FoFs in our sample into quintile portfolios according to their local bias measures. We then compute the average local bias for each quintile during the subsequent two years. Panel A of Table IV reports the average local bias of the quintile portfolios, both at the sorting time and during the next two years. The levels of local bias of the high local bias portfolios remain higher than those of the low local bias portfolios. The difference in the local bias between two extreme portfolios decreases over time but remains highly economically significant. Note that since we use non-overlapping data to estimate the local bias, the *t*-statistics are calculated based on only seven data points. However, the difference in local bias between the two extreme portfolios is highly statistically significant. These results suggest the local bias is a persistent characteristic of FoFs.

Finally, we examine the relation between the degree of home bias and lagged fund characteristics. Specifically, we use a multivariate panel regression based on bi-annual data.[12] The lagged fund characteristics considered include the natural logarithm of assets under management (AUM), fund age, the net return over the prior year, the logarithm of the minimum investment, the lengths of the redemption notice and lockup periods, an indicator variable for personal capital commitment, management fees, incentive fees, an indicator variable for a high-water mark provision, and an indicator variable for the use of leverage.

Panel B of Table IV presents the panel regression results. We find that the degree of local bias is related to a number of characteristics of FoFs in a plausible way. For example, smaller and younger FoFs invest more heavily in local hedge funds. This could be due to that the gains from local investment are larger for FoFs that are more agile. Also, FoFs that concentrate on local portfolios impose higher minimum investment levels and longer redemption notice periods on their investors, which may reflect their concerns of increased return volatility due to the location concentration. Finally, FoFs whose managers invest their personal capital into their funds are biased more toward local hedge funds, which is consistent with a stronger incentive to search for private information and exert monitoring efforts.

[12] We use bi-annual data so that the local bias measure is estimated using non-overlapping data.

3.3. Comparing the Return-Based and Holding-Based Local Bias Measures using Mutual Fund Data

To investigate how well our return-based local bias measure captures the local bias based on actual fund holdings, we compare the two measures using holdings and return data for U.S. equity mutual funds. In our sample period, the holding-based local bias measure suggests that mutual funds on average invest 0.9% more toward their local stocks, a magnitude similar to the one reported in Coval and Moskowitz (2001). Our base measure equals 1.2% and is not statistically different from the holding-based measure. Also, the correlation between the holding-based and return-based measures is 0.33 and is statistically different from zero at one percent confidence level.[13] The similar magnitude and relatively high correlation between the return- and holding-based measure give some credibility to our methodology. One advantage of looking at the mutual fund data is that the estimation error (i.e., return-based local bias relative to the holding-based local bias) is directly observable. Therefore, we examine whether the estimation error is related to future mutual fund alphas. At the end of each quarter, we sort mutual funds into decile portfolios based on their estimation errors. We then compute the average alpha for funds in each portfolio during the next quarter. Funds in the highest estimation error decile have an average alpha of -0.04%, while funds in the lowest estimation error decile have an average alpha of -0.07%. The difference in alphas between the two extreme portfolios is 0.03% with a *t*-statistic of 0.63. Thus, the estimation errors seem to be unrelated to future fund performance.

[13] The correlation between the holding-based measure with the two alternative return-based measures are 0.33 (measure based on nonnegative weights) and 0.40 (measure based on the local factor), respectively.

4. Funds of Funds' Local Preference and Performance

In this section, we examine whether FoFs' local bias is related to their future performance. Specifically, in a panel regression, we regress the next-quarter performance of a FoF on the local bias variable and fund characteristics at the end of the previous quarter. Similar to Table IV, we use the previous 24 months observations to estimate the local bias variable and standardize the variable to exhibit a mean of zero and unit variance for each area and each period. We consider three performance measures: the Fung-Hsieh seven factor alpha, the corresponding appraisal ratio, and the Sharpe ratio. We include both time and MSA fixed effects, and cluster the standard errors by area.[14]

4.1. Main Finding

Table V demonstrates that the local bias measure has a significant predictive power toward future abnormal performance, even after controlling for other fund characteristics. For the Fung-Hsieh seven-factor adjusted alphas, the estimated coefficient for the local bias variable is 0.35, with a *t*-statistic of 5.49. Since the local bias variable is already normalized to have a unit standard deviation, the estimated coefficients also directly reveal the economic significance of the results. A one-standard deviation increase in the local bias predicts an increase in the annualized FH seven-factor alpha of 1.41% in the univariate setting and 1.04% in the presence of a host of control variables.[15] FoFs may also differ in their exposures to different hedge fund

[14] We also cluster the standard errors by time or by funds, and double cluster by time and funds. Our results are robust across these specifications.
[15] In the regression, we use returns at the quarterly frequency.

styles. When we control for fund style differences, the coefficient on the local bias variable drops slightly to 0.19, but it remains statistically significant at the 1% level.

We also utilize two alternative performance measures. First, we calculate the quarterly Sharpe ratio to capture the risk-return tradeoff of hedge fund returns. It is defined as the ratio between the average monthly net returns in excess of the risk-free rate and the volatility in the monthly excess returns. The benefit of the measure is that it is independent of the specific pricing models for hedge fund returns. In addition, we use a modified version of Treynor and Black's (1973) appraisal ratio, which we calculate by dividing the mean of the monthly alphas by their standard deviation. Brown, Goetzmann, and Ross (1995) show that the survivorship bias is positively related to the fund return variance. Thus, the use of fund returns scaled by their standard deviations mitigates the survivorship problems. The scaled measure also accounts for differences in leverage across funds. Again, the results indicate a strong positive association between local bias and future performance. A one standard deviation increase in the local bias results in a 0.07 and 0.05 increase in the FH seven-factor appraisal ratio and Sharpe ratio, respectively.

We examine the performance predictability of the two alternative local bias proxies, and report the results in Table VI. As can be seen, the performance predictability by the home bias variable prevails. The economic magnitude is also similar for all the measures.

4.2. Robustness Checks

We conduct several robustness checks.[16] First, we break the sample into New York and Non New York subsamples. New York has a disproportionally higher percentage of FoFs, thus it is of interest to see whether the return predictability of the local bias variable is driven entirely by the New York sample. As Panel A of Table VII shows, the local bias measure continues to be positively correlated with future performance even when the New York FoFs are excluded. The predictive power for the Sharpe ratio is significantly stronger for the non New York sample, but there is no significant difference between the two subsamples for alphas and appraisal ratios.

Another potential concern is that the outperformance of the locally biased FoFs may be mechanically driven by cross-area variations in hedge fund performance. Suppose that hedge funds in area A consistently outperform funds in other areas on a risk-adjusted basis, then FoFs that invest more in area A will appear to earn abnormal performance. If FoFs in area A display more home bias than other FoFs in the market, we could observe that FoFs in area A outperform those in other areas. Furthermore, within area A, FoFs that appear to be more locally biased will outperform those that are less locally biased. Thus, the effect could generate a mechanical positive relation between local bias and performance, without the presence of local advantages.

To address this concern, we look at a subsample where the local hedge funds perform worse than the non-local hedge funds. Specifically, for each quarter, we only keep areas where their local hedge funds earn a lower equal-weighted alpha than the non-local hedge funds during the previous 24 months. For this subsample, the mechanical link should generate a negative

[16] We only present the robustness tests for our base measure due to space concerns. The results are qualitatively similar for the two alternative measures.

association between the local bias and the performance. However, as can be seen in Panel B of Table VII, the local bias variable is still positively correlated with performance across all specifications, and the coefficients are significant for most of the cases. Therefore, we do not find evidence in support of the mechanical link hypothesis.

Finally, there are cases where a management company simultaneously runs hedge funds and FoFs. Agarwal, Lu, and Ray (2013) systematically examine the simultaneous management, and find that the phenomenon is associated with both value creation and agency issues. In particular, they find that FoFs benefit from gaining access to the successful hedge funds within their own families. To see whether the local advantage is entirely driven by this within family advantage, we exclude the FoFs whose management companies simultaneously run hedge funds.[17] As Panel C of Table VII shows, FoFs' local bias continues to positively and significantly associate with future performance, even after we shut down the family advantage channel.

5. The Impact of Local Bias on Hedge Funds

In the previous sections, we document the existence of local bias by FoFs and establish a link between the local bias and local advantages. However, the potential impact of the local bias on the underlying hedge funds is unclear. In this section, we explore this question from the perspective of hedge funds. We examine whether the local bias creates segmented local markets, which can lead to excessive flow and return comovement.

[17]Agarwal, Lu, and Ray (2013) find that the simultaneous management of hedge funds and FoFs are more likely to take place for off-shore hedge funds and FoFs. Our sample focuses on on-shore funds. Therefore, we identify that only 22% FoFs are affected by the simultaneous management in our sample, as compared with 46% in their sample.

5.1. Flow Comovement

We start by investigating flow comovement between local hedge funds. We hypothesize that the local bias by FoFs will induce comovement in flows between local hedge funds beyond fundamentals. When a FoF sees a large inflow or outflow, it is likely to spread the liquidity shock among several hedge funds it holds, which might create positive comovement among these funds. Furthermore, if FoFs across different areas do not incur perfectly correlated flows, we will observe that hedge funds are influenced more by the flows of their local FoFs due to the local bias. Therefore, hedge funds residing in the same area are likely to face higher flow comovement than funds located in different areas. Another mechanism that could induce local flow comovement is a feedback effect, similar to Brunnermeier and Pedersen (2009). A big loss from a hedge fund may impact its local investors more given the local bias, forcing the local FOFs to take out money from other local hedge funds.

To investigate whether hedge funds located within the same area have higher flow comovement, we compare in Panel A of Table VIII the average pairwise Pearson correlation in flows for funds located in the same MSA, versus funds located in different areas. We find that the average flow correlation between same-area funds and different-area funds is 2.37% and 2.02%, respectively. Thus, funds in the same area have a flow correlation 17% higher than funds from different areas. The difference in correlation is also highly statistically significant, with a *t*-statistic of 6.24.

While the simple comparison of the flow correlation is intuitive, it may be subject to an omitted variable problem. For example, as we have seen in Panel A of Table II, some MSAs have a higher concentration in certain styles. If hedge fund investors follow a style investing strategy as in Barberis and Shleifer (2003), there will be an excessive flow comovement among funds in the same style, which could contribute to the local flow comovement. Moreover, funds in the same area may follow similar strategies and generate similar returns, which is likely to induce flow comovement since flows chase past performance. We address these concerns using a regression framework.

To examine flow comovement, we regress monthly percentage flows of each hedge fund on the average flows of all hedge funds from the fund's corresponding MSA, with several control variables.[18] The control variables include style flow, which is the average flow of all hedge funds sharing the same TASS style as the fund, the past returns of the fund, as well as the past returns of the other local hedge funds. We exclude the hedge fund itself from the local flow and style flow calculation to eliminate a mechanical correlation.

Panel B of Table VIII reports the regression results. We first run a regression of individual flows on local and style flows. The regression coefficient on local flow is highly statistically significant even when controlling for the style effect. In terms of economic importance, the local effect is comparable to the style effect. A one-standard deviation increase in local flows (style flows) is associated with an increase in individual monthly flows of approximately 0.6% (0.7%). We then add the current and past performance information. As can be seen from the table, controlling for fund performance significantly reduces the marginal effect of the style flows. This

[18] We also study local flow comovement following the methodology in Pirinsky and Wang (2006), where we first estimate a time-series regression for each fund, and then compute the cross-sectional averages of the estimated coefficients from the time-series regressions. The results are both qualitatively and quantitatively similar.

is not surprising since funds of the same style are likely to have correlated returns. Controlling for fund performance also reduces the coefficients for local flows but to a much lesser degree, suggesting most of the local flow comovement is beyond the effect of funds' return comovement.

Besides the local clientele effect, the higher flow comovement among local funds may also result from funds belonging to the same fund family, as they are likely to share the same clientele. As a robustness check, we exclude funds from the same family in the local flow calculation. The magnitude of the local flow indeed drops after we take out the family effect. However, the local flow remains statistically significant and economically important.

5.2. Local Contagion

In this section, we examine whether the flow comovement among local funds may induce excess return correlation among local hedge funds. The literature on mutual funds finds that flow-induced trading may have a big impact on mutual fund returns, especially on the downside.[19] However, the flow-induced trading may have an even stronger effect on hedge fund returns given the illiquidity of hedge funds' assets.

5.2.1. Extreme Return Clustering

We study how extreme negative returns, defined as returns that fall in the bottom decile of a fund's monthly returns, cluster among funds located in the same area. To study the clustering effect, it is important to take out the impact of common factors for hedge fund returns, since two

[19] See, for example, Wermers (2003), Coval and Stafford (2007), Bartram, Griffin, and Ng (2010), Chen, Goldstein, and Jiang (2010), Lou (2012), and Anton and Polk (2013).

funds may be more correlated if they have higher loadings on the same factor. Also, hedge fund returns may be serially correlated due to their return smoothing behavior, which may obscure the statistical inference of the analysis. To mitigate the impact of common factors and autocorrelation, we follow Boyson, Stahel, and Stulz (2010) by first filtering the returns of each hedge fund by Fung-Hsieh seven factors, the fund's style return, and its own past quarter returns. We then investigate whether there is any correlation among the residual returns. Bekaert, Harvey, and Ng (2005) define contagion as "correlation over and above what one would expect from economic fundamentals." With this definition, the residual return comovement among local funds can be viewed as local contagion.

Our first test of local contagion implements a logit model, which is extensively used in the contagion literature.[20] The dependent variable is an indicator variable that is set to one if the fund has a return in the bottom decile of its entire time series of returns and zero otherwise. The key independent variable is an indicator variable that is set to one if the average return of the other local hedge funds falls in the bottom decile of its return distribution. Intuitively, the logit model estimates whether a given hedge fund is more likely to have an extreme return when the other funds in the same area incur extreme returns.

Panel A of Table IX reports the regression results. As can be seen in the first column, the local extreme return dummy is positive and statistically significant. This suggests that there is significant extreme return clustering among local hedge funds. Since Boyson, Stahel, and Stulz (2010) find that all hedge funds comove together, we examine whether there is additional local

[20] See, for example, Eichengreen, Rose, and Wyplosz (1996), Bae, Karolyi, and Stulz (2003), and Boyson, Stahel, and Stulz (2008).

contagion after we control for the market level contagion. As can be seen from the second column of the table, the market level distress indicator has a significant impact on individual hedge funds, which is consistent with the findings in Boyson, Stahel, and Stulz (2010). However, even after controlling for the market level contagion effect, the local hedge funds distress variable remains positive and significant.

The local extreme return indicator is based on the average performance of local hedge funds. In principle, an extreme negative return by a single fund could drag the average return into the tail range even if the rest of the local funds are doing fine. Compared with a single fund being in distress, having multiple funds incurring significant losses at the same time may be more devastating due to simultaneous fire sales. Therefore, we look at an alternative measure for local distress that captures the degree of multiple local hedge fund distress. For each hedge fund, we count the number of other local hedge funds that have extreme returns during a month, and divide it by the total number of local hedge funds. We find a positive and highly significant coefficient on the percentage of local funds under distress. When no other local funds are under distress, the probability of a fund incurring its extreme return is 6.9%. However, that probability is increased to 10.2% when 10% of the other local funds have extreme returns.

5.2.2. Local FoFs' Flows

Why do hedge funds located in the same area tend to exhibit extreme returns together? One possible interpretation is correlated money flows from common local clients, as we documented in the previous section. In Panel B of Table IX, we examine the common local client hypotheses.

The percentage of local funds that incur extreme returns increases from 12.0% to 13.4% when local FoFs incur large outflows during the previous quarter. The difference is significant at a 1% level.

5.2.3. *CoVaR*

Besides the probability of incurring a tail event, it's also relevant for fund managers to know how much loss their funds can incur in a tail event. One common measure is the *VaR* (i.e., Value at Risk). In recognizing that financial companies intertwine and often fail together, the recent literature suggests evaluating a financial company's *VaR* conditioning on the performance of other financial companies. In particular, Adrian and Brunnermeier (2011) propose *CoVaR* (i.e., Co-Value at Risk) to measure the Value at Risk (*VaR*) of financial institutions conditional on other financial institutions being under distress. We borrow this measure to examine how a hedge fund's *VaR* changes when other local hedge funds are subject to big losses.

To understand the *CoVaR* measure, let's first recall the traditional definition of *VaR*. For a hedge fund *i*, its *q* percentage VaR_q^i is implicitly defined as the *q* quantile:

$$\Pr(X_i \le VaR_q^i) = q \tag{8}$$

The *CoVaR* is simply a conditional *VaR*, which is given by

$$CoVaR_q^{i|R_{LHF}=VaR_q^{LHF}} = \Pr\left(R_i \le CoVaR_q^{i|R_{LHF}=VaR_q^{LHF}} \mid R_{LHF} = VaR_q^{LHF}\right) = q \tag{9}$$

Intuitively, the *CoVaR* measures hedge fund *i*'s *q* percent *VaR* conditional on other local hedge funds is at *q* percent *VaR*. Following Adrian and Brunnermeier (2011), we use

$\Delta CoVaR_q^{i|LHF}$ to measure how much an individual fund is impacted by the local contagion. Specifically, $\Delta CoVaR_q^{i|LHF}$ is given by

$$\Delta CoVaR_q^{i|LHF} = CoVaR_q^{i|R_{LHF}=VaR_q^{LHF}} - CoVaR_q^{i|R_{LHF}=Median^{LHF}} \tag{10}$$

$\Delta CoVaR_q^{i|LHF}$ measures fund *i*'s increase in Value-at-Risk in the case of a local market distress. We estimate the $\Delta CoVaR_q^{i|LHF}$ for each hedge fund using a quantile regression. We detail the estimation procedure in Appendix B.

Panel A of Table X reports the quantile regression results, which reveal a picture of local contagion similar to what we find in Table IX. A hedge fund is exposed to a higher value at risk (i.e., more negative *VaR*) when local hedge funds face poor returns. Also, when its local FoFs experience large outflows in the previous quarter, the hedge fund faces an increase in value at risk. Panel B calculates the average local *CoVaRs.* Again, it suggests a negative impact from local hedge funds' failure. For example, the 10%-*VaR* is -3.29% per month when other local funds are at their bottom 10% returns. This is 0.15% lower compared with when other local funds are at their median returns. Overall, the results lend further support to the phenomenon of local contagion, and suggest that money withdrawals from the local FoFs may be a driving force of the local contagion.

6. Conclusion

In this paper, we study the geographic preference of FoFs in selecting hedge funds. The findings provide a better understanding of hedge fund investor behavior and offer new insights into the causes and consequences of the well-known “home bias” phenomenon. Further, the empirical evidence suggests that investor behavior can in turn affect the performance of the underlying hedge funds.

We find evidence of local bias for typical FoFs. Cross-sectionally, managers with higher incentives and better abilities to utilize local private information exhibit stronger local preferences. More importantly, despite the well-documented evidence on poor performance of FoFs, we find substantial abnormal performance by locally biased FoFs. Overall, the evidence is consistent with FoF managers’ having a local advantage, for example, superior information, better monitoring, or better access to local hedge funds.

Our paper also examines a related but less explored question: what is the impact of the local bias on the underlying financial markets. In particular, we are interested in comovement that is generated by geographically segmented markets. First, we find excessive comovement in investor flows among local hedge funds. Moreover, we find strong evidence that large outflows of local FoFs increase the probability of “local contagion,” i.e. funds located in the same area are more likely to experience extreme negative returns at the same time.

Our paper makes several contributions to the literature. First, it provides novel evidence on the connection between investors’ local bias and local advantage. Second, it establishes a link between the liquidity shock of local clienteles and extreme return clustering, shedding light on the micro foundation of the hedge fund contagion phenomenon. Finally, it offers rare evidence on fund selection ability by FoFs, which provides some justification for the FoFs' practice of charging a double layer of fees.

Our results also have direct implications for asset allocation decisions by hedge fund investors. The evidence speaks to the tradeoff between local advantages and geographical diversification. On the one hand, investors may want to scale up their local investments to better exploit the local advantage; on the other hand, they may face excessive return comovement within their local portfolio, especially during crisis periods. To the extent that part of the return comovement is generated by the local bias behavior of their own and peers alike, it may be useful to deliberate the degree of local bias in their asset allocation decisions.

References

Ackermann, Carl, Richard McEnally, and David Ravenscraft, 1999, The Performance of Hedge Funds: Risk, Return, and Incentives, *The Journal of Finance* 54, 833-873.

Adrian, Tobias, and Markus Brunnermeier, 2011, CoVaR, Working paper, Princeton University.

Agarwal,Vikas, Naveen Daniel, and Narayan Naik, 2004, Flows, Performance, and Managerial Incentives in the Hedge Fund Industry, Working Paper, Georgia State University.

Agarwal,Vikas, Vyacheslav Fos, and Wei Jiang, 2013, Inferring Reporting-Related Biases in Hedge Fund Databases from Hedge Fund Equity Holdings, *Management Science* 59, 1271-1289.

Agarwal,Vikas, Wei Jiang, Yuehua Tang, and Baozhong Yang, 2013, Uncovering Hedge Fund Skill from the Portfolio holdings They Hide, *The Journal of Finance* 68, 739-783.

Agarwal, Vikas, Yan Lu, and Sugata Ray, 2013, Under One Roof: A Study of Simultaneously Managed Hedge Funds and Funds of Hedge Funds, Working paper, Georgia State University.

Aggarwal, Rajesh, and Philippe Jorion, 2010, The Performance of Emerging Hedge Funds and Managers, *Journal of Financial Economics* 96, 238 -256.

Aiken, Adam, Christopher Clifford, and Jesse Ellis, 2012, Do Funds of Hedge Funds Add Value? Evidence from their Holdings, Working paper, University of Kentucky.

Amin Gaurav, and Harry Kat, 2003, Hedge Fund Performance 1990-2000: Do the 'Money Machines' Really Add Value?, *Journal of Financial and Quantitative Analysis* 38, 251-274.

Anton, Miguel, and Christopher Polk, 2013, Connected Stocks, Forthcoming: *The Journal of Finance*.

Aragon, George, Bing Liang, and Hyuna Park, 2013, Onshore and Offshore Hedge Funds: Are They Twins? Forthcoming: *Management Science*.

Bae, Kee Hong, Andrew Karolyi, and René M. Stulz, 2003, A New Approach to Measuring Financial Contagion, *Review of Financial Studies* 16, 717-764.

Bae, Kee Hong, Rene Stulz, and Hongping Tan, 2008, Do local analysts know more? A cross-country study of the performance of local analysts and foreign analysts, *Journal of Financial Economics* 88, 581-606.

Barberis, Nicholas, and Andrei Shleifer, 2003, Style Investing, *Journal of Financial Economics* 68, 161-199.

Bartram, Söhnke M., and John M. Griffin, and David T. Ng, 2010, How Important are Foreign Ownership Linkages for International Stock Returns? Working Paper, University of Texas at Austin.

Bekaert, Geert, Campbell Harvey, and Angela Ng, 2005, Market Integration and Contagion, *Journal of Business* 78, 39-69.

Boyson, Nicole, Christof Stahel, and Rene Stulz, 2010, Hedge Fund Contagion and Liquidity Shocks, *The Journal of Finance* 55, 1789-1816.

Brown, Stephen, William Goetzmann, and Bing Liang, 2004, Fees on Fees in Funds of Funds, *Journal of Investment Management* 2, 39-56.

Brown, Stephen, William Goetzmann, and Stephen Ross, 1995, Survival, *The Journal of Finance* 50, 853–873.

Brunnermeier, Markus K., and Lasse H. Pedersen, 2009, Market Liquidity and Funding Liquidity, *Review of Financial Studies* 22, 2201-2238.

Butler, Alexander, 2008, Distance Still Matters: Evidence from Municipal Bond Underwriting, *The Review of Financial Studies* 21, 763-784.

Capocci, Daniel, and Georges Hubner, 2004, Analysis of Hedge Fund Performance, *Journal of Empirical Finance* 11, 55-89.

Christoffersen, Susan, and Sergei Sarkissian, 2009, City Size and Fund Performance, *Journal of Financial Economics* 92, 252-275.

Chen, Qi, Itay Goldstein, and Wei Jiang, 2010, Payoff Complementarities and Financial Fragility: Evidence from Mutual Fund Outflows, *Journal of Financial Economics* 97, 239-262.

Choe, Hyuk, Bong-Chan Kho, and Rene Stulz, 2005, Do Domestic Investors Have an Edge? The Trading Experience of Foreign Investors in Korea, *Review of Financial Studies* 18, 795-829.

Coval, Joshua, and Tobias Moskowitz, 1999, Home Bias at Home: Local Equity Preference in Domestic Portfolios, *The Journal of Finance* 54, 2045-2073.

Coval, Joshua, and Tobias Moskowitz, 2001, The Geography of Investment: Informed Trading and Asset Prices, *Journal of Political Economy* 109, 811–841.

Coval, Joshua, and Erik Stafford, 2007, Asset Fire Sales (and Purchases) in Equity Markets, *Journal of Financial Economics* 86, 479-512.

Ding, Bill, Mila Getmansky, Bing Liang, and Russ Wermers, 2009, Share Restrictions and Investor Flows in the Hedge Fund Industry, Working Paper, University of Massachusetts.

Dudley, Evan, and Mahendrarajah Nimalendran, 2011, Margins and Hedge Fund Contagion, *Journal of Financial and Quantitative Analysis* 46, 1227-1257.

Eichengreen, Barry, Andrew Rose, and Charles Wyplosz, 1996, Contagious currency crises: First tests, *Scandinavian Journal of Economics* 98, 463-484.

Ferreira, Miguel, Massimo Massa, and Pedro Matos, 2011, The Geography of Mutual Funds: The Advantage of Distant Investors, Working paper, INSEAD.

French, Kenneth, 2008, Presidential Address: The Cost of Active Investing, *Journal of Finance* 63, 1537-1573.

French, Kenneth, and James Poterba, 1991, Investor Diversification and International Equity Markets, *The American Economic Review* 81, 222-226.

Froot, Ken, Paul O'Connell, and Mark Seasholes, 2001, The Portfolio Flows of International Investors, *Journal of Financial Economics* 59, 151-193.

Fung, William, and David Hsieh, 2004, Hedge Fund Benchmarks: A Risk Based Approach, *Financial Analysts Journal* 60, 65-80.

Fung, William, David Hsieh, Narayan Naik, and Tarun Ramadorai, 2008, Hedge Funds: Performance, Risk, and Capital Formation, *The Journal of Finance* 63, 1777-1803.

Gaspar, Jose-Miguel, and Massimo Massa, 2007, Local Ownership as Private Information: Evidence on the Monitoring-Liquidity Trade-off, *Journal of Financial Economics* 83, 751-792.

Getmansky, Mila, 2012, The Life Cycle of Hedge Funds: Fund Flows, Size, Competition, and Performance, *Quarterly Journal of Finance* 2, 1-53.

Goetzmann, William, Jonathan Ingersoll, and Stephen Ross, 2003, High Water Marks and Hedge Fund Management Contracts, *Journal of Finance* 58, 1685-1718.

Giannetti, Mariassunta, and Luc Laeven, 2012, Local Bias and Stock Market Conditions, Working paper, Stockholm School of Economics.

Hau, Harald, 2001, Location Matters: An Examination of Trading Profits, *Journal of Finance* 56, 1959–1983.

Hochberg, Yael, and Joshua Rauh, 2012, Local Overweighting and Underperformance: Evidence from Limited Partner Private Equity Investments, Forthcoming: *Review of Financial Studies*.

Hong, Harrison, Jeffrey Kubik, and Jeremy Stein, 2005, Thy Neighbor's Portfolio: Word-of-Mouth Effects in the Holdings and Trades of Money Managers, *The Journal of Finance* 60, 2801-2824.

Ivković , Zoran, and Scott Weisbenner, 2005, Local Does as Local Is: Information Content of the Geography of Individual Investors' Common Stock Investments, *The Journal of Finance* 60, 267-306.

Kat Harry, and Gaurav Amin, 2003, Welcome to the Dark Side: Hedge Fund Attrition and Survivorship Bias over the Period 1994-2001, *Journal of Alternative Investments* 57-73.

Klaus, Benjamin, and Bronka Rzepkowski, 2009, Risk Spillover among Hedge Funds: The Role of Redemptions and Fund Failures, Working paper, European Central Bank.

Korniotis, George, and Alok Kumar, 2012, Do Portfolio Distortions Reflect Superior Information or Psychological Biases? *Journal of Financial and Quantitative Analysis* 48, 1-45.

Lhabitant Francois, and Michelle Learned, 2002, Hedge Fund Diversification: How Much is Enough? *Journal of Alternative Investments* 5, 23-49.

Lou, Dong, 2012, A Flow-Based Explanation of Return Predictability, *Review of Financial Studies* 25, 3457-3489.

Malloy, Christopher, 2005, The Geography of Equity Analysis, *Journal of Finance* 60, 719–755.

Pool, Veronika, Noah Stoffman, and Stott Yonker, 2012, No Place Like Home: Familiarity in Mutual Fund Manager Portfolio Choice, *The Review of Financial Studies* 25, 2563-2599.

Pirinsky, Christo, and Qinghai Wang, 2006, Does Corporate Headquarters Location Matter for Stock Returns? *The Journal of Finance* 61, 1991-2015.

Seasholes, Mark, and Ning Zhu, 2010, Individual Investors and Local Bias, *The Journal of Finance* 65, 1987-2010.

Sharpe, William, 1992, Asset Allocation: Management Style and Performance Measurement, *Journal of Portfolio Management* 18, 7-19.

Teo, Melvyn, 2009, The Geography of Hedge Funds, *The Review of Financial Studies* 22, 3531-3561.

Treynor, Jack, and Fischer Black, 1973, How to Use Security Analysis to Improve Portfolio Selection, *Journal of Business* 46, 66–86.

Van Nieuwerburgh, Stijn, and Laura Veldkamp, 2009, Information Immobility and the Home Bias Puzzle, *The Journal of Finance* 64, 1187-1215.

Wermers, Russ, 2003, Is Money Really "Smart"? New Evidence on the Relation Between Mutual Fund Flows, Manager Behavior, and Performance Persistence, Working paper, University of Maryland.

Appendix A

Variable Descriptions

In this appendix, we provide the detailed definitions of the variables used in our paper.

Variable Name	Definition
Local Ret	The equal-weighted returns of all hedge funds (excluding FoFs) from the fund's corresponding MSA, excluding the fund itself.
Local Flow	The equal-weighted flows of all hedge funds (excluding FoFs) from the fund's corresponding MSA, excluding the fund itself.
Style Flow	The equal-weighted flows of all funds in the fund's corresponding TASS style, excluding the fund itself.
Local HF Ret	The average returns of all hedge funds (excluding FoFs) from the FoF's corresponding MSA.
Non Local HF Ret	The average returns of all hedge funds (excluding FoFs) not residing in the FoF's MSA.
MKT FoF Ret	The average returns of all funds of funds in the market, excluding the fund itself.
SP500	The Standard & Poors 500 index monthly total return.
R2000	Russell 2000 index monthly total return - Standard & Poors 500 monthly total return.
Chg_cmt10y	The monthly change in the 10-year Treasury constant maturity yield (month end-to-month end).
Chg_baa	The monthly change in the Moody's Baa yield less 10-year Treasury constant maturity yield (month end-to-month end).
Ptfsbd	Bond Trend-Following Factor as constructed in Fung and Hsieh (2001).
Ptfsfx	Currency Trend-Following Factor as constructed in Fung and Hsieh (2001).
Ptfscom	Commodity Trend-Following Factor as constructed in Fung and Hsieh (2001).
Ret(t-3,t-1)	Average monthly returns during month t-3 to month t-1.
Ret(t-6,t-4)	Average monthly returns during month t-6 to month t-4.
Ret(t-12,t-7)	Average monthly returns during month t-12 to month t-7.

Ret(t-12,t-1)	Average monthly returns during the month t-12 to month t-1.
Management Fee	Hedge funds' management fee in percentage.
Incentive Fee	Hedge funds' incentive fee in percentage.
High-Water Mark Dummy	An indicator variable that equals one if a hedge fund has high watermark provision, and zero otherwise.
Leveraged Dummy	An indicator variable that equals one if a hedge fund uses leverage in the strategy, and zero otherwise.
Personal Capital Dummy	An indicator variable that equals one if a hedge fund is invested by its own fund manager, and zero otherwise.
Log (AUM)	The log of assets under management.
Redemption Notice Period	Hedge funds' redemption notice period in the number of days.
Lockup Period	Hedge funds' lock up period in the number of days.
Age	The number of months of a hedge fund since its inception.
Minimum Investment	Log of (1+minimum investments).

Appendix B
CoVaR Estimation via Quantile Regressions

This appendix explains how we use quantile regressions to estimate the *CoVaR* of a hedge fund. First, for each hedge fund with at least 36 months of observations, we conduct the following *q*-quantile regression:

$$R_{i,t} = a_q^i + \tilde{\beta}_q^i X_{i,t} \tag{B1}$$

where $R_{i,t}$ is the return of fund *i* at time *t*, $X_{i,t}$ is an 3-by-1 vector [R_{LHF} *(t)*, R_{LHF}*(t-3, t-1)*, *Local FOF Flow (t-3,t-1)*]. R_{LHF} is the average return of hedge funds located in the same area as fund *i*, excluding the fund itself. *Local FOF Flow* is the average flow of all funds of funds located in the same area as fund *i*.

Then the *CoVaR* for fund *i* can be obtained from (B1) as:

$$CoVaR_{q,t}^{i|R_{LHF}=VaR_{q,t}^{LHF}} = \hat{\alpha}_q^i + \hat{\beta}_q^i[VaR_{q,t}^{LHF}, R_{LHF}(t-3,t-1), LocalFOFFlow(t-3,t-1)] \tag{B2}$$

where $VaR_{q,t}^{LHF}$ is the *q*th percentile VaR for local hedge funds at time *t*.

We then obtain the predicted value of $VaR_{q,t}^{LHF}$ by running a *q*-quantile regression of $R_{LHF}(t)$ on information at time *t*-1.

$$R_{LHF,t} = a_q^{LHF} + \tilde{\beta}_q^{LHF}[R_{LHF}(t-3,t-1), LocalFOFFlow(t-3,t-1)] \tag{B3}$$

Finally, we plug the predicted value of $VaR_{q,t}^{LHF}$ obtained from (B3) into equation (B2)

$$\Delta CoVaR_{q,t}^{i|LHF} = CoVaR_{q,t}^{i|R_{LHF}=VaR_{q,t}^{LHF}} - CoVaR_{q,t}^{i|R_{LHF}=Median^{LHF}}$$

$\Delta CoVaR_q^{i|LHF}$ is the local contagion susceptibility measure used in Table X.

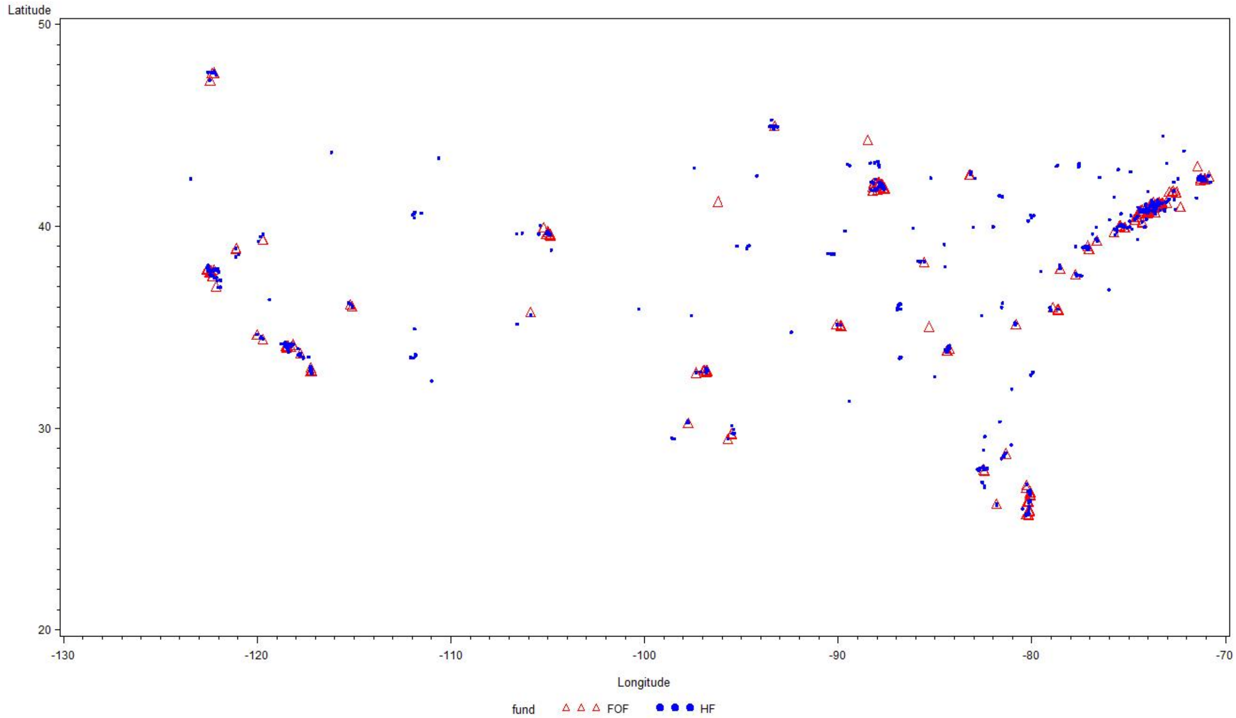

Figure 1. Geographical distribution of U.S. Hedge Funds and Funds of Funds. This graph plots the locations of hedge funds and funds of funds whose management companies are located in the continental United States. Latitude and longitude (decimal degree) data are obtained from the 2010 Census U.S. Gazetteer Files. A negative sign for longitude and latitude denotes West longitude and South latitude, respectively. We add a small random noise from a uniform distribution between (-0.01, 0.01) to each location so that the mass of the companies located in a given area can be seen.

Table I
Summary Statistics

Panel A of this table reports the summary statistics of the main variables used in the paper. Time series averages of the cross-sectional statistics are reported. The sample includes all hedge funds and funds of funds whose management companies are located in the continental U.S. from 1994 to 2010. We apply several filters following the literature. Specifically, we filter out non-monthly filing funds, funds denoted in a currency other than US dollars, and funds with unknown strategies. We then exclude first 18 months' of observations to control for the backfill bias. Finally, we exclude offshore funds and duplicated funds following Aggarwal and Jorion (2010). Hedge fund returns, alpha, appraisal ratio, Sharpe ratio, and flows are winsorized at the top and bottom 0.5% level. Panel B reports the total number of funds and Metropolitan Statistical Areas (MSAs) in the sample as well as the distribution of the number of funds per MSA. We report the time series average across the whole sample period as well as the statistics at the end of year 1994, 2002, and 2010. Panel C of the table reports the distribution of the total number of styles in each MSA for the same years.

Panel A: Hedge Fund Performance and Characteristics

	Hedge Funds (excluding FoFs, 2538 unique funds)					FoFs (573 unique funds)				
	Mean	Median	P25	P75	Std.Dev.	Mean	Median	P25	P75	Std.Dev.
# Funds per period	787	834	588	1,014	273	191	188	119	264	80
Net-Fee Return (%p.m.)	0.84	0.74	-1.19	2.72	4.46	0.65	0.65	-0.42	1.67	2.67
Alpha FH Seven-Factor (%p.m.)	0.55	0.56	-1.56	2.64	4.94	0.42	0.48	-0.64	1.52	2.81
Appraisal Ratio	0.54	0.29	-0.22	0.69	1.77	0.66	0.43	-0.07	0.74	1.53
Sharpe Ratio	0.51	0.27	-0.19	0.66	1.77	0.59	0.38	-0.04	0.65	1.55
Redemption Notice Period(days)	35.12	29.69	20.22	48.77	26.31	49.11	48.32	26.38	75.71	30.17
Lockup Period (months)	4.23	0.00	0.00	7.96	6.61	3.55	0.00	0.00	7.31	5.85
Personal Capital Dummy	0.47	0.39	0.00	1.00	0.49	0.47	0.44	0.00	1.00	0.49
High-Water Mark Dummy	0.59	0.61	0.35	1.00	0.46	0.49	0.56	0.00	0.84	0.46
Management Fee (%)	1.43	1.16	1.00	1.76	0.88	1.43	1.20	1.01	1.63	0.77
Incentive Fee (%)	18.44	20.00	19.63	20.00	5.53	9.62	10.13	1.15	14.76	7.60
Minimum Investment (M$)	1.09	0.71	0.23	1.00	2.35	1.04	0.59	0.23	0.98	2.40
Age (months)	73.32	61.78	37.23	98.69	46.49	76.01	63.18	39.81	102.38	47.44
AUM (M$)	129.70	33.68	10.29	108.21	375.77	101.31	33.69	12.65	91.64	216.33
Flow (%p.m.)	0.36	0.05	-0.97	1.33	9.36	0.35	0.03	-0.84	1.08	7.68
Leveraged Dummy	0.64	1.00	0.00	1.00	0.48	0.49	0.50	0.00	1.00	0.49

Table I - Continued

Panel B: Number of Funds and MSAs

Year	Number of Funds (excluding FoFs)	Number of MSAs	Number of Funds per MSA						
			Mean	Min	P25	Median	P75	Max	Std.Dev.
1994	284	34	8	1	1	2	6	113	20
2002	966	68	14	1	1	2	7	404	51
2010	776	72	11	1	1	2	7	312	38
Average	804	61	13	1	1	2	7	331	43

Panel C: Number of Styles

Year	Number of Funds (excluding FoFs)	Number of Styles per MSA						
		Mean	Min	P25	Median	P75	Max	Std.Dev.
1994	10	3	1	1	1	4	10	2
2002	10	3	1	1	2	3	10	2
2010	10	2	1	1	2	3	10	2
Average	10	3	1	1	2	3	10	2

Table II
Top Six MSAs

This table reports the summary statistics of hedge fund styles and performance for the six MSAs that host the largest number of hedge funds. Panel A presents a cross-tabulation of fund styles and MSAs. Panels B and C present the performance distribution of hedge funds and funds of funds, respectively. Time series averages of the cross-sectional statistics are reported. The sample selection procedure is the same as in Table I.

Panel A: Style Distribution

	Column Percentages						
Style\MSA	Boston	Chicago	Los Angeles	New York	San Francisco	Stamford	Total
Convertible Arbitrage	0.00	7.64	9.35	3.39	3.47	6.93	4.43
Dedicated Short Bias	1.68	0.64	0.72	0.80	3.96	0.00	1.08
Emerging Markets	8.40	2.55	4.32	7.17	6.44	3.90	6.16
Equity Market Neutral	13.45	8.92	7.91	5.78	7.92	3.03	6.59
Event Driven	9.24	5.73	11.51	18.63	7.92	13.42	14.58
Fixed Income Arbitrage	0.84	4.46	7.91	4.48	2.48	8.66	4.81
Global Macro	5.88	7.64	5.76	5.08	5.45	12.55	6.37
Long/Short Equity Hedge	50.42	23.57	41.73	38.15	56.93	32.90	39.36
Managed Futures	7.56	24.84	4.32	8.47	3.47	13.42	9.56
Multi-Strategy	2.52	14.01	6.47	8.07	1.98	5.19	7.07
Total Count	119	157	139	1004	202	231	1852

Table II - Continued

Panel B: Return Distribution for Hedge Funds (excluding FoFs)

MSA	Number of Funds/Period	Net-Fee Return (% p.m.)	Alpha FH Seven-Factor (% p.m.)	Median (Net-Fee Return)	Median (Alpha)	Std.Dev. (Net-Fee Return)	Std. Dev. (Alpha)
Boston	28	0.78	0.45	0.63	0.38	4.32	4.79
Chicago	44	0.86	0.59	0.78	0.57	4.83	5.09
Los Angeles	43	0.78	0.52	0.66	0.45	3.70	4.35
New York	324	0.83	0.58	0.74	0.59	4.07	4.56
San Francisco	64	0.80	0.46	0.69	0.52	4.96	5.37
Stamford, CT	78	0.80	0.54	0.71	0.58	3.98	4.39

Panel C: Return Distribution for Funds of Funds

MSA	Number of Funds/Period	Net-Fee Return (% p.m.)	Alpha FH Seven-Factor (% p.m.)	Median (Net-Fee Return)	Median (Alpha)	Std.Dev. (Net-Fee Return)	Std. Dev. (Alpha)
Boston	3	0.48	0.50	0.54	0.56	1.50	1.69
Chicago	10	0.80	0.60	0.66	0.57	2.07	2.24
Los Angeles	9	0.73	0.55	0.70	0.55	1.68	1.97
New York	100	0.63	0.44	0.63	0.48	2.65	2.60
San Francisco	8	0.82	0.39	0.81	0.39	1.70	2.21
Stamford, CT	17	0.58	0.36	0.61	0.42	2.02	1.98

Table III
Funds of Funds' Local Preference

This table represents FoFs' return comovement with local and nonlocal hedge funds. In Panel A, for each FoF in the sample, we estimate time-series regressions of monthly (*FoF Ret -MKT FoF Ret*) on *Local HF Ret*, *Non Local HF Ret,* Fung-Hsieh seven factors, and the ten TASS Hedge Fund Styles. We require at least 24 months observations for each time series regression. Cross-sectional averages of the estimated coefficients from the time-series regressions are reported in the table. *Local HF Ret* is calculated as the equal-weighted average returns of all hedge funds (excluding FoFs) from the FoF's corresponding MSA. *Non Local HF Ret* is calculated as the average returns of all hedge funds (excluding FoFs) not residing in the FoF's MSA. *MKT FoF Ret* is the average return of all funds of funds in the market. We cluster the standard errors by MSA. The numbers in parentheses are *t*-statistics. We also report the percentage of positive local bias, as well as the percentage of positive significant local bias, where the local bias is defined as the coefficient on *Local HF Ret* minus the coefficient on *Non Local HF Ret.* The *t*-statistics reported below the percentage of positive LB are for testing the hypothesis that the percentage is 50%, and the *t-statistics* below the percentage of positive and significant LB at 5% level are for testing the hypothesis that the percentage is 2.5% (for double-sided tests). In Panel B and C, we estimate two alternative measures of local bias as described in Section 3.1.2 and Section 3.1.3, respectively. *** Statistical significance at 1%. ** Statistical significance at 5%. * Statistical significance at 10% level.

Panel A: Base Measure: Local Bias Based on Difference in Differences

	(1)	(2)	(3)
Local HF Ret	0.15***	0.17***	0.10***
	(2.87)	(2.79)	(2.81)
Non Local HF Ret	-0.14***	-0.16***	-0.12*
	(-3.72)	(-3.44)	(-1.92)
Control for FH Seven Factors	No	Yes	No
Controls for Ten TASS Hedge Fund Styles	No	No	Yes
Non Parametric Tests:			
Percentage Positive LB	67.35***	67.81***	60.50***
	(7.26)	(7.45)	(4.40)
Percentage Positive and Significant LB	36.99***	22.83***	18.49***
At 5% Level	(46.23)	(27.25)	(21.44)
Adj. R2	0.25	0.34	0.45
N	438	438	438

Table III - Continued

Panel B: Alternative Measure 1: Local Bias Based On Nonnegative Weights

	(1)	(2)	(3)
Local Bias	0.24***	0.14***	0.31***
	(5.04)	(8.09)	(9.12)
Control for FH Seven Factors	No	Yes	No
Controls for Ten TASS Hedge Fund Styles	No	No	Yes
Non Parametric Tests:			
Percentage Positive LB	65.75***	64.15***	60.05***
	(6.94)	(6.18)	(4.29)
Percentage Positive and Significant LB	7.07***	2.97	17.12***
At 5% Level	(6.14)	(0.62)	(19.60)
N	438	438	438

Panel C: Alternative Measure 2: Local Bias Based on Local Factor Model

	(1)	(2)	(3)
Local Factor	0.14***	0.13***	0.09***
	(2.80)	(2.61)	(3.06)
Market Factor	1.01***	1.00***	0.99***
	(21.30)	(27.29)	(21.50)
Control for FH Seven Factors	No	Yes	No
Controls for Ten TASS Hedge Fund Styles	No	No	Yes
Non Parametric Tests:			
Percentage Positive LB	62.10***	62.56***	56.16***
	(5.06)	(5.26)	(2.58)
Percentage Positive and Significant LB	31.96***	18.26***	11.87***
At 5% Level	(39.50)	(21.13)	(12.56)
Adj. R2	0.54	0.61	0.66
N	438	438	438

Table IV
Properties of Funds of Funds' Local Preference

This table summarizes the persistence and determinants of FoFs' local bias. To construct the *Local Bias* variable, for each FoFs we run the following time-series regression using the previous 24 months' data: *(FoF Ret –Market FoF Ret) = c0 + c1 * Local HF Ret + c2* Non Local HF Ret*, where *Local HF Ret* is calculated as the average returns of all hedge funds (excluding FoFs) from the FoF's corresponding MSA. *Non Local HF Ret* is calculated as average returns of all hedge funds (excluding FoFs) not residing in the FoF's MSA. We then calculate the *Local Bias* as (*c1-c2)*. Finally, we standardize the *Local Bias* measure to have zero mean and unit standard deviation for each MSA and each period. We require an area to have at least five FoFs to be included in the analysis. Panel A reports the time-series means of the average *Local Bias* for the current quarter and the subsequent two years for each of the quintile portfolios sorted on the current quarter *Local Bias*. We report the difference between the high and low portfolios and the corresponding *t*-statistics. In addition, we report the time-series means of number of funds per period at the sorting and holding period. Panel B reports the panel regression of the FoFs' local bias on lagged-quarter fund characteristics using bi-annual data. Time and location fixed effects also are included, and the standard errors are clustered by location. We multiply the regression coefficients for variables *Age*, *Redemption Notice Period*, and *Lockup Period* by 10 for exhibition purpose. *** Statistical significance at 1%. ** Statistical significance at 5%. * Statistical significance at 10% level.

Panel A: Persistence of Local Preference

	Diff-in-Diff Measure		Measure Based on Non Negative Weights		Local Factor Based Measure	
	Year 0	Year 2	Year 0	Year 2	Year 0	Year 2
Low Port	-1.44	-0.80	-1.38	-0.62	-1.38	-0.41
2	-0.24	-0.25	-0.70	-0.36	-0.29	-0.05
3	0.15	0.08	0.02	0.09	0.06	0.08
4	0.40	0.22	0.80	0.31	0.37	-0.01
High Port	1.13	0.40	1.25	0.43	1.24	0.23
High-Low	2.57	1.20***	2.62	1.07***	2.62	0.64***
		(6.59)		(4.19)		(2.62)
#Fund/Period	167	114	160	110	167	114

Table IV - Continued
Panel B: Determinants of Local Preference

	Diff-in-Diff Measure	*Measure Based on Non Negative Weights*	*Local Factor Based Measure*
Log (AUM) (t-1)	-0.05**	-0.06**	-0.06*
	(-2.42)	(-2.15)	(-1.77)
Age (t-1)/10	-0.03***	-0.02**	-0.01**
	(-4.36)	(-2.08)	(-2.26)
Ret (t-12,t-1)	0.87***	0.14	0.28*
	(3.73)	(0.22)	(1.70)
Minimum Investment	0.11***	0.09**	0.10***
	(4.46)	(2.19)	(4.78)
Redemption Notice Period/10	0.03**	0.03**	0.04*
	(2.42)	(1.99)	(1.89)
Lockup Period/10	-0.03	0.00	-0.03
	(-0.61)	(0.03)	(-0.94)
Personal Capital Dummy	0.13**	0.18**	0.01
	(2.00)	(2.49)	(0.07)
Management Fee	-0.12**	-0.27**	-0.02
	(-2.15)	(-2.16)	(-0.09)
Incentive Fee	-0.01	0.00	0.00
	(-1.54)	(0.04)	(0.87)
High-Water Mark Dummy	-0.01	-0.01	-0.10
	(-0.09)	(-0.07)	(-1.25)
Leveraged Dummy	0.08	0.06	0.07**
	(1.17)	(0.90)	(2.00)
Adj R2	0.09	0.08	0.02
Number of observations	1,043	1,043	999

Table V
Funds of Funds' Local Bias and Performance: Base Measure

This table reports the panel regression results for FoFs' performance on local bias and other fund characteristics at a quarterly frequency. Three performance measures are examined. Alpha is the Fung-Hsieh (2001) seven-factor adjusted return over the subsequent quarter. AR is the corresponding appraisal ratio. SR is the Sharpe Ratio over the next quarter. To construct the *Local Bias* variable, for each FoF in the sample, we run the following time-series regression using the previous 24 months' data: *(FoF Ret –Other FoF Ret) = c0 + c1 * Local HF Ret + c2* Non Local HF Ret*, where *Local HF Ret* is calculated as the equal-weighted returns of all hedge funds (excluding FoFs) from the FoF's corresponding MSA. *Non Local HF Ret* is calculated as equal-weighted returns of all hedge funds (excluding FoFs) not residing in the FoF's MSA. We then calculate the *Local Bias* variable as the difference of estimated coefficients *c1* and *c2*. Finally, we standardize the *Local Bias* measure by subtracting the mean and dividing by the standard deviation of the *Local Bias* variable for each MSA and each period. We require a fund to have at least 12 months of observations within the 24 month window to be included in the analysis. All the other control variables are defined in Table A in the appendix. The TASS style exposure controls are not reported due to space concerns. We lag all the control variables by one quarter. We include time and location fixed effects. The numbers in parentheses are the *t*-statistics, with standard errors clustered by location. The sample selection procedure is the same as in Table I. We multiply the regression coefficients for variables *Log(AUM)*, *Age*, *Incentive Fee*, *Redemption Notice Period*, and *Lockup Period* by 10 for exhibition purpose. *** Statistical significance at 1%. ** Statistical significance at 5%. * Statistical significance at 10% level.

Table V – Continued

	Fung-Hsieh Seven Factor Alpha (%)			Sharpe Ratio			Appraisal Ratio for Fung-Hsieh Seven-Factor Model		
Local Bias	0.35***	0.26***	0.19***	0.05***	0.02***	0.02**	0.07***	0.05***	0.04***
	(5.49)	(6.44)	(4.72)	(7.40)	(3.43)	(2.54)	(4.94)	(5.01)	(3.80)
Log (AUM) (t-1)/10		0.01	0.01		0.09	0.06		0.12**	0.09
		(0.03)	(0.03)		(1.50)	(0.89)		(2.47)	(1.45)
Age (t-1)/10		0.01*	0.01*		0.00	0.00		0.00	0.00
		(1.73)	(1.80)		(-1.39)	(-0.86)		(0.43)	(0.62)
Ret (t-12,t-1)		3.47***	3.61***		0.37***	0.48***		0.25***	0.42***
		(5.29)	(5.00)		(2.86)	(3.51)		(2.59)	(4.58)
Minimum Investment		0.12***	0.09***		0.02	0.01		0.04**	0.03*
		(4.55)	(3.48)		(0.93)	(0.74)		(2.03)	(1.78)
Redemption Notice		0.04**	0.02		0.02***	0.02***		0.02***	0.02***
Period/10		(2.17)	(1.32)		(6.73)	(5.80)		(5.55)	(3.93)
Lockup Period/10		-0.02	-0.01		-0.03***	-0.03***		-0. 04**	-0.03***
		(-0.31)	(-0.09)		(-3.27)	(-5.54)		(-2.56)	(-2.98)
Personal Capital Dummy		-0.09	-0.08		0.02	0.03		0.02	0.04*
		(-0.91)	(-0.80)		(0.69)	(1.36)		(0.95)	(1.76)
Management Fee		-0.41***	-0.29***		-0.05	-0.05		-0.06**	-0.06*
		(-4.72)	(-3.37)		(-1.27)	(-1.21)		(-1.97)	(-1.69)
Incentive Fee/10		0.02	0.07		-0.02***	-0.01*		-0.02**	-0.01*
		(0.31)	(1.39)		(-2.80)	(-1.92)		(-2.08)	(-1.82)
High-Water Mark Dummy		0.12	0.08		0.02	0.02		-0.00	-0.00
		(1.59)	(0.98)		(1.46)	(1.58)		(-0.23)	(-0.22)
Leveraged Dummy		-0.04	-0.02		-0.02***	-0.02***		-0.04**	-0.04**
		(-0.33)	(-0.14)		(-2.68)	(-2.73)		(-2.19)	(-2.53)
Control for TASS Styles Exposures	No	No	Yes	No	No	Yes	No	No	Yes
Adj. R2	0.22	0.25	0.25	0.51	0.54	0.55	0.32	0.36	0.38
N	8,877	7,475	7,475	8,877	7,475	7,475	8,869	7,469	7,469

Table VI

Funds of Funds' Local Bias and Performance: Alternative Measures

This table reports the panel regression results for FoFs' performance on local bias and other fund characteristics at a quarterly frequency. Three performance measures are examined. Alpha is the Fung-Hsieh (2001) seven-factor adjusted return over the subsequent quarter. AR is the corresponding appraisal ratio. SR is the Sharpe Ratio over the next quarter. We use two specifications to construct the *Local Bias* variable. In panel A, for each FoF in our sample, we run the following two time-series regressions using the previous 24 months' data: *FoF Ret = c0 + c1 * Local HF Ret +c2*Non Local Ret* and *Market FoF Ret = c0' +c1'*Local HF Ret + c2'* Non Local HF Ret*, restricting *c1*, *c2*, *c1'* and *c2'* to be nonnegative. The local bias is defined as $\left(\frac{c1}{c1+c2}-\frac{c1'}{c1'+c2'}\right)$. *Local HF Ret*, *Non Local HF Ret* and *Market FOF Ret* are defined similarly as in Table V. In panel B, for each FoF in the sample, we run the following time-series regression using the previous 24 months' data: *(FoF Ret –TBill Ret) = c0 + c1 *(Local HF Ret- Non Local HF Ret)+c2*(Market FoF Ret-TBill Ret)*. The *Local Bias* variable is estimated as the coefficient *c1*. We standardize the *Local Bias* measure by subtracting the mean and dividing by the standard deviation of the *Local Bias* variable for each MSA and each period. We require a fund to have at least 12 months of observations within the 24 month window to be included in the analysis. The coefficients on the control variables are similar to Table V and are not reported due to space concerns. We lag all the control variables by one quarter. We include time and location fixed effects. The numbers in parentheses are the *t*-statistics, with standard errors clustered by location. The sample selection procedure is the same as in Table I. *** Statistical significance at 1%. ** Statistical significance at 5%. * Statistical significance at 10% level.

Table VI - Continued

Panel A: Local Bias Based On Nonnegative Weights

	Fung-Hsieh Seven Factor Alpha (%)			Sharpe Ratio			Appraisal Ratio for Fung-Hsieh Seven-Factor Model		
Local Bias	0.20***	0.13***	0.07	0.04***	0.02**	0.02**	0.07***	0.05***	0.04***
	(4.33)	(3.89)	(1.41)	(5.12)	(2.49)	(2.33)	(2.84)	(3.47)	(3.10)
Control for Fund Characteristics	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Control for TASS Styles Exposures	No	No	Yes	No	No	Yes	No	No	Yes
Adj. R2	0.24	0.26	0.27	0.54	0.57	0.58	0.33	0.37	0.39
N	8,264	6,960	6,960	8,264	6,960	6,960	8,257	6,955	6,955

Panel B: Local Bias Based on Local Factor Model

	Fung-Hsieh Seven Factor Alpha (%)			Sharpe Ratio			Appraisal Ratio for Fung-Hsieh Seven-Factor Model		
Local Bias	0.26***	0.28***	0.19***	0.03***	0.02**	0.01*	0.04**	0.03***	0.02**
	(2.94)	(5.67)	(3.97)	(3.17)	(2.56)	(1.88)	(2.00)	(3.20)	(2.03)
Control for Fund Characteristics	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Control for TASS Styles Exposures	No	No	Yes	No	No	Yes	No	No	Yes
Adj. R2	0.22	0.25	0.25	0.51	0.54	0.55	0.32	0.36	0.38
N	8,877	7,475	7,475	8,877	7,475	7,475	8,869	7,469	7,469

Table VII
Funds of Funds' Local Bias and Performance: Subsample Analyses

This table reports the quarterly panel regression results for FoFs' performance on local bias and other fund characteristics for various subsamples. The variables and regression specifications are similar to Table V. The coefficients on the control variables are similar to Table V and are not reported due to space concerns. Panel A reports the results for the New York and Non New York subsamples. It also tests the difference in coefficients for the *Local Bias* variable between the two subsamples. Panel B reports the panel regression results for the subsample where the equal-weighted average alpha for local hedge funds is less than that of the nonlocal hedge funds during the previous 24 months. We require a fund to have at least 12 months of observations within the 24 month window to be included in the analysis. Panel C focuses on the subsample of FoFs who are not managed by multi-fund families. The numbers in parentheses are the *t*-statistics, with standard errors clustered by location. The sample selection procedure is the same as in Table I. *** Statistical significance at 1%. ** Statistical significance at 5%. * Statistical significance at 10% level.

Panel A: New York and Non New York Subsamples

	Fung-Hsieh Seven Factor Alpha (%)			Sharpe Ratio			Appraisal Ratio for Fung-Hsieh Seven-Factor Model		
	NY	Non NY	Difference	NY	Non NY	Difference	NY	Non NY	Difference
Local Bias	0.16	0.14*	0.02	0.00	0.04**	-0.04*	0.04***	0.03	0.01
	(1.46)	(1.77)	(0.12)	(0.03)	(2.39)	(-1.91)	(2.80)	(1.33)	(0.03)
Control for Fund Characteristics	Yes	Yes		Yes	Yes		Yes	Yes	
Control for TASS Styles Exposures	Yes	Yes		Yes	Yes		Yes	Yes	
Adj. R2	0.24	0.32		0.56	0.56		0.38	0.40	
N	4,793	2,682		4,793	2,682		4,791	2,678	

Table VII - Continued

Panel B: Subsample of Weak Performing Areas

	Fung-Hsieh Seven Factor Alpha (%)			Sharpe Ratio			Appraisal Ratio for Fung-Hsieh Seven-Factor Model		
Local Bias	0.15**	0.14	0.22***	0.04***	0.03*	0.03***	0.04***	0.03*	0.03***
	(1.97)	(1.43)	(2.61)	(3.85)	(1.65)	(3.05)	(3.08)	(1.72)	(2.62)
Control for Fund Characteristics	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Control for TASS Styles Exposures	No	No	Yes	No	No	Yes	No	No	Yes
Adj. R2	0.25	0.28	0.29	0.61	0.64	0.65	0.39	0.41	0.42
N	3,279	2,790	2,790	3,279	2,790	2,790	3,277	2,789	2,789

Panel C: Subsample of Stand-Alone FoFs

	Fung-Hsieh Seven Factor Alpha (%)			Sharpe Ratio			Appraisal Ratio for Fung-Hsieh Seven-Factor Model		
Local Bias	0.35***	0.42***	0.29***	0.03**	0.03***	0.02**	0.06***	0.06***	0.05***
	(4.06)	(4.59)	(2.81)	(2.37)	(2.91)	(2.14)	(4.98)	(4.67)	(3.82)
Control for Fund Characteristics	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Control for TASS Styles Exposures	No	No	Yes	No	No	Yes	No	No	Yes
Adj. R2	0.27	0.30	0.30	0.56	0.61	0.61	0.35	0.40	0.42
N	6,555	5,400	5,400	6,485	5,400	5,400	6,548	5,395	5,395

Table VIII
Local Flow Comovement

This table reports the flow comovement among local hedge funds. Panel A compares the average pairwise flow correlation for funds located in the same MSA versus funds located in different areas. The first and third columns calculate correlations based on raw percentage flows. The second and fourth columns calculate the correlation of residual flows orthogonalized by each fund's past quarter, past half-year and past one-year returns. In the third and fourth columns, the same MSA pairs exclude pairs of funds from the same fund family. In Panel B, for each hedge fund in the sample (excluding funds of funds), we estimate panel regressions of monthly percentage flows on *Local Flow*, with several control variables. *Local Flow* is calculated as the equal-weighted flow of all hedge funds (excluding FoFs) from the fund's corresponding MSA, excluding the fund itself. *Style Flow* is the equal-weighted flow of all funds in the fund's corresponding TASS style, excluding the fund itself. All the other control variables are defined in Table A in the appendix. In the fourth to sixth columns, we exclude funds from the same fund family when calculating *Local Flow*. We cluster the standard errors by MSA. The numbers in parentheses are *t*-statistics. We require a fund to have at least 24 months of observations to be included in the analysis. We exclude areas that host less than six hedge funds. The sample selection is the same as in Table I. *** Statistical significance at 1%. ** Statistical significance at 5%. * Statistical significance at 10% level.

Panel A: Pair-wise Flow Correlation

	Whole Sample		Exclude Fund Pairs From the Same Family	
	Flow Correlation (%)	Return-Adjusted Flow Correlation (%)	Flow Correlation (%)	Return-Adjusted Flow Correlation (%)
Same MSA	2.37	1.52	2.28	1.44
Different MSA	2.02	1.24	2.02	1.24
Same - Different	0.36 ***	0.28***	0.27 ***	0.20***
	(6.24)	(5.02)	(4.68)	(3.56)

Table VIII - Continued
Panel B: Regression on Local Flows

	Whole Sample			Exclude Funds from the Same Family		
Local Flow	0.19***	0.15***	0.17***	0.12**	0.09**	0.10**
	(3.98)	(4.20)	(4.00)	(2.11)	(2.04)	(2.08)
Style Flow	0.26***	0.18***	0.19***	0.28***	0.19***	0.20***
	(14.84)	(11.95)	(11.56)	(15.89)	(12.88)	(12.29)
Ret(t-3,t-1)		0.18***	0.19***		0.18***	0.19***
		(27.52)	(20.44)		(28.31)	(21.71)
Ret(t-6,t-4)		0.16***	0.17***		0.17***	0.17***
		(20.76)	(19.21)		(20.86)	(19.31)
Ret(t-12,t-7)		0.20***	0.22***		0.20***	0.21***
		(11.32)	(11.04)		(11.60)	(11.07)
Local Ret(t-3,t-1)			-0.06***			-0.04*
			(-2.71)			(-1.74)
Local Ret(t-6,t-4)			-0.05**			-0.03*
			(-2.55)			(-1.67)
Local Ret(t-12,t-7)			-0.14***			-0.12***
			(-5.37)			(-3.94)
Intercept	-0.00	-0.01***	-0.01***	0.00	-0.01***	-0.01***
	(-1.07)	(-17.45)	(-17.44)	(-0.35)	(-16.09)	(-15.84)
Adj. R^2	0.01	0.03	0.03	0.01	0.03	0.03
N	119,964	110,125	110,125	118,265	108,552	108,552

Table IX
Local Contagion

This table reports the extreme negative return clustering among local funds. For each hedge fund (excluding FoFs), we first filter the returns by Fung-Hsieh seven factors, average returns of all funds sharing the same style as the fund, and the fund's own past quarter returns. We then work with the residual returns. In panel A, we run logistic regressions, where the dependent variable indicates whether a fund's return in a particular month belongs to the lower 10% of the fund's return distribution. The independent variables include an indicator variable of whether the average returns of the other local hedge funds fall in the bottom 10% during the month, the *Percentage of Local Distress* variable, which is the number of other local hedge funds that also have negative extreme returns during the month divided by the total number of local hedge funds, an indicator variable of whether the average returns of the market portfolio of hedge funds fall in the bottom 10% during the month, an indicator variable of whether the average returns of the local stocks fall in the bottom 10% of the return distribution, the *Percentage of Market Distress*, which is the number of hedge funds in the market incurring bottom 10% returns divided by the total number of hedge funds, and the *Percentage of Local Stock Distress*, which is the number of local stocks incurring bottom 10% returns divided by the total number of local stocks. In the fifth to the eighth columns, we exclude funds from the same fund family in the *Local Ret* calculation. In Panel B, we regress log(*Percentage of Local Stress*) on an indicator variable of whether the local funds of funds incur flows that fall in its lower 25% during the previous quarter. The numbers in parentheses are *t*-statistics, where the standard errors are clustered by MSAs. The sample selection procedure is the same as in Table I. *** Statistical significance at 1%. ** Statistical significance at 5%. * Statistical significance at 10% level.

Panel A: Worst Return Clustering

	Dependent Variable: *Ret (t) < bottom 10%*							
	Whole Sample				Exclude Funds from the Same Family			
Local Ret(t) < bottom 10%	0.25***	0.22***			0.14***	0.10***		
	(5.14)	(3.83)			(3.87)	(2.59)		
Market Ret(t)<bottom 10%		0.11***				0.11**		
		(2.51)				(2.13)		
Local Stock Ret(t) < bottom 10%		0.39***				0.40***		
		(12.52)				(13.37)		
Percentage of Local Distress(t)			4.29***	2.55***			4.26***	2.41***
			(4.67)	(5.66)			(4.37)	(5.16)
Percentage of Market Distress(t)				5.48***				5.61***
				(11.97)				(12.05)
Percentage of Local Stock Distress(t)				0.89***				0.89***
				(2.82)				(2.72)
Intercept	-2.16***	-2.22***	-2.61***	-3.12***	-2.15***	-2.21***	-2.60***	-3.12***
	(-481.55)	(-300.41)	(-24.47)	(-46.88)	(-417.73)	(-193.58)	(-23.05)	(-44.99)
N	136,049	135,898	136,049	120,009	134,257	134,106	134,257	118,876

Panel B: Local Contagion and Local FoF Flows

	Dependent Variable: log(*Percentage of Local Distress*)		
Local FoF Flow (t-3, t-1) <bottom 25%	0.11***	0.09***	0.08***
	(3.03)	(2.59)	(2.74)
Nonlocal FoF Flow (t-3, t-1)<bottom 25%		0.08**	0.01
		(2.50)	(0.09)
Intercept	-2.12***	-2.21***	-2.12***
	(-44.06)	(-41.99)	(13.35)
Time Fixed Effect	No	No	Yes
N	2,095	2,095	2,095

Table X
Local Hedge Funds' *CoVaR*

This table reports the *CoVaR* measure proposed by Adrian and Brunnermeier (2011) to measure a fund's local contagion susceptibility. We filter each hedge fund's returns by the Fung-Hsieh seven factor model, the fund's style returns, and its past quarter returns. We then work with the residual returns. To construct the *CoVaR* measure, we run for each hedge fund the 10% (or 25%) quantile regressions of returns on the current and past quarter local hedge fund returns and its local FOF flows during the past quarter. Panel A presents the average coefficents from the quantile regressions. The numbers in parentheses are the *t*-statistics with the standard errors adjusted for heteroscedasticity and autocorrelation. In Panel B, we report the summary statistics of *CoVaR* and *ΔCoVaR*. *ΔCoVaR* is the difference between 10% (or 25%) *CoVaR* and the 50% *CoVaR*, where *q*% *CoVaR* is the predicted value from a *q*% quantile regression of the local hedge fund return on the lagged local hedge fund returns and local FOF flows. *ΔCoVaR* gives the percentage point change in a hedge fund's *q*% VaR when the other local hedge funds realized their *q% VaR*. Appendix B provides further information on the estimation of the *CoVaR* variables. *** Statistical significance at 1%. ** Statistical significance at 5%. * Statistical significance at 10% level.

Panel A: Quantile Regression

	CoVaR (10%)	*CoVaR* (25%)
Local Ret (t)	0.31***	0.32***
	(7.07)	(6.40)
Local Ret (t-3, t-1)	0.05***	0.00
	(2.76)	(0.01)
Local FoF Flow (t-3, t-1)	5.80***	1.58*
	(2.85)	(1.67)
Intercept	-3.21***	-1.61***
	(30.55)	(25.97)
N	1,348	1,348

Panel B: Summary Statistics of Local *CoVAR* (%)

	N	Mean	Std Dev	25th Pctl	Median	75th Pctl
CoVaR(10%)	122,750	-3.29	2.40	-4.31	-2.76	-1.59
ΔCoVaR(10%)	122,750	-0.15	0.84	-0.41	-0.10	0.18
CoVaR(25%)	122,750	-1.66	1.33	-2.20	-1.37	-0.76
ΔCoVaR (25%)	122,750	-0.08	0.32	-0.16	-0.04	0.05