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Birds of a Feather: Do Hedge Fund Managers Flock Together?

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Abstract. Mandatory filings for UK hedge funds suggest that managers having worked at the same prior employer invest more similarly in terms of distances of returns. If they overlapped in employment, increasing the chance of social ties, investments become even more similar. The joint effect accounts for up to two thirds of the difference in investing behavior. Results are robust to fund- and manager-level controls as well as to identification concerns. With controls, the same-employer effect is concentrated in the systematic component (beta), whereas the overlap effect is concentrated in the idiosyncratic components (alpha and residuals). Managerial ties make any two funds more similar in their stock holdings. Moreover, portfolios of connected funds outperform their peers in terms of alpha, return volatility, and Sharpe ratio.

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1. Introduction

Social ties influence the decisions of economic agents, for example, households, fund managers, or top executives.[1] We show for the secretive hedge fund industry that prior employment networks as well as personal ties arising from such networks lead to more similar investment decisions and performance of UK hedge fund managers, explaining up to two thirds of differences in returns.

Researchers typically decompose hedge fund returns into systematic components (beta) and idiosyncratic components (abnormal return of the manager (alpha) and residuals). Yet factor models such as Fung and Hsieh (2004) leave a large portion of hedge fund returns unexplained by standard systematic factors; Patton and Ramadorai (2013) report an average adjusted R^2 of only 32%. The analysis of alpha is often reduced to variation because of hedge fund–specific variables, such as fees and investment styles (Joenvääärä et al. 2021), geography (Teo 2009), or managerial characteristics and skill (Li et al. 2011). The role of social networks is, however, largely ignored. Similarly, beta exposure to various factors is typically estimated without concern for the role of managerial networks.

A few concurrent studies provide some evidence of a relation between hedge fund performance and prior industry work experience (Papageorgiou et al. 2011) and manager–broker personal connections (Kellard et al. 2017). However, a thorough investigation of how and how much managerial networks based on prior employment affect similarities among a comprehensive sample of hedge fund returns is sorely missing. This paper aims to fill this void, also looking at the role of managerial characteristics, such as education, gender, and location.

The hedge fund industry presents an ideal laboratory to study the effect of social networks among managers, who make crucial decisions on investments. We use so-far-unexplored mandatory filings of UK hedge fund management companies. The data cover the complete employment record (in finance-related jobs) and personal characteristics of every single UK hedge fund manager from 2002 through 2013, which we augment with hand-collected education records. Through the names of management companies, we match the employment data with commercial hedge fund databases. The resultant database of performance, fund characteristics, and work trajectories is much larger and more encompassing than the hand-collected data sets of, for example, Kellard et al. (2017) or Spilker (2022).

Our hypotheses design is guided by Manski (1993), who outlines three different channels that can lead to similar investment decisions. These are firm culture (skills learned at the previous workplace), social ties (managers know each other and personally exchange ideas), and managerial characteristics. We, thus, build measures of firm culture and social ties, controlling for managerial characteristics. The dummy variable *Firm* identifies potential skills learned at a prior employer. The dummy indicates that managers worked for the same past employer but at potentially nonoverlapping times. The dummy variable *Overlap* identifies potential social ties of managers overlapping for a significant time (in our setup, at least 24 months) working for the same employer. Note that *Overlap* can only be one if *Firm* is one. Thus, it captures the additional peer effect of managers who overlapped in time and possibly interacted in the workplace. Such managers are more likely to be socially connected to each other and potentially still share investment ideas with one another; see Stein (2008) and Crawford et al. (2017).

The great majority of funds in our data set share managerial connections, and we ask whether such connections trigger similarities in hedge fund returns. Given the high degree of complexity in hedge fund trading, we test for the impact of employment history on the pair-wise distance (i.e., expected absolute differences and variance of differences) in raw returns as well as in systematic risk factors (beta) and idiosyncratic components, namely, abnormal performance (alpha) and shocks (residuals). We estimate all components at the fund level following the widely used Fung and Hsieh (2004) seven-factor model.[2]

As expected, both *Firm* and *Overlap* reduce distances in performance and its components. In other words, funds whose managers were trained at the same prior employer and overlapped in time perform more similarly. The corresponding coefficients are strongly statistically and economically significant. They imply for connected funds that the monthly expected absolute difference in raw returns is 75 basis points (bps) lower (out of 324 bps, i.e., −23%) for hedge funds connected through both channels. Using variances instead of absolute differences, the two effects reduce the variance of differences in raw returns of 24.24% by a much larger 64%. The relative effect is comparable for the distance in factor loadings (betas, −26%) and idiosyncratic risk (residuals, −25%) and is highest for the distance in abnormal performance (alpha), which is 24 bps lower out of 73 bps (−32%). Using variances, the effects are even stronger: −51% for factor loadings and an impressive −76% for idiosyncratic risk. These conclusions are robust at reduced levels once we control for fund-level characteristics, including investment style, fees, size, and age; leverage; and colocated headquarters in the same UK postal code; see Hong et al. (2005). They are also robust to alternative factor models and estimation strategies.

Interestingly, we find that distances in systematic components (beta) are mainly driven by *Firm* effects, whereas distances in idiosyncratic components (alpha and residuals) are mainly driven by *Overlap* effects. We argue that previous employers (*Firm*) are more likely to have policies on systematic components (e.g., sector limits, exposure limits to certain risk factors, prospectuses prescribing the investments of a fund, or firm-specific models), an argument that resonates with Beunza and Stark (2012) and MacKenzie (2003). Social networks (*Overlap*) are used for discussion of individual bets, researching particular investment strategies, or finding out about market conditions (Kellard et al. 2017) with effects showing up more strongly in the idiosyncratic components (alpha and residuals).

We are aware that our variables may be subject to several confounding effects. For example, smart managers may all invest in certain assets. Then, if smart managers are more likely to be hired by some prestigious firm, *Firm* might simply be a proxy for the underlying managerial characteristic. Therefore, we control in our estimation for the manager's sex, age, and skill. Grinblatt et al. (2012) find that investors with higher skill (in terms of IQ) outperform their peers. We proxy skill through education by noting the highest academic degree attained according to the manager's LinkedIn profile. See Li et al. (2011) for evidence that manager education explains hedge fund performance. Alternatively, we measure the strength of the hedge fund labor market in the year the manager entered the fund as an (inverse) proxy for the skill of the average manager in that period.

We find that the role of *Firm* and, in particular, *Overlap* is not affected by the inclusion of these controls. We also introduce a firm fixed effect to control for firm selection of employees on the basis of different managerial characteristics (e.g., skill) and to allow for heterogeneity in portable alpha (e.g., techniques learned at an employer). Again, *Overlap* remains strongly significant. Thus, skills acquired at firms might be relevant along with social ties.

To strengthen our argument, we verify whether the role of *Overlap* increases along dimensions that make social ties more likely. The number of employees at the management company is one such dimension as *Overlap* in the case of two small teams is more likely to lead to social ties that influence investment behavior than *Overlap* for two large teams. We also construct an alternative measure for the dummy version that scales by the fraction of actual over possible connections to capture the strength of ties. Finally, longer *Overlap* should reinforce the effect. Indeed, the importance of *Overlap* strengthens as predicted.

We confirm our results by using data on portfolio holdings for a select 87 companies that manage funds in the United States and have more than US$100 million under management. The Securities and Exchange Commission (SEC) requires these funds to disclose quarterly holdings data in so-called 13F filings, which provide a direct and granular view of managerial allocation decisions. Consistent with the analysis on hedge fund returns and their components, we find that pairs of companies whose managers are connected by having worked for the same prior employer (i.e., *Firm* equals one) and, additionally, at the same time (i.e., *Overlap* equals one) are characterized by a smaller distance in stock holdings compared with unconnected pairs. Furthermore, the statistical and economic significance of these effects widens significantly when we restrict the analysis to the set of funds headquartered in the United Kingdom, for which the majority of employees should be UK employees that appear in the Financial Services Register (FSR) filings. We are, thus, reassured that social ties genuinely affect investment decisions at hedge funds. Results not only hold when using estimated factor loadings, but also when using actual portfolio holdings.

Managerial employment networks seem to be important drivers of similarities in hedge fund performance. Firm culture seems to matter when managers have been exposed to common training at a prior employer. Such managers trade similarly but do not necessarily share information or ideas. An important additional effect stems from employments that overlap in time, thereby making social ties more likely. These findings beg the question as to what is the economic value of social ties? In other words, do managerial connections ultimately enhance or dampen hedge fund performance? Should investors seek to construct or eschew hedge fund management companies whose managers are more tightly connected with managers of other management companies?

We address these questions in two complementary ways. First, we ask estimate fund-level regressions relating fund performance to the number of its managerial connections. Whereas *Firm* connections do not seem to affect fund performance, do *Overlap* connections matter? Alpha is positively affected by *Overlap*, and standard deviation, our proxy for risk, is significantly lower for hedge funds with more *Overlap* connection.

The conclusions from the fund-level analysis do not immediately extend to a fund-of-funds setting. Whereas alpha and excess return scale linearly with the number of constituent funds, standard deviation and Sharpe ratios do not. We, thus, simulate 70,000 fund-of-funds portfolios of 16 hedge funds each. Half of those we design to have no connections in the eight pairs of two hedge funds each that constitute the 16 hedge funds. For the other half, we chose possibly connected hedge funds to pair with the initial eight hedge funds. We compute equally weighted portfolio returns and repeat the analysis.

Firm connections increase excess returns and alpha, significantly decrease standard deviation (risk), and significantly increase Sharpe ratios. *Overlap* connections lead to generally stronger results than in the case of *Firm* connections with all coefficients now being significant. Both types of connection (and more so the *Overlap* ones) make hedge funds and, particularly, fund-of-funds more attractive. These conclusions are confirmed in a standard decile-sorting setup. Altogether, our analyses provide novel evidence that managerial connections are value-enhancing.

The paper is organized as follows. Section 2 relates our paper to the literature. Section 3 describes the data set and the construction of our measures of connectedness. Section 4 outlines our estimation strategy and presents the empirical results linking hedge fund performance to connections via employment history. Section 5 collects robustness tests, including the analysis of holdings. In Section 6, we address identification concerns by adding managerial attributes and testing for interaction effects. In Section 7, we quantify the economic value of social ties at the fund and portfolio levels. We offer concluding remarks in Section 8.

2. Literature

We contribute to the literature on factor models by showing how firm culture and social ties lead to more similar investments. The two components account for up to two thirds of the variance of differences of hedge fund returns.

Deuskar et al. (2011) study former mutual fund managers newly working for hedge funds. These managers persistently underperform and tend to be hired during periods of expansion of the hedge fund industry. We use the latter insight in defining our control for skill. Papageorgiou et al. (2011) look at the effect of past work experience on performance. Spilker (2022) documents more similar investments for hedge fund managers who worked at the same prior hedge fund. We extend his evidence to all previous employers in the financial industry.

Our work on social ties relates to Hong et al. (2004), who find that more socially interactive individual investors tend to participate more in the stock market. Mutual fund managers who invest in firms at which they are connected to the CEO through educational background outperform unconnected managers (Cohen et al. 2008) and are more likely to vote against shareholder-initiated proposals to limit executive compensation (Butler and Gurun 2012). Teo (2009) shows that hedge funds geographically nearer to the investment region outperform their peers, which he attributes to local information advantages. We add here that hedge fund managers connected through employment histories invest more similarly. This is consistent with Hong et al. (2005), who document that colocated mutual fund managers invest more similarly. Our results, however, persist even when we control for colocated headquarters of management companies.

We contribute to the large literature documenting the importance of director and CEO networks; see Hwang and Kim (2009), Fracassi (2017), and Engelberg et al.

(2013). Cohen et al. (2010) document that analysts with educational links to company senior managers outperform their peers in terms of more precise stock recommendations. Educational and prior employment linkages between company and bank managers reduce syndicate interest rates (Engelberg et al. 2012), whereas those between directors and senior executives at acquiring and target firms instead tend to diminish overall value creation (Ishii and Xuan 2014). Similar effects extend to the secretive hedge fund industry, in which manager identities are often unknown. Mandatory filings with the financial regulator in the United Kingdom serve to overcome this lack of information.

Finally, our work relates to research on the outperformance of more over less connected managers. For U.S. mutual funds, Pool et al. (2015) show that abnormal overlap in neighboring managers' holdings generates positive and significant abnormal returns. Even closer to our setting, Rossi et al. (2018) look at UK pension fund managers. They find that managers who are better connected (either directly or through having a common consultant) deliver higher risk-adjusted returns. These findings suggest that information transmission through managerial interactions is value-enhancing. To the best of our knowledge, we are the first to document that similar dynamics extend to the hedge fund industry, in which manager identity is often unknown.

3. Data and Methodology

Manski (1993) suggests that manager connections can lead to similarities in hedge fund performance because of (i) firm culture, that is, skills learned at a common prior employer lead later to similar investment decisions; (ii) social ties, that is, managers who come to know each other at a common prior employer continue to exchange ideas and trading strategies; or (iii) managerial characteristics, for example, comparably smart managers end up at the same employers and subsequently deliver similar (good or bad) performance. We use information from previously unexplored regulatory data to empirically study the relevance of these channels.

3.1. Data and Managerial Characteristics

Our analysis requires the intersection of hedge fund databases and managers' employment histories. We combine seven major hedge fund databases (Morningstar, Eurekahedge, BarclayHedge, Hedge Fund Research, Trading Advisor Selection System, Center for International Securities and Derivatives Markets, and Preqin) using names of the management companies.[3] The merging procedure and filters follow Hodder et al. (2014) and are similar to Joenväärä et al. (2021). We remove duplicates and different share classes of the same fund within each company by grouping funds if their return correlations are above 0.99. Within each group, we keep the fund with the longest time series of returns. We require at least 24 months of data.

The great majority of management companies have multiple share classes for the same strategy that are denominated in various currencies. We opt for the class denominated in U.S. dollars as this is by far the most common.

The data consist of monthly information on 78,633 hedge funds (in 15,884 management companies) from January 1986 through December 2016, of which 74,788 are dead funds and 3,845 are live funds. Keeping the dead funds addresses potential survivorship bias. To address backfill bias, we follow Kosowski et al. (2007) and Teo (2009) and remove the initial 12 monthly returns for each hedge fund.

Next, we retrieve information about the employment histories of hedge fund employees from the publicly available FSR from 2002 through 2016 (for details see the appendix). All UK financial firms, including normally secretive management companies that control hedge funds, need to report detailed information on the current and past employment of their key employees. The FSR should be devoid of any selection bias and is survivorship bias–free as it keeps track of dead companies.

We merge the FSR and the hedge fund data according to the management company name. The resulting sample includes 685 UK-domiciled companies managing 2,930 distinct hedge funds (788 live and 2,142 dead) from January 2002 through December 2016.

From the FSR database, we obtain the employee names and numeric IDs, the full employment history with names of former employers (only if registered by the Financial Conduct Authority) with entry and exit dates, gender, and job description. We select senior managers of the management company (directors, CEOs, and partners), who determine the general strategy at all hedge funds owned.[4]

We collect manager age by manually looking up manager names in the Companies House database at https://companycheck.co.uk. We further collect the highest university degree by manually looking up manager names on LinkedIn.

From the hedge fund data, in addition to net-of-fee returns, we obtain a wealth of fund-level characteristics, such as management fee, performance fee, fund age, and investment style. The data also include (for a much smaller number of funds) a leverage indicator. We measure management company size through the number of employees as assets under management are very poorly recorded in the hedge fund database. We manually gather the postcode for the headquarters of the management company in the Companies House database, in which filing is mandatory. Two postcodes are defined as equal if they have the same outward code.[5]

3.2. Firm Culture and Social Ties

We define two network measures based on the employment histories of our manager. For a manager working for a hedge fund with management company i and another manager working for a hedge fund with a different management company j,

- *Firm* equals one if the managers worked for the same firm at some, potentially different, time for a minimum of 12 months each.
- *Overlap* equals one if *Firm* is one and the managers overlapped at that firm for at least 24 months (chosen so that the two managers could establish social ties).

For *Firm* and *Overlap*, two management companies are connected if any manager of management company i is connected with any manager of management company j. In Section 6.2, we show that alternative, scaled specifications provide even stronger evidence. We take into account all prior work experiences during the relevant network period (the median is two prior employers).

As the FSR is organized only at the management company level, we construct all our variables at that level. This should work against our empirical approach as we might classify unconnected hedge funds at different management companies as linked, implying that our empirical results should be considered as a lower bound for the relevance of connections. We drop all pairs of hedge funds at the same management company. For those pairs, we cannot distinguish ties because of prior employment connections from ties because of within-management company rules and culture.

Firm and *Overlap* should capture different channels, as outlined by Manski (1993), of similarity in hedge fund investment. *Firm* presumably measures portable skills and expertise that managers acquired at the former employer (firm culture). For example, two managers who both worked at Goldman Sachs tend to management of fixed income products because of the training in fixed income they received at Goldman. *Overlap* presumably measures the potential for personal interactions through mutual work experience (social ties). We posit that such social ties are stronger for employees who overlapped in their working experience. To the extent that managers continue to discuss ideas with their former colleagues (Kellard et al. 2017), these social ties may lead to similar investments. Finally, we control for managerial characteristics such as manager age, gender, skill, and education.

3.3. Measures of Similarity in Investments

We ask whether connected hedge funds invest more similarly than unconnected ones. Unfortunately, holdings data are not available for our sample of UK hedge funds. Therefore, following Kosowski et al. (2007), Deuskar et al. (2011), and others, we decompose raw hedge fund returns r according to the seven-factor model of Fung and Hsieh (2004):[6]

$$r_{i,t} - rf_t = \alpha_i + \boldsymbol{\beta}_i' \boldsymbol{F}_t + \epsilon_{i,t}, \tag{1}$$

where $r_{i,t}$ is the net-of-fees return of hedge fund i in month t, rf_t is the risk-free rate, $\boldsymbol{F}_t$ collects the factor returns, α_i measures abnormal performance, $\boldsymbol{\beta}_i$ measures the factor loadings, and $\epsilon_{i,t}$ is the mean-zero idiosyncratic error term. We standardize all factors to exhibit unit standard deviation.

We define dependent variables that capture distances between fund i and fund j returns (and their components) based on either expected absolute differences (L1-norm) or variances of differences (L2-norm) of returns. The smaller any distance between two funds is, the more similar are their investments.

3.3.1. Expectation of Absolute Differences (L1-Norm).

We can decompose the expected absolute differences in raw fund returns as follows:

$$E[|r_{i,t} - r_{j,t}|] \leqslant |\alpha_i - \alpha_j| + |\boldsymbol{\beta}_i - \boldsymbol{\beta}_j|' |\boldsymbol{F}_t| + E[|\epsilon_{i,t} - \epsilon_{j,t}|]. \tag{2}$$

We note the resulting inequality because of the triangle relation of absolute values. To aid our further discussion, we label the terms involved in the following manner:

$$\Delta r_{L1} \leqslant \Delta\alpha_{L1} + \Delta\beta_{L1} + \Delta\epsilon_{L1}, \tag{3}$$

where $\Delta\beta_{L1}$ constitutes the difference in systematic fund returns, whereas $\Delta\alpha_{L1}$ and $\Delta\epsilon_{L1}$ capture differences in idiosyncratic fund returns. We estimate expectations by taking time-series averages.

3.3.2. Variance of Differences (L2-Norm).

As an alternative, we decompose variances of differences of raw fund returns and obtain the following equality:

$$Var(r_{i,t} - r_{j,t}) = Var((\boldsymbol{\beta}_i - \boldsymbol{\beta}_j)' \boldsymbol{F}_t) + Var(\epsilon_{i,t} - \epsilon_{j,t}). \tag{4}$$

To facilitate discussion, we analogously label the terms involved in the following manner:

$$\Delta r_{L2} = \Delta\beta_{L2} + \Delta\epsilon_{L2}, \tag{5}$$

where $\Delta\beta_{L2}$ captures the difference in systematic fund returns, whereas $\Delta\epsilon_{L2}$ measures the difference in the idiosyncratic component of fund returns.

We estimate the distances over three-year windows starting in 2008, which are then rolled over with a one-year gap. Thus, the first set of estimates uses fund return data over the 2008–2010 period to construct distance measures at the fund-pair level (Δr, $\Delta\alpha$, $\Delta\beta$, $\Delta\epsilon$, separately for the L1- and L2-norms); next, we move forward by one year and recompute the distances based on the 2009–2011 period and so on until the last 2014–2016 period in our sample. Given the length of our data, the one-year gap between windows strikes a balance between sample availability and overlap in the estimation period. The three-year estimation window (i.e., 36 monthly observations) is chosen to mitigate estimation noise given that our performance attribution model in (1) features a wealth of eight regressors (seven factors plus the constant). We require managers and hedge fund returns to be present for at least 24 months in the estimation window.

3.4. Methodology

We estimate a pooled panel regression relating the estimated distance in performance measures (Δr, $\Delta\alpha$, $\Delta\beta$, and $\Delta\epsilon$) to the social ties variables (*Firm* and *Overlap*), cross-sectional controls, and style and time dummies:

$$\begin{aligned}\Delta y_{ij,t\to t+2} = {} & \text{const} + \beta_1 Firm_{ij,t-1} + \beta_2 Overlap_{ij,t-1} \\ & + \xi\,\text{SameStyle}_{ij} + \boldsymbol{\gamma}'\boldsymbol{X}_{ij,t-1} + \psi\,\text{TimeDummy}_t \\ & + u_{ij,t\to t+2}, \end{aligned} \tag{6}$$

where Δy denotes alternatively Δr, $\Delta\alpha$, $\Delta\beta$, and $\Delta\epsilon$ for the expected absolute differences ($L1$) and variances ($L2$), respectively. The subscripts highlight the fact that the dependent variable is constructed for each pair of funds i and j using data from year t to year $t+2$ (the estimation window), whereas the explanatory variables are measured using information up to the end of year $t-1$ with $t = \{2008, 2009, \ldots, 2014\}$. In constructing *Firm* and *Overlap*, we make use of all information since 2002, when FSR reporting became mandatory. For the controls, we first average them at the management company level and then compute the absolute difference. All controls that have "Δ" in their names are differences, so we expect them to enter the model with a positive sign.

The style dummy (*SameStyle*) is one if both funds follow the same style and zero otherwise. This implies that our results should be interpreted as capturing deviations from the common style. In general, all variables that have "Same" in their names are dummies and are defined such that their expected sign is negative. Our findings are robust to using a single-factor style model in place of the Fung and Hsieh (2004) seven-factor model; see Section 5.

The vector $\boldsymbol{X}_{ij,t-1}$ collects pair-level controls. Hong et al. (2005) provide evidence that managers operating in the same city exhibit correlated investment strategies, consistent with information diffusion through word-of-mouth communication. We account for this effect by including a dummy (*SameZip*) that equals one if the hedge funds' headquarters are colocated in the same postcode district and zero otherwise. We further control for the log of the absolute distances in the funds' characteristics, namely, fund age (*log*Δ*FundAge*), fund size (*log*Δ*EmpSize*), management fee (Δ*MgmtFee*), and performance fee (Δ*PerfFee*), and for the log of the pair average employee size (*logMeanEmpSize*) and fund age (*logMeanFundAge*). Finally, we include time (that is, estimation window) fixed effects. Standard errors are doubly clustered at the fund i and fund j level as in Pool et al. (2015) and Fracassi (2017). Our null hypothesis is that connected managers should invest more similarly, so we expect *Firm* and *Overlap* to enter the regression with a negative sign.

3.5. Summary Statistics

After applying the filters, the final database consists of 1,483 hedge funds that are run by 443 distinct management companies or about three funds per company. Collectively, we identify a total of 1,799 managers who are employed at any time in a UK management company during our 2002–2016 sample period.

Table 1, panel A, collects descriptive statistics at the fund level across the seven estimation windows. About 50% of all hedge funds have at least one *Firm* connection, counting only connections to other management companies and excluding hedge funds at the same management company. Connections through *Overlap* amount to 38%. These numbers reinforce the view that ties are not confined to a select few funds. The remaining variables, fund age in months (*FundAge*), number of employess (*EmpSize*), management fee (*MgmtFee*), and performance fee (*PerfFee*), are controls in line with Joenvaäärä et al. (2021).

In panel B, we report the style breakdown of the funds in the sample. The largest style by far is equity long/short, representing 47% of all hedge funds, in line with the proportion for the industry in general in Lo (2007). There are 12 styles altogether with the last one being a residual "other."

In panel C, we report statistics from the estimation of the Fung and Hsieh (2004) factor model separately across hedge funds connected or unconnected via *Firm*. The unadjusted R^2 is close to 0.50 for both groups with the difference being insignificant. This figure shows that the factor models leave much return variance unexplained, which is consistent with prior studies. The average monthly alpha is positive for both groups, about 0.06% for connected hedge funds and 0.11% for unconnected ones, and the difference is statistically insignificant. On average, the funds have a beta on the Standard and Poor's (S&P) 500 of about one third with the difference again being insignificant. All estimates are characterized by large standard deviations compared with the mean.

Table 2, panel A, reports descriptive statistics at the fund-pair level, in which we exclude pairs of funds that belong to the same management company. We observe for 3% of all pairs a connection through *Firm* and for 1% one through *Overlap*. Whereas these numbers may sound low, recall that half of all funds have at least one *Firm* connection and 38% at least one *Overlap* connection.

Table 1. Descriptive Statistics (Fund-Window)

Panel A. Connection measures and controls						
	Number of observations	Average	Median	Standard deviation	Minimum	Maximum
Firm	5,463	0.50	1	0.50	0	1
Overlap	5,463	0.38	0	0.49	0	1
FundAge	5,370	67	53	53	0	394
EmpSize	4,720	60	18	209	1	2,679
MgmtFee, %	5,324	1.58	1.50	0.49	0.00	4.50
PerfFee, %	5,256	17.12	20	6.17	0.00	30

Panel B. Style breakdown						
	Equity L/S	Relative value	Global macro	Equity	Fixed income	Emerging markets
Fraction by style, %	47	15	12	6	6	5

Panel C. Performance-attribution measures						
	Number of observations	Average	Median	Standard deviation	Minimum	Maximum
Hedge funds connected through *Firm*						
R^2	2,736	0.47	0.46	0.21	0.01	0.99
Alpha	2,736	0.06	0.13	0.88	−7.68	12.92
Beta S&P500	2,736	0.31	0.20	0.39	−1.07	3.14
Hedge funds unconnected through *Firm*						
R^2	2,727	0.48	0.46	0.21	0.03	0.99
Alpha	2,727	0.11	0.14	1.05	−8.27	12.92
Beta S&P500	2,727	0.32	0.20	0.41	−1.43	3.69

Notes. We report descriptive statistics at the fund-window level. In panel A, *Firm* and *Overlap* connection are dummy variables that equal one if a fund is connected through a corresponding tie at any time. *FundAge* is the number of months since the fund entered the database with the longest history. *EmpSize* is the number of employees of the management company. *MgmtFee* is the fund management fee (in percentage), whereas *PerfFee* is the fund performance fee (also in percentage). Panel B records the fraction of all hedge funds in particular styles. In panel C, we estimate the Fung and Hsieh (2004) seven-factor model for each fund separately for each estimation window. We report summary statistics for the R^2 from the factor model, the factor model intercept alpha (in monthly percentages), and the beta on the first factor (S&P 500) Beta S&P500 separately for funds connected and unconnected through *Firm*.

So managers are well-embedded in social networks, just not every manager with every other manager.

Table 2, panel B, collects statistics for our dependent variables (Δr, $\Delta\alpha$, $\Delta\beta$, $\Delta\epsilon$) for expected absolute differences ($L1$) and variances of differences ($L2$) of returns, respectively. All variables are winsorized at the top and bottom 0.5% to reduce the influence of outliers. We note that distances are smaller for connected than unconnected funds (with all differences being significant at the 1% level) in line with our economic reasoning. For example, the average $\Delta\alpha_{L1}$ across pairs of connected funds is some 0.19 percentage points lower than that of unconnected fund pairs (0.73% versus 0.91%). At the same time, we observe (weighted averages across all hedge funds) an economically wide dispersion in monthly expected absolute differences of raw returns (Δr_{L1} of 3.97% ± 2.42% standard deviation), abnormal performance ($\Delta\alpha_{L1}$ of 0.91% ± 0.91%), systematic components ($\Delta\beta_{L1}$ 6.68% ± 4.77%), and residuals ($\Delta\epsilon_{L1}$ of 2.92% ± 1.95%). Considering that the average absolute excess return in the evaluation period is 2.66%, these figures show considerable cross-sectional heterogeneity. The high values for $\Delta\beta_{L1}$ occur because these are expected absolute differences of betas times factors and because of our factor scaling; as the Fung and Hsieh (2004) factors differ widely in standard deviation, we normalize them to have unit variance.

Table A.1 contrasts the average and median fund characteristics in our sample with those from the full database (including non-UK hedge funds). Differences are small and insignificant along many dimensions, which suggests that our UK funds are quite representative of the universe of hedge funds used in prior studies.

Finally, we provide more detail on prior employers by classifying them into 11 industries within the financial services sector: banking, brokerage firms, consultancy firms, hedge funds, insurance companies, investment banks, investment management, mutual funds, pension funds, private equity, and the residual group other. The classification is obtained by matching the company name with the Registrar of Companies that is maintained by the UK Companies House database and by manual verification.[7] Figure 1 reports the distribution of the prior industry employment. Managers predominantly worked in investment management, hedge funds, and mutual funds, but other industries are also fairly represented.

Table 2. Descriptive Statistics (Fund-Pair)

	Number of observations	Average	Median	Standard deviation	Minimum	Maximum
		Panel A. Connection measures and controls				
Firm	2,512,818	0.03	0	0.17	0	1
Overlap	2,512,818	0.01	0	0.11	0	1
SameZip	1,882,570	0.00	0	0.06	0	1
log∆FundAge	2,423,301	3.57	4	1.08	0	5.98
log∆EmpSize	1,808,564	3.21	3.30	1.51	0	7.89
∆MgmtFee	2,420,909	0.52	0.50	0.48	0	4.50
∆PerfFee	2,365,703	4.86	0	6.92	0	30
logMeanEmpSize	1,808,564	3.48	3.42	0.95	0.69	7.52
logMeanFundAge	2,423,301	3.91	4.02	0.69	0	5.86
		Panel B. Distances in performance				
Hedge funds connected through *Firm*						
Δr_{L1}	72,959	3.24	2.83	1.82	0.87	17.28
$\Delta \alpha_{L1}$	72,959	0.73	0.55	0.71	0.01	5.79
$\Delta \beta_{L1}$	72,959	5.31	4.55	3.43	1.01	34.62
$\Delta \epsilon_{L1}$	72,959	2.37	2.10	1.32	0.63	15.15
Δr_{L2}	72,959	24.24	13.71	39.98	1.18	602.28
$\Delta \beta_{L2}$	72,959	11.54	5.06	20.20	0.22	224.93
$\Delta \epsilon_{L2}$	72,959	12.66	7.31	23.12	0.68	418.09
Hedge funds unconnected through *Firm*						
Δr_{L1}	2,439,859	3.97	3.40	2.42	0.87	17.28
$\Delta \alpha_{L1}$	2,439,859	0.91	0.65	0.91	0.01	5.79
$\Delta \beta_{L1}$	2,439,859	6.68	5.51	4.77	1.01	34.62
$\Delta \epsilon_{L1}$	2,439,859	2.92	2.46	1.95	0.63	15.15
Δr_{L2}	2,439,859	39.68	19.78	69.34	1.18	602.28
$\Delta \beta_{L2}$	2,439,859	18.07	7.89	29.63	0.22	224.93
$\Delta \epsilon_{L2}$	2,439,859	21.54	10.06	45.25	0.68	418.09

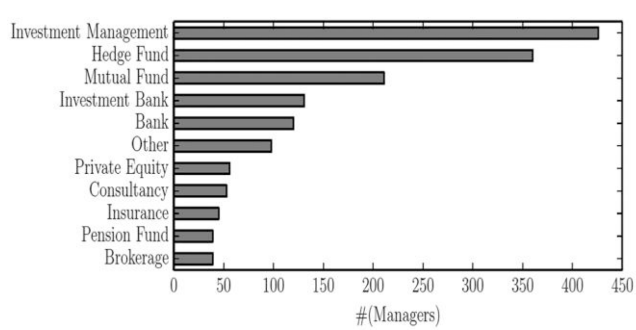
Notes. We report descriptive statistics at the fund-pair level. In panel A, *Firm* and *Overlap* connection are dummy variables that equal one if a fund is connected through a corresponding tie at any time. *SameZip* equals one when both headquarters are located in the same UK postal code. *FundAge* is the number of months since the fund entered the database with the longest history. *EmpSize* is the log of the number of employees of the management company. *MgmtFee* is the fund management fee (in percentage), whereas *PerfFee* is the fund performance fee (also in percentage). ∆ is the absolute difference of two quantities, Mean is the average across the two funds, and log is the natural logarithm. In panel B, we estimate the Fung and Hsieh (2004) seven-factor model for each fund separately for each estimation window. We report summary statistics for the L1- and L2-norm distances in returns and their components between any pair of funds belonging to two distinct management companies as explained in Section 3.4, separately for funds connected and unconnected through *Firm*.

4. Results

Do social ties arising from shared employment histories influence investment behavior? Indeed, firm culture (through the sharing of a common employer) and social ties (developed through personal connections at a prior employer) do show up in more similar hedge fund returns. When we estimate the model in Equation (6) for expected absolute distance in returns (Δr_{L1}), the loadings on *Firm* and *Overlap* are -0.477 and -0.276, and both are highly significant; see Table 3, panel L1, Model 1. The dummy *SameStyle* enters negatively (-0.076 with a t-statistic of -1.17), which confirms the intuition that funds in the same style invest more similarly.

The effect on absolute returns is also economically large. The average distance Δr_{L1} for connected funds is 3.24 percentage points per month (Table 2, panel B). The distance in returns for pairs of funds whose managers

Figure 1. Prior Employer Industry Distribution



Notes. We classify prior employers into 11 industries within the financial services sector: banking, brokerage firms, consultancy firms, hedge funds, insurance companies, investment banks, investment management, mutual funds, pension funds, private equity, and the residual group other. This figure reports the corresponding distribution of the prior industry employment.

share a common past employer at the same time is closer by 0.75 percentage points or −23% in relative terms.

We augment the regression by including fund-level controls in Model 2, which reduces our sample size by 39%. If connected managers tend to establish or join funds with similar fund structures (say, because they develop similar attitudes toward performance-based compensation schemes), including the controls potentially captures part of the overall effect of manager ties. Consistent with this argument, we see that the coefficient of *Firm* is reduced in absolute value to −0.208 with a *t*-statistic of −2.39 at par with that of *Overlap*. The economic significance is still large: a reduction of about 13% compared with connected fund pairs.

Models 3–8 report analogous specifications for expected absolute differences in the return components $\Delta\alpha_{L1}$, $\Delta\beta_{L1}$, and $\Delta\epsilon_{L1}$. A few noteworthy conclusions emerge. First, the loadings on the connection measures always enter the regression with the expected negative sign and are significant at the 1% level. Second, the inclusion of controls reduces the effects of *Firm* more than the effects of *Overlap*. Thus, social ties that are captured by *Overlap* explain the lion's share of (L1-)distances in alpha. This is consistent with the evidence in Pool et al. (2015) that word-of-mouth information exchange is an important component of fund (over)performance. Third, the economic significance of the effects is preserved across all specifications. For example, the abnormal performance of fund pairs that are connected via *Firm* and *Overlap* is some 24 basis points closer (Model 3) than that of connected funds, that is, a reduction of about 32% relative to the average in Table 2. For distances in factor loadings and residuals, the economic effect is comparable at about −25%.

Across specifications, sharing the same style leads to the expected reduction in investment variables, significantly so for $\Delta\alpha_{L1}$ and $\Delta\beta_{L1}$. Of the control variables, colocated headquarters (*SameZip*) are strongly significant (except for $\Delta\alpha_{L1}$), in line with Hong et al. (2005), Pool et al. (2015), and Teo (2009). Size (as proxied by the log of the average number of employees) and (log average) fund age stand out as important determinants, consistent with Joenvaäärä et al. (2021). Both controls have negative coefficients, leading to more similar investments (in raw returns and also across the components alpha, beta, and residuals) for larger and older firms. The distance in performance fee also enters significantly with the expected positive sign for Δr_{L1} and $\Delta\beta_{L1}$.

We turn to the results for variances of differences in returns in Table 3, panel L2. Results for *Firm* remain very strong (only in Model 6 for $\Delta\epsilon_{L2}$ with controls drops the significance from the 1% to the 5% level). For *Overlap*, significance drops in the models with controls to the 5% level and turns insignificant for $\Delta\beta_{L2}$ with controls.

An interesting pattern emerges, which continues in the robustness results and also shows up for the absolute difference results. Distances in factor exposures $\Delta\beta_{L2}$ are mainly driven by *Firm* effects, whereas $\Delta\epsilon_{L2}$ is also driven by *Overlap* effects. We argue that managers often learn at their previous employers (the *Firm* effect) about systematic components ($\Delta\beta$). Examples would be sector limits, exposure limits to certain risk factors, prospectuses prescribing the investments of a fund, or firm-specific models; see Beunza and Stark (2012) and MacKenzie (2003). Managers often learn through their social networks (the *Overlap* effect) about idiosyncratic components ($\Delta\alpha$ and $\Delta\epsilon$). Examples here are discussions of individual bets, research on particular investment strategies, or information about market conditions; see Kellard et al. (2017).

The control variables for the variance specification follow the patterns for the expected absolute differences with funds investing more similarly if they share the same style, are colocated, are larger, and are older.

5. Robustness Tests

We split our robustness tests into two parts. First, we analyze our results for the few hedge funds for which we have holdings from 13F filings. Second, we collect changes to the methodology.

5.1. Analysis of Stock Holdings

Because hedge funds in the United Kingdom are not required to report their holdings, our results are based on distances in performance and factor exposures from commercial hedge fund return data sets. We complement this analysis with evidence from portfolio holdings that we can compute for a select few companies that manage funds in the United States and have more than US$100 million under management. The SEC requires these funds to disclose quarterly holdings data in so-called 13F filings. We identify 87 management companies that are present in both our data set and U.S. 13F filings throughout the period we consider. At the cost of a much-reduced sample size, these data on actual portfolio holdings provide a direct view of managerial allocation decisions.

Analogous to our previous analysis, we measure the distance in portfolio holdings between two companies as the L1- and L2-norm distances in the relative share of all stocks for the pair in a given quarter.[8] We obtain the distance in year *t* by averaging the quarterly distances in that year. We then use these holding-based distances as dependent variables in our panel regression model of Equation (6). Panel A of Table 4 contains the corresponding estimates across all company pairs and years for which 13F filings are available.

We note that, independent of the norms L1 or L2, both *Firm* and *Overlap* are negatively and significantly

Table 3. Social Ties and Hedge Fund Returns

				Panel L1				
Dependent variable	Δr_{L1}	Δr_{L1}	$\Delta \alpha_{L1}$	$\Delta \alpha_{L1}$	$\Delta \beta_{L1}$	$\Delta \beta_{L1}$	$\Delta \epsilon_{L1}$	$\Delta \epsilon_{L1}$
Firm	−0.477***	−0.208**	−0.134***	−0.045**	−0.947***	−0.425***	−0.362***	−0.135**
	(−5.26)	(−2.39)	(−5.23)	(−2.08)	(−6.15)	(−3.00)	(−5.29)	(−2.17)
Overlap	−0.276***	−0.206***	−0.103***	−0.100***	−0.457***	−0.335***	−0.222***	−0.159***
	(−4.10)	(−2.78)	(−4.60)	(−4.09)	(−4.01)	(−2.69)	(−4.02)	(−2.63)
SameStyle	−0.076	−0.108*	−0.050**	−0.041**	−0.285**	−0.275**	−0.032	−0.067
	(−1.17)	(−1.74)	(−2.35)	(−2.03)	(−2.36)	(−2.43)	(−0.56)	(−1.31)
SameZip		−0.651***		−0.004		−0.995***		−0.472***
		(−5.10)		(−0.09)		(−4.34)		(−4.78)
log∆FundAge		−0.023		−0.010*		−0.040		−0.012
		(−1.31)		(−1.82)		(−1.20)		(−0.84)
log∆EmpSize		−0.006		0.021***		0.007		0.002
		(−0.38)		(3.14)		(0.21)		(0.14)
∆ *MgmtFee*		−0.048		−0.016		−0.056		−0.080
		(−0.76)		(−0.66)		(−0.45)		(−1.62)
∆ *PerfFee*		0.012**		0.001		0.032***		−0.000
		(2.09)		(0.73)		(2.78)		(−0.10)
logMeanEmpSize		−0.287***		−0.102***		−0.546***		−0.248***
		(−5.99)		(−5.13)		(−6.23)		(−6.50)
logMeanFundAge		−0.183***		−0.026		−0.298**		−0.161***
		(−2.65)		(−1.40)		(−2.32)		(−2.86)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations ('000)	2,513	1,528	2,513	1,528	2,513	1,528	2,513	1,528
R^2	0.048	0.078	0.008	0.015	0.017	0.028	0.029	0.063
				Panel L2				
Dependent variable	Δr_{L2}	Δr_{L2}			$\Delta \beta_{L2}$	$\Delta \beta_{L2}$	$\Delta \epsilon_{L2}$	$\Delta \epsilon_{L2}$
Firm	−11.401***	−4.598***			−4.535***	−2.327***	−6.857***	−2.207**
	(−5.64)	(−3.01)			(−5.21)	(−2.96)	(−5.18)	(−2.43)
Overlap	−4.038***	−2.683**			−1.324***	−0.741	−2.709***	−1.955**
	(−3.61)	(−2.17)			(−2.72)	(−1.38)	(−3.49)	(−2.29)
SameStyle	−2.280	−3.227**			−1.136*	−1.082*	−1.089	−2.038**
	(−1.19)	(−2.05)			(−1.76)	(−1.69)	(−0.81)	(−2.02)
SameZip		−10.778***				−4.941***		−5.752***
		(−4.40)				(−4.25)		(−4.08)
log∆FundAge		−0.111				−0.116		−0.050
		(−0.24)				(−0.60)		(−0.18)
log∆EmpSize		−0.429				−0.256		−0.159
		(−1.18)				(−1.60)		(−0.71)
∆MgmtFee		−0.799				0.299		−1.059
		(−0.56)				(0.42)		(−1.33)
∆PerfFee		0.097				0.162***		−0.061
		(0.83)				(2.58)		(−0.99)
logMeanEmpSize		−5.118***				−1.755***		−3.308***
		(−5.37)				(−4.06)		(−5.60)
logMeanFundAge		−5.880***				−2.181***		−3.464***
		(−3.28)				(−2.95)		(−3.16)
Time fixed effects	Yes	Yes			Yes	Yes	Yes	Yes
Observations ('000)	2,513	1,528			2,513	1,528	2,513	1,528
R^2	0.020	0.043			0.043	0.062	0.007	0.025

Notes. For each fund in the sample, we estimate the Fung and Hsieh (2004) seven-factor model over three-year windows (rolling forward by one year) to obtain abnormal performance (α), factor loadings (β), and idiosyncratic returns (ϵ). We then compute the L1- and L2-norm distance in returns and their components between any pair of funds belonging to two distinct management companies as explained in Section 3.4. The table reports the OLS estimates of the pooled regression of the distances (organized in two panels corresponding to the L1 and L2 measures) on the network connection measures (*Firm* and *Overlap*), a dummy that equals one for pairs of funds in the same style (SameStyle), funds characteristics defined as in Table 2, and time fixed effects. The explanatory variables are measured using information up to December 2007, 2008, … , and 2013 respectively. t-statistics based on standard errors clustered at the fund i and fund j level appear in parenthesis below the estimates.

Statistical significance at the 1%, 5%, and 10% level is denoted by ***, **, and *, respectively.

Table 4. Social Ties and Stock Holdings

	L1			L2		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. All companies						
Firm	−0.007***		−0.009***	−0.005***		−0.005***
	(−3.29)		(−3.75)	(−7.03)		(−7.06)
Overlap		−0.005*	0.003		−0.004***	0.001
		(−1.67)	(0.77)		(−4.61)	(1.35)
SameStyle	−0.005***	−0.005***	−0.005***	−0.003***	−0.003***	−0.003***
	(−3.20)	(−3.15)	(−3.19)	(−3.95)	(−3.90)	(−3.95)
dlogAUM	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000
	(−0.14)	(−0.15)	(−0.14)	(−0.60)	(−0.60)	(−0.59)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,823	4,823	4,823	4,823	4,823	4,823
R^2	0.001	0.001	0.001	0.001	0.001	0.001
Panel B. UK-based companies						
Firm	−0.021***		−0.013**	−0.013***		−0.010***
	(−4.22)		(−2.19)	(−5.35)		(−4.02)
Overlap		−0.027***	−0.016**		−0.014***	−0.005**
		(−5.34)	(−2.51)		(−5.79)	(−2.33)
SameStyle	−0.008	−0.008	−0.008	−0.006*	−0.005	−0.006*
	(−1.32)	(−1.27)	(−1.36)	(−1.68)	(−1.57)	(−1.70)
dlogSize	−0.000	−0.000	−0.000	−0.001	−0.001	−0.001
	(−0.19)	(−0.23)	(−0.21)	(−0.86)	(−0.90)	(−0.88)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	432	432	432	432	432	432
R^2	0.018	0.018	0.021	0.021	0.017	0.022

Notes. We match the hedge fund management companies in our sample to U.S. 13F mandatory filings. We then compute pairwise L1- and L2-norm distances in stock holdings in a given quarter and average them within the year. The table reports the OLS estimates of the pooled regression of these distances on the network connection measures (*Firm* and *Overlap*), the average *SameStyle* dummy across the funds of a given pair of companies, the difference in log assets under management (*dlogAUM*) computed from the 13F data, and time fixed effects. The explanatory variables are measured using information up to December 2007, 2008, …, and 2013, respectively. Panel A uses all matched companies, whereas panel B uses only those headquartered in the United Kingdom. *t*-statistics based on standard errors clustered at the pair level appear in parenthesis below the estimates.

Statistical significance at the 1%, 5%, and 10% level is denoted by ***, **, and *, respectively.

related to distances in holdings when entering the model separately. In other words, pairs of companies whose managers are connected through prior employment history have more similar asset allocations compared with unconnected pairs. The dummy *SameStyle* enters negatively and significantly as in the main results. When the two variables enter the model jointly, *Firm* remains significant, whereas *Overlap* turns insignificant. This weakening should not come as a surprise as the sample shrinks by a factor of 500 when compared with the main results in Table 3.

Another potential reason for the weaker results is the mismatch between our sample of UK hedge fund employees and the U.S. filing requirement. If the hedge fund is based in the United States but has some UK employees, the effect of social ties based on only the UK employees might indeed be weak. To test this argument, we restrict the sample to hedge funds headquartered in the United Kingdom. Then, the majority of employees should be UK employees that appear in the FSR filings. Thus, we expect results based on UK-based social ties to strengthen. This is indeed what we see in panel B of Table 4. Both *Firm* and *Overlap* are now negative and statistically significant across all specifications. The coefficients are also much larger in magnitude and economically relevant. With an average L1-norm distance for UK pairs of 2.9%, these estimates imply that connected UK companies have a large overlap in their asset-allocation decisions.

The evidence that our results persist in the much-reduced subset of hedge funds for which we observe stock holdings reassures us that they are not an artifact of our main method of estimating loadings within a factor model. Our finding dovetails with Pool et al. (2015) that socially connected mutual fund managers have more similar holdings.

5.2. Other Robustness Tests

In our first robustness test, we replace the Fung and Hsieh (2004) model with a (single) style factor model constructed as the equally weighted average return of the fund style; see panel A of Table 5. Results (omitting Δr, for which no factor model is estimated) are very comparable to those in Table 3 with just mild reductions in the size of the coefficients and in significance levels for the L1 measure. Replacing the S&P 500 factor

Table 5. Social Ties and Hedge Fund Returns, Robustness Analysis

	L1				L2		
	Δr_{L1}	$\Delta\alpha_{L1}$	$\Delta\beta_{L1}$	$\Delta\epsilon_{L1}$	Δr_{L2}	$\Delta\beta_{L2}$	$\Delta\epsilon_{L2}$
Panel A. Style factor model							
Firm	NA	−0.033	−0.163***	−0.127*	NA	−1.826***	−2.463**
		(−1.64)	(−2.65)	(−1.79)		(−2.97)	(−2.15)
Overlap		−0.077***	−0.148***	−0.163**		−0.588	−2.357**
		(−3.52)	(−2.84)	(−2.53)		(−1.32)	(−2.35)
SameStyle		−0.046***	−0.120***	−0.046		−0.627	−2.462**
		(−2.60)	(−2.76)	(−0.86)		(−1.16)	(−2.01)
Observations ('000)		1,528	1,528	1,528		1,528	1,528
Panel B. FTSE factor model							
Firm	NA	−0.021	−0.383***	−0.160***	NA	−2.134***	−2.398***
		(−1.00)	(−2.60)	(−2.62)		(−2.60)	(−2.69)
Overlap		−0.090***	−0.331***	−0.129**		−0.963*	−1.727**
		(−3.84)	(−2.60)	(−2.17)		(−1.72)	(−2.05)
SameStyle		−0.037**	−0.321***	−0.064		−1.105*	−2.025**
		(−1.97)	(−2.95)	(−1.27)		(−1.67)	(−2.04)
Observations ('000)		1,528	1,528	1,528		1,528	1,528
Panel C. Weighted least squares							
Firm	NA	−0.061**	−0.432***	−0.075*	NA	−2.377***	−0.925**
		(−2.21)	(−3.07)	(−1.78)		(−2.89)	(−2.23)
Overlap		−0.092**	−0.354***	−0.090**		−0.719	−0.817**
		(−2.53)	(−2.79)	(−2.17)		(−1.24)	(−2.10)
SameStyle		−0.060**	−0.261**	0.005		−1.101*	−0.345
		(−2.11)	(−2.32)	(0.18)		(−1.72)	(−0.99)
Observations ('000)		1,528	1,528	1,528		1,528	1,528
Panel D. Single cross-sectional estimation							
Firm	−0.327**	−0.073**	−0.652**	−0.186	−7.587**	−4.334***	−3.155*
	(−2.01)	(−2.05)	(−2.48)	(−1.52)	(−2.51)	(−2.98)	(−1.74)
Overlap	−0.343**	−0.107***	−0.584**	−0.260**	−5.138**	−1.924*	−3.200*
	(−2.30)	(−2.74)	(−2.32)	(−2.12)	(−1.99)	(−1.80)	(−1.81)
SameStyle	−0.036	−0.032	−0.189	−0.024	−1.887	−0.299	−1.497
	(−0.49)	(−1.45)	(−1.45)	(−0.43)	(−1.07)	(−0.37)	(−1.38)
Observations ('000)	639	639	639	639	639	639	639
Panel E. Management-company level regression							
Firm	−0.253**	−0.067**	−0.523***	−0.179**	−5.975***	−2.717***	−3.218***
	(−2.25)	(−2.21)	(−2.84)	(−2.17)	(−3.08)	(−2.73)	(−2.84)
Overlap	−0.266**	−0.121***	−0.460**	−0.219**	−5.160***	−1.855**	−3.310***
	(−2.45)	(−3.99)	(−2.53)	(−2.56)	(−2.70)	(−2.26)	(−2.60)
SameStyle	−0.173*	−0.091***	−0.401**	−0.142*	−5.752**	−1.846*	−3.876**
	(−1.74)	(−2.84)	(−2.11)	(−1.74)	(−2.19)	(−1.87)	(−2.10)
Observations ('000)	222	222	222	222	222	222	222
Panel F. Companies with only one fund							
Firm	−0.423**	−0.104**	−0.934***	−0.281**	−7.980**	−3.929**	−3.827**
	(−2.57)	(−2.12)	(−3.40)	(−2.44)	(−2.57)	(−2.43)	(−2.24)
Overlap	−0.216	−0.145***	−0.341	−0.210*	−6.633*	−2.509*	−4.027*
	(−1.40)	(−2.98)	(−1.27)	(−1.77)	(−1.84)	(−1.67)	(−1.78)
SameStyle	−0.114	−0.067*	−0.240	−0.082	−3.512	−1.179	−2.121
	(−0.99)	(−1.78)	(−1.06)	(−0.84)	(−0.98)	(−0.96)	(−0.89)
Observations ('000)	57	57	57	57	57	57	57
Panel G. Time-varying *Firm* effect							
*Firm*1	−0.178**	−0.028	−0.382***	−0.111*	−4.145***	−2.135***	−1.931**
	(−2.36)	(−1.26)	(−2.98)	(−1.96)	(−2.99)	(−3.27)	(−2.20)
*Firm*2	−0.089	−0.039*	−0.187	−0.079	−4.035**	−1.758*	−2.175**
	(−1.01)	(−1.75)	(−1.26)	(−1.37)	(−2.07)	(−1.67)	(−2.16)
*Firm*3	0.200	0.058*	0.436	0.190	8.921*	3.372	5.338*
	(1.23)	(1.70)	(1.52)	(1.58)	(1.82)	(1.54)	(1.94)

Table 5. (Continued)

	L1				L2		
	Δr_{L1}	$\Delta \alpha_{L1}$	$\Delta \beta_{L1}$	$\Delta \epsilon_{L1}$	Δr_{L2}	$\Delta \beta_{L2}$	$\Delta \epsilon_{L2}$
Panel G. Time-varying *Firm effect*							
Overlap	−0.256***	−0.112***	−0.426***	−0.199***	−3.622***	−1.034*	−2.609***
	(−3.38)	(−4.52)	(−3.36)	(−3.28)	(−2.70)	(−1.70)	(−2.91)
SameStyle	−0.107*	−0.041**	−0.274**	−0.066	−3.212**	−1.075*	−2.030**
	(−1.73)	(−2.02)	(−2.42)	(−1.30)	(−2.04)	(−1.68)	(−2.02)
Observations ('000)	1,528	1,528	1,528	1,528	1,528	1,528	1,528

Notes. The table shows four alternative specifications of the models with fund controls in Table 3. In panel A, we use only the equally weighted hedge fund style factor in the factor model. In panel B, we replace the S&P 500 with the FTSE 100 in our factor model. In panel C, we estimate the model via weighted least squares, in which weights depend on the (inverse of) the uncertainty in the dependent variables. In panel D, we estimate a single cross-sectional model averaging across the first stage estimation windows. In panel E, we estimate the model on observations averaged at the management company (instead of fund) pair level. In panel F, we estimate the model only on companies in our sample that manage only one fund. In panel G, we allow for three different *Firm* dummies depending on the period at which the employees worked at the firm. The coefficients on the cross-sectional fund controls, time fixed effects, and the dummy *SameZip* are omitted to save on space. *t*-statistics based on standard errors clustered at the pair level appear in parenthesis below the estimates.

Statistical significance at the 1%, 5%, and 10% level is denoted by ***, **, and *, respectively.

with the Financial Times Stock Exchange (FTSE) 100 in the Fung and Hsieh (2004) model, given that we focus on UK-based hedge funds, gives results very similar to the main results; see panel B of Table 5.

Next, we examine fund leverage. Two connected managers could load on the same mix of risk factors, but only one of them levers up. Leverage would amplify the magnitude of betas and, in turn, their distance. To rule out this possibility, we repeat our analysis focusing only on fund pairs with the same leverage. The estimates are even closer to those in Table 3 than the preceding two tests; see Table A.2. We are, thus, reassured that our findings do not depend on a specific performance-attribution model.

We further assess the sensitivity of results to changes in the econometric model. We account for the fact that our dependent variables are estimated with noise. Whereas ordinary least squares (OLS) estimation is consistent even if the dependent variable is measured with error, it is likely not efficient as the assumption of homoskedasticity is clearly violated. To this end, we rely on a weighted least squares (WLS) estimator that over-weights pairs of funds for which the performance measures are more precisely estimated.[9] The WLS model (omitting Δr, for which no weights are needed) again confirms the significant role of *Firm* and *Overlap*; see panel C of Table 5.

As a further econometric check, we instead run a single cross-sectional estimation averaging across windows instead of pooling observations. This model reassures us that our inference is not picking up latent time-series autocorrelation in residuals.[10] The corresponding estimates are again in line with those from the baseline specification; see panel D of Table 5.

Thus far, we conducted our analysis at the fund level. We now repeat our study at the management company level. To this end, we average all variables across all funds within each pair. Consequently, the number of observations decreases from 1,528 to 222 thousand. Results in panel E of Table 5 are comparable to (and sometimes even stronger than) those in baseline Table 3 with social ties measures being associated to a statistically significant lower distance in performance. Therefore, our conclusions continue to hold even at the management company level.

The base case over-counts connections because connections at the management company level do not imply that every hedge fund of one management company is also connected to every hedge fund of another management company. All our base-case results are, thus, conservatively estimated and constitute a lower bound for the true effect. Here, we repeat our analysis for management companies that only have one hedge fund. The coefficients for *Firm* and *Overlap* all stay negative and are significant in all cases but two; see panel F of Table 5. The loss of significance is most likely because of the much lower number of observations (only 4% of the base case). Interestingly, the point estimates are always larger than in the base case of Table 3. This is true for both *Firm* and, especially in relative terms, *Overlap*. We interpret these stronger results as evidence that we can better capture social ties when our identification is more precise (management companies with a single hedge fund instead of many hedge funds).

A final concern is that firm culture (e.g., investment strategy and training) could be time-varying.[11] To address this issue, we allow for different *Firm* dummies depending on the period at which the employees worked at the firm.

Specifically, we split the network period into three equal-length subperiods. In each subperiod, we record the fractions of time during which each employee worked at the connecting firm (say, one out of three years (= 1/3) for one employee pairing and two out of three years (= 2/3) for another). The *Firm* dummy is then one if the average of all fractions is greater than 1/3, which is the median in our sample, and zero otherwise. The *Firm* dummies are denoted *Firm*1, *Firm*2, and *Firm*3 for the three subperiods.

We include all three *Firm* dummies in our regression along with *Overlap*. The results in panel G of Table 5 show that the *Firm* dummies remain mostly negative with the *Firm* effect concentrated in the earlier two thirds of the network period. Older employee connections seem to carry more weight in influencing hedge investment behavior. Overlap is still negative and significant.

6. Identification of Network Effects

We sharpen our identification by showing that our conclusions are robust to the inclusion of managerial characteristics and by testing further hypotheses related to firm culture and social ties.

6.1. Managerial Characteristics

We first address the question of whether our variables proxy for managerial characteristics. This could be the case if employment were correlated with managerial skill so that two hedge fund managers were previously hired by the same employer because they are similarly skilled. Assuming skill is persistent through time, the two managers would later deliver more similar (raw and abnormal) performance at their respective hedge funds.

We, thus, control for managerial characteristics by including the log difference in the manager age (in months) *Log*Δ*MgrAge*, which captures career concerns and possibly correlates with risk tolerance. We also include the dummy *SameSex*, for which one indicates the same sex and zero otherwise, given a voluminous literature documenting differences in trading behavior and performance between men and women. In the case of fund pairs that are connected by multiple managers, we first average all controls at the management company level and then compute the absolute difference.

We also add two proxies for managerial skill. The first skill variable is the dummy *SameEdu*, for which one indicates that both managers have either a master's or PhD degree. We gather information on the highest degree of a manager by manually checking the managers' LinkedIn profiles, which we could find for a subset of 875 managers. Li et al. (2011) document that manager education is a key determinant of performance.

Our second skill variable is the absolute difference in hiring climate Δ*HiringClim*. We argue that, in hot markets for managers, on average, less skilled managers are hired (that is, demand is high, and firms cannot be picky) than in cold markets when only the best managers are hired (that is, demand is low, and management companies can be picky). We define *Hiring Climate* as the net number of people hired in the financial industry at the time the manager was hired. Management company *Hiring Climate* is taken as the average of its managers' *Hiring Climate*. Deuskar et al. (2011) argue that mutual fund managers flock to work for hedge funds exactly when the hedge fund industry is expanding rapidly.

The results for adding these variables to the regression model in Equation (6) are presented in Table 6.

Distance in manager age is generally not a statistically significant determinant of distance in performance; *SameSex* is significant in two models with the expected negative sign; that is, same sex teams make more similar investment decisions. The dummy *SameEdu* is strongly significant in all but one model, confirming the prior that similarly skilled and educated managers tend to deliver similar performance. Results are weaker for Δ*HiringClim*, for which only one model is significant with a positive coefficient as expected. The aggregate hiring climate seems to be a much weaker measure of individual skill than the highest degree achieved (*SameEdu*). Importantly, we note that managerial characteristics leave the role for *Firm* and *Overlap* pretty much intact in case of the expected absolute differences of returns (L1-norm) with a slight reduction in significance for *Overlap* for variances of differences (L2-norm).

6.2. Firm Culture and Social Ties

We perform additional tests in order to enhance our identification of the firm culture and social ties channels. First, we replace the *Firm* dummy with separate firm effects for each prior employer that establishes the connection.[12] The individual fixed effects go a long way toward absorbing both managerial characteristics (insofar as there are any effects left after controlling for managerial characteristics), the kind of people a prior employer selected, and the kind of training it offered. Table 7 shows that, if anything, the extent and the significance of *Overlap* become more compelling in the fixed effect model for expected absolute differences of returns (L1-norm). Results for variances of differences of returns (L2-norm) weaken somewhat. The F-test for the null hypothesis that the firm fixed effects are jointly zero is rejected across all specifications with p-values below 0.1%.

Next, we modify the definition of *Firm* and *Overlap* to capture the strength of the connection among two funds. We do this by taking the ratio of the number of pairwise connections (across all managers) by the total number of possible connections (i.e., the product of the

Table 6. Social Ties and Managerial Characteristics

	Panel L1				Panel L2		
Dependent variable	Δr_{L1}	$\Delta\alpha_{L1}$	$\Delta\beta_{L1}$	$\Delta\epsilon_{L1}$	Δr_{L2}	$\Delta\beta_{L2}$	$\Delta\epsilon_{L2}$
Firm	−0.197**	−0.033	−0.475***	−0.116*	−4.753***	−2.566***	−2.079*
	(−2.08)	(−1.56)	(−3.09)	(−1.66)	(−2.59)	(−2.92)	(−1.81)
Overlap	−0.195**	−0.090***	−0.279**	−0.172**	−1.969	−0.086	−1.919*
	(−2.46)	(−4.01)	(−2.15)	(−2.56)	(−1.35)	(−0.15)	(−1.81)
SameStyle	−0.083	−0.034*	−0.208*	−0.070	−3.469**	−0.858	−2.467**
	(−1.29)	(−1.70)	(−1.75)	(−1.32)	(−2.05)	(−1.26)	(−2.23)
SameZip	−0.616***	−0.004	−1.000***	−0.430***	−12.300***	−5.838***	−6.310***
	(−4.55)	(−0.08)	(−4.24)	(−4.30)	(−4.34)	(−4.15)	(−3.96)
Δ*MgrAge*	−0.025	−0.014***	−0.015	−0.026	−0.479	−0.119	−0.382
	(−1.08)	(−2.61)	(−0.33)	(−1.37)	(−0.66)	(−0.49)	(−0.77)
SameSex	−0.079	−0.042*	−0.260*	−0.005	0.142	−1.378	1.443
	(−1.00)	(−1.78)	(−1.83)	(−0.08)	(0.08)	(−1.46)	(1.53)
SameEdu	−0.274**	−0.059	−0.592***	−0.213**	−9.123***	−4.374***	−4.753***
	(−2.48)	(−1.51)	(−3.04)	(−2.40)	(−3.49)	(−3.72)	(−2.88)
Δ*HiringClim*	0.052	0.029***	0.127	0.048	1.644	0.388	1.086
	(1.20)	(2.83)	(1.41)	(1.18)	(1.03)	(1.06)	(0.98)
Fund Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations ('000)	867	867	867	867	867	867	867
R^2	0.068	0.016	0.050	0.047	0.034	0.062	0.019

Notes. We add the following managerial characteristics to the analysis of Table 3: log distance in managers' age, *log*Δ*MgrAge* in months; the dummy *SameSex*, which is one for managers with same sex and zero otherwise; the dummy *SameEdu*, which is one for pairs of funds whose managers both have either a master's or PhD degree and zero otherwise; and the distance in hiring climate, Δ*HiringClim*, constructed as explained in Section 6. The two panels report the estimates for the L1 and L2 distance measures, respectively. The estimates for the funds characteristics and time fixed effects are omitted for brevity. *t*-statistics based on standard errors clustered at the fund *i* and fund *j* level appear in parenthesis below the estimates.

Statistical significance at the 1%, 5%, and 10% level is denoted by ***, **, and *, respectively.

number of managers in the two firms). We define the corresponding variables as *FirmShare* and *OverlapShare*. That is, a *FirmShare* equal to one implies that all managers of fund *i* are connected through prior employment to all managers of fund *j*. We expect more similar performance for fund pairs with a higher percentage of all possible ties. Table 8 shows that the two scaled measures have the expected negative sign. The estimates of *OverlapShare* are more negative than those of *Overlap* in the base results and significant at higher levels of significance. For *Firm*, the evidence is similarly strong to the baseline measures. These findings suggest that our setup genuinely captures the effect of managerial networks. Pool et al. (2015) make a related argument when using managers' density-adjusted residence as a proxy for the strength of social connection.

Third, conditional on a given share of connections, social ties ought to matter more between two small management companies than between two large management companies. Ideas originating through a network should be more likely to trigger investment decisions when the connecting managers need to agree with few other people. We test this hypothesis by augmenting the model with the interaction term between *OverlapShare* and *logMeanEmpSize*.[13]

As expected, Table 9 shows positive and significant interaction terms, and the coefficient on *OverlapShare* is negative and about three to four times higher in absolute terms than in Table 8. Social ties seem to exert greater influence in smaller hedge funds. Interestingly, the interaction coefficients are statistically stronger for the idiosyncratic components ($\Delta\alpha$ and $\Delta\epsilon$), suggesting that social ties are a major driver of similarities in the idiosyncratic performance of hedge funds as opposed to the systematic components.

Finally, social ties should increase with the length of time two managers overlapped at a previous workplace as longer times together make it more likely that stronger relationships are established. To test this prediction, we redefine *Overlap* as being one if the managers of a pair of funds overlap by at least one month at the former employer and then interact this variable with the log of the number of months the two managers spent together, *Months*.[14] As expected, Table 10 shows negative and statistically significant interaction terms for expected absolute differences of returns; results are somewhat weaker for variances of return differences. Interestingly, in the specifications with controls and managerial characteristics, *Firm* is driven out, suggesting that social ties possibly outweigh the effects of a prior employer in explaining similarities in hedge fund investing. Again, in the spirit of Pool et al. (2015), this test supports the claim that our variables truly proxy for the extent of personal connections: as social ties become more intensive, there is less of a difference in both returns and abnormal performance.

Table 7. Social Ties and Identification of Peer Effects: Prior Employer Fixed Effects

Panel L1

Dependent variable	Δr_{L1}	Δr_{L1}	$\Delta\alpha_{L1}$	$\Delta\alpha_{L1}$	$\Delta\beta_{L1}$	$\Delta\beta_{L1}$	$\Delta\epsilon_{L1}$	$\Delta\epsilon_{L1}$
Overlap	−0.281***	−0.285***	−0.114***	−0.103***	−0.473***	−0.435***	−0.230***	−0.233***
	(−3.35)	(−3.23)	(−4.89)	(−4.27)	(−3.25)	(−3.04)	(−3.56)	(−3.63)
SameStyle	−0.075	−0.076	−0.050**	−0.033*	−0.284**	−0.194	−0.031	−0.066
	(−1.16)	(−1.20)	(−2.35)	(−1.65)	(−2.35)	(−1.64)	(−0.55)	(−1.26)
p-value firm fixed effects, %	<0.1	<0.1	<0.1	<0.1	<0.1	<0.1	<0.1	<0.1
Fund controls	No	Yes	No	Yes	No	Yes	No	Yes
Managerial characteristics	No	Yes	No	Yes	No	Yes	No	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations ('000)	2,513	867	2,513	867	2,513	867	2,513	867
R^2	0.045	0.066	0.006	0.015	0.031	0.048	0.028	0.045

Panel L2

Dependent variable	Δr_{L2}	Δr_{L2}			$\Delta\beta_{L2}$	$\Delta\beta_{L2}$	$\Delta\epsilon_{L2}$	$\Delta\epsilon_{L2}$
Overlap	−2.698	−2.997*			−0.504	−0.594	−2.231*	−2.416**
	(−1.50)	(−1.90)			(−0.61)	(−0.76)	(−1.96)	(−2.42)
SameStyle	−2.252	−3.375**			−1.126*	−0.771	−1.071	−2.458**
	(−1.18)	(−2.00)			(−1.75)	(−1.16)	(−0.80)	(−2.21)
p-value firm fixed effects, %	<0.1	<0.1			<0.1	<0.1	<0.1	<0.1
Fund controls	No	Yes			No	Yes	No	Yes
Managerial characteristics	No	Yes			No	Yes	No	Yes
Time fixed effects	Yes	Yes			Yes	Yes	Yes	Yes
Observations ('000)	2,513	867			2,513	867	2,513	867
R^2	0.019	0.033			0.041	0.061	0.006	0.018

Notes. For each pair distance in performance, we reestimate the model in either Table 3 (without fund controls, odd columns) or Table 6 (which includes fund controls and managerial characteristics, even columns) when replacing *Firm* with individual firm (i.e., prior employer) specific fixed effects, and report the *p*-value for the *F*-test that the fixed effects estimates are jointly zero. The two panels report the estimates for the L1 and L2 distance measures, respectively. *t*-statistics based on standard errors clustered at the fund *i* and fund *j* level appear in parenthesis below the estimates.

Statistical significance at the 1%, 5%, and 10% level is denoted by ***, **, and *, respectively.

7. Economic Value of Social Ties

Our analysis shows that distances in hedge fund returns (and their components) are significantly lower for funds connected via managerial prior employment history. A natural question arises as to what is the economic value of social ties? In other words, do managerial connections ultimately enhance or dampen hedge fund performance? Should investors seek to construct or eschew hedge fund management companies whose managers are more tightly connected with managers of other management companies?

The implications of our findings from both an individual fund level and a portfolio perspective are a priori ambiguous. If the overlap in fund allocations is driven by the transmission of relevant information within connected funds, then managerial ties ought to be value-enhancing and allow funds to exploit profitable opportunities and trends ahead of unconnected funds. This would, in turn, boost their (abnormal) performance and curb their volatility and downside risk. At the same time, it is well-established that institutional investors tend to herd by following each other into the same securities at the same time; see, for example, Lakonishok et al. (1992) and Sias (2004). If herding is driven by the exchange of value-irrelevant information and views among connected managers, these correlated trades might lead to overexposure to a number of limited positions and, thus, to a lack of diversification. Furthermore, these common bets could possibly cause an amplification of losses during a market reversal because of, for example, liquidity spirals or downward price pressure because of fire sales. We answer these questions by investigating the link between fund-level performance and our social ties measures in Section 7.1 and by relating suitably constructed hedge fund portfolios to the degree of portfolio connectedness in Section 7.2.

7.1. Individual Hedge Funds

We estimate fund-level regressions relating fund performance to the number of its managerial connections. The dependent variables are the fund average excess return, alpha, standard deviation, and Sharpe ratio, which we compute over the same estimation windows as in the pair setup. We measure the strength of fund managerial ties by the number of its *Firm* and *Overlap* connections across all fund pairs as of the start of the estimation window. We include as controls fund characteristics and time and style fixed effects. This analysis is similar in spirit to that in Li et al. (2011), who relate hedge fund

Table 8. Social Ties and Identification of Peer Effects: Scaled Network Measures

Panel L1

Dependent variable	Δr_{L1}	Δr_{L1}	$\Delta \alpha_{L1}$	$\Delta \alpha_{L1}$	$\Delta \beta_{L1}$	$\Delta \beta_{L1}$	$\Delta \epsilon_{L1}$	$\Delta \epsilon_{L1}$
FirmShare	−0.511***	−0.172	−0.145***	−0.023	−1.015***	−0.417**	−0.387***	−0.090
	(−5.02)	(−1.54)	(−4.71)	(−0.87)	(−5.65)	(−2.22)	(−4.58)	(−0.96)
OverlapShare	−0.346***	−0.342**	−0.117***	−0.125***	−0.603***	−0.539**	−0.281***	−0.309***
	(−3.23)	(−2.56)	(−2.74)	(−2.73)	(−3.36)	(−2.55)	(−3.09)	(−2.65)
SameStyle	−0.077	−0.079	−0.050**	−0.033	−0.286**	−0.199*	−0.032	−0.069
	(−1.18)	(−1.24)	(−2.35)	(−1.64)	(−2.36)	(−1.67)	(−0.56)	(−1.31)
Fund controls	No	Yes	No	Yes	No	Yes	No	Yes
Managerial characteristics	No	Yes	No	Yes	No	Yes	No	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations ('000)	2,512	867	2,512	867	2,512	867	2,512	867
R^2	0.047	0.067	0.007	0.016	0.033	0.050	0.030	0.047

Panel L2

Dependent variable	Δr_{L2}	Δr_{L2}			$\Delta \beta_{L2}$	$\Delta \beta_{L2}$	$\Delta \epsilon_{L2}$	$\Delta \epsilon_{L2}$
FirmShare	−13.088***	−4.939**			−5.306***	−2.774***	−7.760***	−1.998
	(−5.63)	(−2.10)			(−5.78)	(−2.93)	(−4.78)	(−1.21)
OverlapShare	−6.151***	−6.030**			−2.044***	−1.390	−4.081***	−4.669***
	(−3.26)	(−2.52)			(−2.66)	(−1.47)	(−2.97)	(−2.58)
SameStyle	−2.286	−3.451**			−1.138*	−0.796	−1.093	−2.508**
	(−1.19)	(−2.02)			(−1.76)	(−1.18)	(−0.81)	(−2.24)
Fund controls	No	Yes			No	Yes	No	Yes
Managerial characteristics	No	Yes			No	Yes	No	Yes
Time fixed effects	Yes	Yes			Yes	Yes	Yes	Yes
Observations ('000)	2,512	867			2,512	867	2,512	867
R^2	0.020	0.034			0.042	0.062	0.007	0.019

Notes. For each pair distance in performance, we reestimate the model in either Table 3 (without fund controls, odd columns) or Table 6 (which includes fund controls and managerial characteristics, even columns) when our social ties variables are redefined as the ratio between the number of, alternatively, firm or overlap connections between two funds over the total number of possible connections, denoted by *FirmShare* and *OverlapShare*, respectively. The two panels report the estimates for the L1 and L2 distance measures, respectively. *t*-statistics based on standard errors clustered at the fund *i* and fund *j* level appear in parenthesis below the estimates.

Statistical significance at the 1%, 5%, and 10% level is denoted by ***, **, and *, respectively.

performance metrics to manager characteristics. We report the corresponding estimates in Table 11.

Overall, we find no evidence that fund performance is related to *Firm* connections. Controlling for all other characteristics, performance appears to be decreasing in *Firm*, whereas risk is increasing. However, all coefficients are far from being statistically significant. As a result, the effect on the Sharpe ratio is small and insignificant.

The results for the strength of *Overlap* connections are more noteworthy. Alpha is positively affected by *Overlap* with a coefficient of 0.178 that is marginally insignificant (*t*-statistic of 1.61), suggesting that managers can outperform the Fung and Hsieh (2004) model by means of personal connections. *Overlap* also significantly lowers hedge fund risk (*t*-statistic of −3.52), which again suggests that managerial ties that lead to information sharing about investment ideas could reduce risk. The resulting Sharpe ratio, as expected, improves in the number of *Overlap* connections but is insignificant.

Overall, this fund-level evidence lends support to the argument that *Overlap* connections influence the risk–return trade-off positively through higher returns (and alpha) and lower risk, whereas *Firm* connections do not have much impact.

7.2. Portfolio Analysis

The conclusions from the fund-level analysis do not immediately extend to a fund-of-funds setting. Whereas alpha and excess return scale linearly with the number of constituent funds, standard deviation and Sharpe ratios do not. In particular, standard deviation could be reduced further at the portfolio level than at the individual fund level when the investor chooses more-connected hedge funds that discuss investments and reduce risk in the process. However, as argued, as more-connected hedge funds invest more similarly, a lack of diversification might ultimately increase risk. We set out to investigate this question empirically.

As we do not know the composition of existing fund-of-funds, we rely on a randomization exercise. Specifically, we simulate 10,000 portfolios of 16 hedge funds in each of our seven estimation windows for a total of 70,000 artificial portfolios. In the simulation, we always start by choosing eight random hedge funds. Then, in half the portfolios, we chose for each initial hedge fund

Table 9. Social Ties and Identification of Peer Effects: Interaction with Hedge Fund Employee Size

Panel L1								
Dependent variable	Δr_{L1}	Δr_{L1}	$\Delta\alpha_{L1}$	$\Delta\alpha_{L1}$	$\Delta\beta_{L1}$	$\Delta\beta_{L1}$	$\Delta\epsilon_{L1}$	$\Delta\epsilon_{L1}$
FirmShare	−0.213**	−0.172	−0.053**	−0.023	−0.437***	−0.417**	−0.137*	−0.091
	(−2.28)	(−1.54)	(−1.99)	(−0.87)	(−2.75)	(−2.22)	(−1.79)	(−0.96)
OverlapShare	−1.078***	−1.027**	−0.649***	−0.591***	−1.730***	−1.275*	−1.129***	−0.828**
	(−3.41)	(−2.33)	(−5.18)	(−2.88)	(−3.10)	(−1.69)	(−4.65)	(−2.57)
OverlapShare × *logMeanEmpSize*	0.183**	0.176	0.133***	0.120**	0.288**	0.189	0.213***	0.133*
	(2.41)	(1.64)	(3.64)	(2.03)	(2.12)	(1.02)	(3.77)	(1.78)
SameStyle	−0.082	−0.079	−0.037*	−0.033	−0.269**	−0.199*	−0.036	−0.069
	(−1.37)	(−1.24)	(−1.83)	(−1.64)	(−2.50)	(−1.67)	(−0.73)	(−1.30)
Fund controls	No	Yes	No	Yes	No	Yes	No	Yes
Managerial characteristics	No	Yes	No	Yes	No	Yes	No	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations ('000)	1,809	867	1,809	867	1,809	867	1,809	867
R^2	0.071	0.067	0.012	0.016	0.053	0.050	0.057	0.047
Panel L2								
Dependent variable	Δr_{L2}	Δr_{L2}			$\Delta\beta_{L2}$	$\Delta\beta_{L2}$	$\Delta\epsilon_{L2}$	$\Delta\epsilon_{L2}$
FirmShare	−5.255***	−4.949**			−2.602***	−2.778***	−2.585**	−2.004
	(−3.08)	(−2.10)			(−3.30)	(−2.93)	(−2.20)	(−1.22)
OverlapShare	−28.176***	−27.361***			−6.615**	−9.507**	−21.150***	−17.248***
	(−4.78)	(−3.28)			(−2.25)	(−2.18)	(−5.87)	(−3.64)
OverlapShare × *logMeanEmpSize*	5.552***	5.470***			1.170	2.082*	4.283***	3.226***
	(4.13)	(2.78)			(1.63)	(1.91)	(5.55)	(3.10)
SameStyle	−2.653*	−3.450**			−1.184**	−0.796	−1.365	−2.507**
	(−1.76)	(−2.02)			(−1.99)	(−1.18)	(−1.39)	(−2.24)
Fund controls	No	Yes			No	Yes	No	Yes
Managerial characteristics	No	Yes			No	Yes	No	Yes
Time fixed effects	Yes	Yes			Yes	Yes	Yes	Yes
Observations ('000)	1,809	867			1,809	867	1,809	867
R^2	0.037	0.034			0.054	0.062	0.021	0.019

Notes. For each pair distance in performance, we reestimate the models in Table 8 when adding the interaction term of *OverlapShare* with average hedge fund size, *logMeanEmpSize*. The two panels report the estimates for the L1 and L2 distance measures, respectively. *t*-statistics based on standard errors clustered at the fund *i* and fund *j* level appear in parenthesis below the estimates.

Statistical significance at the 1%, 5%, and 10% level is denoted by ***, **, and *, respectively.

an unconnected pairing fund at that point in time for a total of eight pairs of unconnected hedge funds. For this subset of portfolios, the count of connections in the eight pairings is zero.

Next, for the other half, we chose for each initial hedge fund a possibly connected pairing fund at that point in time. Whenever a starting fund does not share any connection with any other fund, we simply draw a random pairing fund. We then count the number of actual connections for the eight pairings in this second half of the portfolios, which takes values from zero (all initial fund pairings happen to be unconnected) to eight (all initial fund pairing fund turn out to be connected).

We assume equal allocation to each of the 16 participating hedge funds and compute accordingly the portfolio excess returns over each of the three-year estimation windows and, in analogy with the earlier analysis, the portfolio alpha, standard deviation, and Sharpe ratio. We then separately investigate the effect of firm culture and social ties by regressing these portfolio risk and return measures on the number of portfolio *Firm* or *Overlap* connections.

Panel A.1 of Table 12 shows the effect of the number of *Firm* connections on the four variables of interest. Results are broadly in line with the findings at the individual fund level of Table 11 but are stronger already. Excess returns and alpha are positively affected by *Firm* but insignificantly so. In contrast, risk is significantly reduced at the portfolio level for *Firm* connections. Having worked for the same firms in the past reduces overall risk. This risk reduction is stronger than any potential countervailing effect because of reduced diversification. The Sharpe ratio at the portfolio level is significantly and positively affected by *Firm* connections.

Panel A.2 shows the effects of the number of *Overlap* connections. Results are generally even stronger than in the case of *Firm* connections. Excess returns and alpha are positively affected by *Overlap* but insignificantly so. Risk is significantly reduced at the portfolio level for

Table 10. Social Ties and Identification of Peer Effects: Interaction with Number of Overlapping Months

Panel L1								
Dependent variable	Δr_{L1}	Δr_{L1}	$\Delta\alpha_{L1}$	$\Delta\alpha_{L1}$	$\Delta\beta_{L1}$	$\Delta\beta_{L1}$	$\Delta\epsilon_{L1}$	$\Delta\epsilon_{L1}$
Firm	−0.333**	0.042	−0.121***	−0.028	−0.699***	−0.143	−0.227**	0.072
	(−2.44)	(0.28)	(−3.32)	(−0.95)	(−3.00)	(−0.59)	(−2.24)	(0.68)
Overlap	0.132	0.033	0.077	0.132**	0.295	0.345	0.041	−0.032
	(0.66)	(0.14)	(1.15)	(2.11)	(0.84)	(0.87)	(0.29)	(−0.20)
Overlap × *Months*	−0.150***	−0.131**	−0.049**	−0.060***	−0.277***	−0.278**	−0.105***	−0.090*
	(−2.80)	(−1.98)	(−2.46)	(−2.77)	(−2.89)	(−2.40)	(−2.76)	(−1.85)
SameStyle	−0.076	−0.079	−0.050**	−0.033	−0.285**	−0.198*	−0.032	−0.069
	(−1.17)	(−1.23)	(−2.35)	(−1.63)	(−2.36)	(−1.67)	(−0.56)	(−1.30)
Fund controls	No	Yes	No	Yes	No	Yes	No	Yes
Managerial characteristics	No	Yes	No	Yes	No	Yes	No	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations ('000)	2,513	867	2,513	867	2,513	867	2,513	867
R^2	0.048	0.068	0.007	0.016	0.033	0.050	0.030	0.047
Panel L2								
Dependent variable	Δr_{L2}	Δr_{L2}			$\Delta\beta_{L2}$	$\Delta\beta_{L2}$	$\Delta\epsilon_{L2}$	$\Delta\epsilon_{L2}$
Firm	−6.887*	1.127			−2.603*	0.295	−4.357**	0.792
	(−1.91)	(0.35)			(−1.67)	(0.20)	(−2.03)	(0.44)
Overlap	−1.812	−3.709			−0.493	−1.624	−1.158	−1.868
	(−0.39)	(−0.69)			(−0.21)	(−0.59)	(−0.45)	(−0.66)
Overlap × *Months*	−1.859**	−1.300			−0.819	−0.475	−1.061**	−0.846
	(−2.08)	(−1.02)			(−1.64)	(−0.70)	(−2.14)	(−1.18)
SameStyle	−2.274	−3.440**			−1.134*	−0.793	−1.085	−2.501**
	(−1.19)	(−2.02)			(−1.75)	(−1.17)	(−0.81)	(−2.24)
Fund controls	No	Yes			No	Yes	No	Yes
Managerial characteristics	No	Yes			No	Yes	No	Yes
Time fixed effects	Yes	Yes			Yes	Yes	Yes	Yes
Observations ('000)	2,513	867			2,513	867	2,513	867
R^2	0.020	0.034			0.043	0.062	0.007	0.019

Notes. For each pair distance in performance, we reestimate the model in either Table 3 (without fund controls, odd columns) or Table 6 (which includes fund controls and managerial characteristics, even columns) when redefining *Overlap* as one if the fund managers overlap by at least a month at the prior employer and interacting it with the log of the number of months of overlap (*Months*). The two panels report the estimates for the L1 and L2 distance measures, respectively. *t*-statistics based on standard errors clustered at the fund *i* and fund *j* level appear in parenthesis below the estimates.
Statistical significance at the 1%, 5%, and 10% level is denoted by ***, **, and *, respectively.

Table 11. Economic Value of Social Ties: Level Analysis

	(1) Average return	(2) Alpha	(3) Standard deviation of excess returns	(4) Sharpe ratio
Firm connections	−0.000	−0.041	0.078	−0.028
	(−0.43)	(−0.67)	(0.33)	(−1.26)
Overlap connections	0.000	0.178	−1.259***	0.040
	(0.22)	(1.61)	(−3.52)	(1.03)
MgmtFee	−0.020	3.571	32.492*	−2.522**
	(−0.50)	(0.78)	(1.70)	(−2.05)
PerfFee	−0.004	0.925**	−4.203***	−0.031
	(−1.28)	(2.39)	(−2.81)	(−0.21)
EmpSize	0.000	0.017**	−0.169***	0.019***
	(0.27)	(2.39)	(−5.89)	(4.30)
FundAge	−0.001**	−0.068*	−0.232	−0.049***
	(−2.30)	(−1.87)	(−1.60)	(−2.87)
Time fixed effects	Yes	Yes	Yes	Yes
Style fixed effects	Yes	Yes	Yes	Yes
Observations	3,764	3,764	3,764	3,764
R^2	0.082	0.098	0.120	0.081

Notes. For each fund in the sample, we compute average excess returns, alpha with respect to the Fung and Hsieh (2004) seven-factor model, standard deviation of excess returns, and Sharpe ratio (average excess return over standard deviation) over three-year windows (rolling forward by one year). The table reports the OLS estimates of the pooled regression of each of these statistics on the strength of a fund managerial ties as measured by the number of its *Firm* and *Overlap* connections across all fund pairs, fund characteristics defined as in Table 1, and time and style fixed effects. The explanatory variables are measured using information up to December 2007, 2008, … , and 2013 respectively. *t*-statistics based on standard errors clustered at the fund level appear in parenthesis below the estimates.
Statistical significance at the 1%, 5%, and 10% level is denoted by ***, **, and *, respectively.

Table 12. Economic Value of Social Ties: Portfolio Analysis

Panel A. Fund-of-funds analysis

	Panel A.1. Firm connections				Panel A.2. Overlap connections			
	(1) Average return	(2) Alpha	(3) Standard deviation of excess returns	(4) Sharpe ratio	(1) Average return	(2) Alpha	(3) Standard deviation of excess returns	(4) Sharpe ratio
Number of Connections	0.001	0.002	−0.028***	0.003**	0.004*	0.005*	−0.026***	0.005**
	(0.39)	(0.64)	(−7.64)	(2.52)	(1.87)	(1.71)	(−6.73)	(3.46)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	70,000	70,000	70,000	70,000	70,000	70,000	70,000	70,000
R^2	0.325	0.417	0.208	0.313	0.328	0.430	0.213	0.315

Panel B. Decile analysis

	Panel B.1. Firm connections				Panel B.2. Overlap connections			
	(1) Average return	(2) Alpha	(3) Standard deviation of excess returns	(4) Sharpe ratio	(1) Average return	(2) Alpha	(3) Standard deviation of excess returns	(4) Sharpe ratio
D10	0.227	0.072	1.978	0.115	0.248	0.095	1.955	0.127
D1	0.314	0.132	2.747	0.111	0.276	0.089	2.768	0.096
Difference	−0.087	−0.060	−0.769*	0.004	−0.028	0.006	−0.813*	0.031
	(−0.37)	(0.43)	(−1.66)	(0.03)	(−0.07)	(0.64)	(−1.71)	(1.23)

Notes. Panel A: At the end of each year from 2007 to 2013, we draw 5,000 portfolios of eight random funds each. We then randomly match each fund in a portfolio with either an unconnected or a (possibly) connected fund, for which the connection is established either through *Firm* or *Overlap*. This procedure avails ourselves with 10,000 portfolios of 16 funds each per year, for which the number of pairwise connections to the starting set of eight funds varies from zero (no connected funds) to eight (all connected funds). We compute the portfolio monthly excess return over the following three-year window as the equally weighted average excess return of the constituent funds. For each portfolio, we then compute average excess returns, alpha with respect to the Fung and Hsieh (2004) seven-factor model, standard deviation of excess returns, and Sharpe ratio (average excess return over standard deviation) over the three-year window. The table reports the OLS estimates of the pooled regression of each of these statistics on the number of *Firm* connections (in panel A.1) and *Overlap* connections (in panel A.2) of a portfolio and time fixed effects. The explanatory variables are measured using information up to December 2007, 2008, … , and 2013, respectively. *t*-statistics based on standard errors clustered at the time level appear in parenthesis below the estimates. Panel B: At the beginning of each estimation window, we sort funds into deciles according to either the number of *Firm* connections (in panel B.1) or *Overlap* connections (in panel B.2). For the decile with the highest number of connections (denoted D10), we form equally weighted portfolios, track their performance over time, average across the portfolios during a given calendar month, and compute the corresponding statistics. For the group of funds with no connections (D1), we proceed in a similar fashion except that we work on bootstrapped portfolios with the same number of funds as D10 and report averages across those bootstrapped portfolios. *t*-statistics based on the bootstrap distribution appear in parenthesis below the difference D10 − D1.

Statistical significance at the 1%, 5%, and 10% level is denoted by ***, **, and *, respectively.

Overlap connections. The increased likelihood of personal communication and possibly the exchange of valuable information about investment decisions significantly reduces overall risk. The Sharpe ratio at the portfolio level is also significantly and positively affected by *Overlap* connections.

To complement our simulation exercise, we also report results based on standard decile sorting.[15] At the beginning of each estimation window, we sort funds into deciles according to the number of either *Firm* or *Overlap* connections. For the decile with the highest number of connections (denoted D10), we form equally weighted portfolios, track their performance over time, average across the portfolios during a given calendar month, and then compute the corresponding time series statistics. We proceed similarly for the decile of funds without connections (denoted D1).[16] The resulting decile portfolios are larger than the 16 funds used in the simulation analysis. However, the decile sorting ignores the information content of the intermediate deciles.

Yet, despite the differences, the main results remain in place. Panel B of Table 12 reports performance figures for the D10 portfolio, the D1 portfolio, and their differences. The *t*-statistics are based on the bootstrapped distribution of D1 funds. As in panel A, connections via *Firm* and *Overlap* result in lower standard deviations. Sharpe ratios also increase, especially through *Overlap* connections, but only insignificantly so.

We conclude that both *Firm* and, especially, *Overlap* connections make hedge fund returns more attractive. The effect is particularly prominent in a portfolio context, in which the risk-return profile of funds-of-funds is more appealing for more-connected funds-of-funds.

The attractiveness is driven by reduced risk and increased Sharpe ratios and, to a lesser extent, by higher excess returns and alpha.

The finding that more connected managers outperform their peers is in line with empirical evidence from concurrent studies (Pool et al. 2015, Rossi et al. 2018) and theoretical predictions from information network models (Walden 2019). Yet the bulk of the positive effect on Sharpe ratios comes from lower return standard deviations. This novel finding suggests that being more connected is less about finding high alpha investments and more about controlling portfolio risk. The finding aligns with the interviews in Kellard et al. (2017), which reveal an intense discussion culture among connected hedge fund managers. These critical assessments seem to reduce risks more than to increase alpha. One possible mechanism would be the avoidance of aggressive and excessive trading that is usually associated with investors' overconfidence and other self-enhancement biases (see Malmendier and Taylor 2015 for a review). Another possible explanation is that social ties allow managers to combine private signals and filter out noisy information, thereby dampening trade volatility.

8. Conclusion

We study the impact on hedge fund investment of managerial employment networks. Funds employing managers with shared employment histories are more similar in terms of raw returns. When we decompose raw returns, fund returns are also more similar in terms of abnormal performance, systematic risk, and residuals. These findings persist when controlling for fund-level variables and managerial characteristics, namely, for education and skill. Thus, past employment networks do not merely proxy for managerial characteristics, but actually trigger similar investments.

We separately estimate the effect of firm culture (managers have worked at the same firm) and social ties (managers overlapped during that time). Both effects are statistically and economically relevant. Firm culture seems more relevant for systematic risk, whereas social ties seem more relevant for idiosyncratic components (abnormal returns and residuals). These findings are robust to a number of variations in model design and to the inclusion of managerial characteristics. The effects of firm culture and social ties become stronger when we refine our hypotheses by considering team size, number of connections across teams, and duration of social ties. Moreover, connected managers display a larger overlap in their stock holdings and attain better risk–return profiles than unconnected peers. Our results highlight the important role of employment network effects that ultimately lead to exchange of information and correlated investment decisions.

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Appendix. Details of the Financial Services Register

The FSR is compiled by the Financial Conduct Authority (FCA). The FCA regulates insurance, investment, and banking companies that are domiciled in the United Kingdom. The FCA was formerly known as the Financial Services Authority (FSA).

The FSA was created in 1997 with responsibility for banking supervision, listing authority, and investment services regulation. With the Financial Services and Markets Act of 2000, which came into force on December 1, 2001, it started to exercise statutory powers to regulate the financial services industry. In the wake of the financial crisis of 2007–2008, the Financial Services Act of 2012 established a new system for regulating financial services in order to protect and improve the United Kingdom's economy, and the FSA was abolished effective April 1, 2013. Its responsibilities were then split between two new agencies (the Prudential Regulation Authority and the Financial Conduct Authority) and the Bank of England. The FCA continues to maintain the Financial Services Register originally developed by the FSA. To measure the effect of ties in the hedge fund industry, it is reasonable to consider the introduction of the 2000 act as an exogenous regulatory change.

The FSR requires all financial companies in the United Kingdom to report detailed information on current and past employment of their key employees. Using the FSR has clear advantages with respect to other available sources. The fact that the FCA requires reporting rather than voluntary disclosure increases the completeness and accuracy of the information, which is comparable to current databases of U.S. executives such as the widely used Boardex. Companies that fail to report a key employee may be subject to FCA investigations and, ultimately, to fines.

As the FSR is available only for UK companies and is reliable only as of 2002, we limit ourselves to the years 2002 through 2016 for UK-domiciled management companies. Note that records exist only for management companies and not for individual hedge funds.

The controlled function (CF) code specifies the employee's role in the management company. See the full list at http://www.fsa.gov.uk/doing/regulated/approved/persons/functions.

A detailed description of each CF code can be found in the CFA handbook: http://fshandbook.info/FS/html/handbook.

Table A.1. Hedge Fund Data Representativeness

	MgmtFee (1)	*PerfFree* (2)	*FundAge* (3)	*Leverage* (4)	*Aum* (5)	*Alive* (6)
Constant	1.545***	18.170***	106.399***	0.373***	460.771	0.665***
	(47.53)	(65.45)	(51.51)	(14.77)	(2.53)	(39.09)
FSA	0.046	−0.819*	−6.824**	−0.057	−119.512	−0.006
	(1.17)	(−1.95)	(−2.46)	(−1.47)	(−0.54)	(−0.20)
Observations	7,199	7,175	7,470	4,358	4,407	4,247
R^2	0.001	0.003	0.002	0.002	0.000	0.000

Notes. This table reports the regression of fund characteristics of the universe of hedge funds on a constant and an *FSA* dummy for funds in the combined FSA data set that is used in our study. Variable definitions follow from Table 2. *Alive* is a dummy for funds that are alive by the end of the period. In parentheses, we report *t*-statistics based on *t*-statistics based on standard errors clustered on the level of the style and the management company.

Statistical significance at the 1%, 5%, and 10% level is denoted by ***, **, * respectively.

Table A.2. Social Ties and Hedge Fund Returns, Additional Robustness Analysis

	L1				L2		
	Δr_{L1}	$\Delta\alpha_{L1}$	$\Delta\beta_{L1}$	$\Delta\epsilon_{L1}$	Δr_{L2}	$\Delta\beta_{L2}$	$\Delta\epsilon_{L2}$
Firm	−0.270***	−0.054*	−0.479***	−0.216***	−5.950***	−2.446***	−3.450***
	(−2.92)	(−1.94)	(−3.00)	(−3.47)	(−3.77)	(−2.78)	(−4.12)
Overlap	−0.184**	−0.080**	−0.344**	−0.112*	−2.357*	−1.089	−1.255
	(−2.23)	(−2.48)	(−2.28)	(−1.88)	(−1.74)	(−1.54)	(−1.54)
SameStyle	−0.090	−0.039*	−0.273**	−0.036	−2.222	−1.075	−1.060
	(−1.44)	(−1.72)	(−2.40)	(−0.70)	(−1.38)	(−1.64)	(−1.03)
Observations ('000)	588	588	588	588	588	588	588

Notes. The table shows an alternative specification of the models with fund controls in Table 3. We restrict the sample to funds with the same amount of leverage. The coefficients on the cross-sectional fund controls, time fixed effects, and the dummy *SameZip* are omitted to save on space. *t*-statistics based on standard errors clustered at the pair level appear in parenthesis below the estimates.

Statistical significance at the 1%, 5%, and 10% level is denoted by ***, **, and *, respectively.

We use the CF code to identify the directors (CF code 1), CEOs (CF code 3), and partners (CF code 4) who constitute our network.

Endnotes

[1] Personal connections explain household stock market participation (Hong et al. 2004) and investment decisions of mutual and pension fund managers (Hong et al. 2005, Cohen and Frazzini 2008, Pool et al. 2015, Rossi et al. 2018) as well as corporate policy decisions of directors and top executives (Fracassi 2017).

[2] Compare Fracassi (2017) for a related two-stage estimation of network effects on returns in a corporate finance setting.

[3] Joenvaäärä et al. (2021) argue that individual hedge fund databases are not representative of the industry as a whole. They show that differences among databases may induce survivorship biases and alter inferences on the determinants of hedge fund performance, which is the focus of our study. For these reasons, we rely on a comprehensive data set.

[4] This choice is supported by our hedge fund data from which we know the names for a subset of 139 managers. These are mostly classified as directors (40%), CEOs (16%), or partners (23%).

[5] UK postcodes consist of five to seven alphanumeric characters, which are separated by a space. The outward code is the first half of the postcode (before the space).

[6] The factors are the excess return of the S&P 500; a size factor as the difference between the Russell 2000 and the S&P 500 indexes; the change in the 10-year treasury constant maturity yield; the change in the credit spread of Moody's BAA bond over the 10-year Treasury bond; and the excess return on portfolios of lookback straddle options on currencies, commodities, and long-term bonds. We obtain the factors from https://faculty.fuqua.duke.edu/dah7/HFRFData.htm.

[7] Data on live companies are readily obtainable from http://www.companieshouse.gov.uk/. We can easily identify hedge funds through our own merged database. Mutual funds we identify in the Morningstar database. Finally, we classify the remaining firms by manual web-based investigation. Investment management firms are investment advisers, which cannot be clearly subsumed under private equity, mutual fund, or hedge fund.

[8] Following the literature, if a stock is present in one company but missing in the other, we set the relative share in the latter to zero.

[9] We weight each pair observation by the average (across the two funds) absolute *t*-statistics of their alpha, the average (across the two funds and the seven factors) absolute *t*-statistics of their beta, and the inverse of the average (across the two funds) time-series standard deviation of their residuals.

[10] With only seven time windows, we cannot reliably cluster our errors at the time level.

[11] We thank an anonymous referee for raising this point.

[12] Note that, because multiple managers can connect two funds, there could be more than one firm fixed effect that takes a value of one for a given pair of funds.

[13] *EmpSize* is the overall number of employees at the management company. We obtain similar results when interacting with the (pair average) number of employees we classify as managers.

[14] We take the average of the overlapping months in the case of multiple managers connecting two funds.

[15] We thank an anonymous referee for this suggestion.

[16] As the funds without connections number more than the funds in one decile, the resulting portfolio standard deviation would be mechanically lower and the Sharpe ratio mechanically higher. To maintain comparability with decile D10, we report average statistics across randomly sampled portfolios of decile D1 funds with the same number of funds as in decile D10.

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