Whom You Know Matters:
Mutual Fund Workplace Networks and Investment Performance

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ABSTRACT

Do workplace ties among mutual fund managers channel value-relevant information, and what organizational structures facilitate workplace information flows? We introduce a novel measure of skill-weighted inter-fund comanager connections (ICC) to answer this question. ICC funds exhibit more similar portfolio holdings to connected funds and higher risk-adjusted returns than non-ICC funds. Causality is identified through plausibly exogenous shocks from superstar manager departures. Sharing value-relevant information is the source of this advantage: ICC funds generate abnormal returns on overlapping holdings in non-local and hard-to-research stocks. Finally, we present the first evidence of the evolution of workplace networks in the mutual fund industry.

Delegated investment managers earn economic rent from their informational advantages. Prior research shows that connections with other informed economic agents play an important role in explaining mutual fund portfolio decisions and performance. For instance, extant studies link fund performance to educational ties with corporate board members (Cohen, Frazzini, and Malloy 2008) and social connections with financial analysts and auditors (Gu et al. 2019; Chen et al. 2022). Other work highlights the role of geographical proximity in explaining fund portfolio overlaps, attributing such overlaps to social connections among portfolio managers (Hong, Kubik, and Stein 2005; Pool, Stoffman, and Yonker 2015). However, relatively little is known about the extent to which professional managers' social connections in the workplace influence their portfolio performance.

Fund managers' professional ties are primarily forged within their respective fund families. On the one hand, membership in a fund family facilitates better performance through economies of scale and enhanced information sharing (e.g. Chen et al. 2004; Brown and Wu 2016). On the other hand, managers within the same family face both competitive and collaborative incentives (e.g., Evans, Prado, and Zambrana 2020). However, it remains unclear how fund managers effectively navigate these interactions within a fund family. This study builds on two disparate literatures—connections-based information sharing and fund family affiliation—to examine the impact of workplace information sharing through intra-family social connections. To this end, we draw on the organizational structure of mutual funds to develop a measure of these connections and investigate their implications for portfolio composition and performance.

Over the past two decades, mutual fund management has evolved into a team-based endeavor.[1] While it is widely recognized that teams manage multiple funds, it is less well known that some managers serve on multiple teams simultaneously.[2] For example, within a given fund family,

[1] Figure A1 plots the evolution of fund managerial structure over time. As of 2018, over 70% of the active equity mutual funds are overseen by a group of managers. This trend is also widely documented in the literature (see, e.g., Patel and Sarkissian 2017; Harvey, Liu, Tan, and Zhu 2021).

[2] Some previous studies investigate the role of multi-fund managers, who oversee multiple funds at the same time (e.g., Choi, Kahraman, and Mukherjee 2016; Agarwal, Ma, and Mullally 2023). However, multi-fund managers are not necessarily those with multiple team membership. It is true vice versa: multi-team managers naturally are multi-fund managers. Since team management is a necessary but not sufficient condition to managers' multiple team membership, this cross-team connection trend is an independent evolution instead of a pure by-product of team-management.

Managers A and B oversee Fund 1, A and C manage Funds 2 and 3, C manages Fund 4 alone, and D manages Funds 5 and 6. These cross-team managerial linkages create a crucial condition for workplace information sharing across different fund management units, including both those managed by a single manager (e.g., Fund 4) and those managed by a team (e.g., Funds 1, 2, and 3). We hypothesize that the effectiveness and intensity of information sharing hinge on both (1) the strength and (2) the scale of these connections. The scale of connections is intuitive, as a greater number of connections is likely to increase the available information set. The strength of connections, however, depends on both the incentives to share information and the inherent informational advantage of the sources themselves.

In the above fund management structure, Manager A is a comanager connected to Fund 4, just as Manager B is to Funds 2 and 3, and Manager C is to Fund 1. Funds 5 and 6 lack any such connections, as Manager D is not connected to Funds 1, 2, 3, or 4. In this context, A has a greater incentive to share information with B and C, as A comanages Fund 1 with B and Funds 2 and 3 with C. While it is possible that A (or B or C) might share information with D, we hypothesize that they are less likely to do so for two reasons. First, A, B, and C do not comanage Funds 5 and 6 and, therefore, have no direct stake in their performance. Second, comanagers (e.g., A and B or A and C) are likely to spend more time working together, thus developing stronger personal relationships compared to their interactions with D. Figure 1A illustrates the concept of manager-connected funds (MCFs), which are defined as funds with at least one comanager connection. For instance, Fund A has both Dylan and Evan as its comanager connections. As shown in Figure 1B, MCFs have become increasingly common over the past three decades, with over half of active equity mutual funds having at least one manager serving on another team since 2005.

The second component of connection strength is the extent to which a comanager possesses value-relevant information. To capture this, we introduce a manager skill element into the interfund comanager connection (ICC) measure. Specifically, we adopt the approach of Berk, Van Binsbergen, and Liu (2017), and assign a skill weight of 1 to each comanager connection if the aggregate assets under management (AUM) of the comanager is within the top tercile, and 0 otherwise.[3] Using the example in Figure 1A, if Dylan is a top-AUM manager while Evan is not, the ICC measure for the focal Fund A would be 1 after applying the skill weight, as shown in Figure 2A (further details are provided in Section 3.2). In summary, we develop a novel fund-level measure of interfund comanager connections by counting the number of top-AUM managers connected through common managerial ties.[4]

We hypothesize that interfund comanager connections facilitate the transmission of valuable information, which subsequently results in superior fund performance. This hypothesis is tested in two stages. In the first stage, we assess whether the ICC measure effectively captures an information-sharing channel operating within the workplace. To validate this measure, we examine whether ICC funds exhibit greater portfolio similarity to their connected funds compared to non-ICC funds.[5] By comparing the average portfolio similarity between ICC and non-ICC funds, we find that higher ICC is associated with larger holdings overlap, with ICC funds showing, on average, three times higher portfolio similarity to their connected funds than matched non-ICC control funds. To further strengthen our analysis, we use a propensity-score-matched sample and run fund-level regressions of average portfolio similarity on the ICC measure, incorporating the same control variables used to generate the propensity scores and a variety of fixed effects. The results indicate that a one-standard-deviation increase in ICC leads to a 12% increase in average portfolio similarity for ICC funds relative to control funds. Both the univariate comparison and the multivariate regression test provide strong evidence that the ICC measure captures a plausibly operating channel of workplace information sharing.

In the second stage, we examine whether the information transmitted through interfund comanager connections is valuable by estimating panel regressions of fund abnormal performance measures on ICC, while controlling for variables known to influence fund performance and

[3] The construction of the managerial skill measure, manager AUM, is detailed in section (3.2) and figure A2 in the appendix. Using different cutoffs of top quartiles and top quintiles does not significantly alter our results.
[4] A manager-connected fund (MCF) is an ICC fund conditioning on having at least one top-AUM manager connected. Being an MCF is a necessary condition for being an ICC fund. Figure A1.2 shows that the evolution of ICC funds appears largely as a concurrent trend to that of MCFs.
[5] The non-ICC funds refer to a control group of funds that are similar to ICC funds based on propensity score matching but have top AUM manager connections within any of the connected funds for ICC funds.

potential confounders. In the baseline regression, we exploit within-fund variation by using a fund fixed-effects specification, which eliminates the influence of time-invariant fund heterogeneities on the interfund connection effect. This specification remains robust to the inclusion of time, style, and family fixed effects, with our results maintaining both statistical significance and economic magnitude. Consistent with our hypothesis that connections with skilled comanagers from other funds contribute to superior abnormal performance, the baseline results indicate that a one-standard-deviation increase in ICC leads to a performance improvement of up to 30 basis points per year, as measured by Fama-French-Carhart four-factor alphas.

A central step in analyzing the relationship between ICC and fund performance is to determine whether the performance gains can be attributed to connections with other-fund comanagers or to the skill of the own-fund managers. The within-fund specification used in the baseline test mitigates omitted variable bias by controlling for all time-invariant fund characteristics, including unobserved manager skill. However, this specification may still be subject to finite-sample bias.[6] In a similar spirit to Pástor, Stambaugh, and Taylor (2015), it is possible that better-performing managers are more likely to establish connections with other-fund comanagers, such that the observed relationship between other-fund comanager connections and fund performance could instead reflect the own-fund managerial skill.

To address concerns of endogeneity, we exploit changes in ICC arising from the departures of superstar managers who serve as comanager connections for other funds. In this quasi-experiment, the plausibly exogenous variation in ICC arises because the departure decisions of superstar managers from connected funds are independent of the performance of the focal fund. Such departures lead to a reduction in manager connections for the focal funds but do not affect the abilities of the focal managers. More importantly, to ensure that these departure decisions are not performance-driven, we classify superstar managers as those with long tenures who oversee a

[6] Pástor, Stambaugh, and Taylor (2015) point this out when evaluating the diseconomy of scale in mutual funds. In their paper, the core relation of interest is the size-performance relation as opposed to the connection-performance relation in this paper. To pull out the causal effect of ICC on fund performance, we pursue the quasi-experimental approach instead of applying the recursive demeaning approach to get an IV for the ICC measure.

significant share of total family assets within large fund companies.[7] Chen, Du, and Sun (2024) use Bill Gross's departure from PIMCO as a shock to fund size, as Gross was a seasoned and influential bond fund manager within the company. Similarly, the rationale for focusing on these senior key managers affiliated with influential fund families is that they generally maintain an interdependent relationship with their respective investment companies. These managers are often perceived by fund investors as integral to the fund's brand, and their departure is typically followed by investor outflows. Therefore, their departure decisions are least likely to be an ex-ante arrangement of the fund families, ruling out concerns about confounding relationships with ICC funds' managerial ability.

To exploit the exogenous variation in ICC resulting from the departures of superstar managers, we identify treated funds as ICC funds with superstar manager connections, and control funds as non-ICC funds matched to ICC funds using propensity scores across the sample period (i.e., never-treated units). The key identifying assumption is that, in the absence of superstar comanager departures from connected funds, ICC funds and their matched control funds would have exhibited similar performance trajectories.

Using a difference-in-differences (DiD) specification, with the same vector of covariates and fixed effects as in the baseline regression, we find that the departure-induced declines in the ICC measure are associated with significant reductions in abnormal performance, confirming the positive ICC-performance relationship observed in the baseline analysis. Moreover, the performance effects in this DiD framework are both statistically significant and economically sizable. Specifically, a one-standard-deviation decrease in ICC leads to an annual decline of 240 basis points in Carhart four-factor alphas. Further investigation of the dynamic relationship between ICC and fund performance confirms the absence of any pre-trend, providing additional support for the validity of causal inference. One might argue that superstar departures could impair focal fund performance by increasing the workload of focal managers across non-focal funds.

[7] This classification of superstar managers takes on several cutoff values in manager tenure, the size of affiliated fund family, the share of family AUM. In Section (5.2), we will elaborate on the specific classification standards and the rationale of setting up these thresholds in the identification.

Section 7 presents a diagnostic test to rule out this potential channel and affirms the exogenous nature of this shock. Taken together, these results strengthen our confidence in drawing causal inferences regarding the impact of interfund comanager connections on fund performance.

After documenting the significant and positive performance impact of interfund comanager connections, we further exploit an important type of focal fund heterogeneity–whether focal fund is team-managed or solo-managed–to examine the differential performance impact across funds. Given the valuable information shared through interfund comanager connections, a natural question arises regarding how well the focal management unit (team vs. solo) processes this information. To address this question, we develop a set of competing sub-hypotheses based on the behavioral trade-offs inherent in different management structures. The first hypothesis posits that team-managed funds benefit more from the performance effect of ICC due to fewer information capacity constraints compared to solo-managed funds (Peng 2005). The second hypothesis suggests that solo-managed funds may benefit more from ICC due to lower coordination costs relative to team-managed funds (Chen et al. 2004). The results from subsample analyses show that the positive performance impact of ICC is concentrated in team-managed funds, supporting the first hypothesis that team management is less constrained by information capacity. Additionally, we find stronger performance effects of ICC for funds from smaller fund families, possibly due to the greater reliance of smaller families on interfund comanager connections.

To assess the robustness of our findings, we identify portfolio-leader managers as an alternative source of information for the focal funds and construct an alternative ICC measure based on a manager's portfolio-leader identity. We collect portfolio-leader data for the sample funds, generate the portfolio-leader-based ICC, and re-estimate the previous models. The results are consistent with previous findings: funds with higher ICC exhibit greater holding similarity with connected portfolios, demonstrate superior risk-adjusted performance, and the performance effect of ICC is driven by team-managed funds and funds from smaller families.

We further examine whether the documented ICC-performance relationship is driven by the transmission of value-relevant information. Although the results are not uniformly strong, they suggest that connections enhance fund performance through certain overlapping stocks.

Specifically, by constructing portfolios based on these overlapping stocks, we find that ICC funds benefit primarily from buying overlapping non-local stocks and hard-to-research stocks.

The remainder of the paper is structured as follows. Section 2 discusses the related literature and our paper's contribution. Section 3 describes the data and the construction of the ICC measure. Section 4 presents evidence on the relationship between ICC and portfolio similarity. In Section 5, we discuss the empirical strategies and report results on the ICC-performance relationship. Section 6 examines the underlying economic mechanisms. Section 7 provides evidence on whether ICC-related trades are informed, by evaluating the performance of ICC funds based on overlapping stocks. Section 8 conducts robustness tests and Section 9 concludes.

2 Related Literature

This paper contributes to several strands of the literature. First, it extends research on the implications of managerial connections for investment decisions and fund performance. Cohen, Frazzini, and Malloy (2008) show that educational ties with corporate board members influence mutual fund performance. Gu et al. (2019) demonstrate that mutual fund managers leverage social connections with analysts to generate superior returns. Chen et al. (2022) document that social ties with firm auditors also affect portfolio decisions. Hong et al. (2005) and Pool et al. (2015) highlight the role of word-of-mouth communication in fund managers' portfolio choices when they reside in the same city or neighborhood, respectively. Rossi et al. (2018) examine peer-type network connections within the UK pension fund industry and find that more centrally connected pension fund managers deliver superior risk-adjusted performance.[8] This paper advances the connection literature on asset management by introducing an important work tie: the connections that a focal manager brings from comanagers when concurrently working on non-focal funds. For each fund

[8] Both invoking the co-management setting notwithstanding, our study is distinct from Rossi et al. (2018) not only in the different industries of interest, but also in the nature of the connection measure: we track the direct other-fund comanagers of shared managers' and aggregate them to each fund managed by shared managers, while Rossi et al. (2018) exploits both the direct comanagers and the indirect auditor-sharing managers to measure the centrality of managers. Essentially, we focus on the informational role of fund-level connections as opposed to the manager-level network centrality in Rossi et al. (2018) that mainly represents the number of connections. We care more about the quality of each individual connection nodes outside the examined fund unit.

with comanager connections facilitated by shared managers, we construct a count measure that aggregates all skilled comanagers across other funds, and then assess its performance impact. We show that more comanager connections lead ICC funds to yield better performance.

Second, this paper contributes to the literature on the effectiveness and implications of workplace information sharing. Sandvik et al. (2020) demonstrate that management practices facilitating information diffusion among coworkers improve sales productivity, while Jarosch et al. (2021) document information spillover effects of skilled coworkers on wage growth. However, little is known about the implications of workplace information sharing for professional money managers. Focusing on the mutual fund industry, this paper extends this literature by highlighting the importance of management practices in fostering information spillovers within the workplace. Specifically, mutual fund managers share valuable information or profitable strategies, and generate positive externalities in funds managed by connected managers.[9] In addition to introducing a novel channel for workplace information sharing through comanager linkages, a major contribution of this study is demonstrating that such information sharing has positive performance implications. Given that fund performance is tied to both manager productivity and compensation, this represents an important, yet previously unexplored, outcome variable in the literature.

More broadly, this paper contributes to the literature on fund managerial structure. Given the growing trend toward team management, there is mixed evidence regarding its impact on performance. While some studies argue in favor of the team approach (e.g., Patel and Sarkissian 2017; Adams, Nishikawa, and Rao 2018; Harvey et al. 2021), others question its efficacy, noting that team-managed funds often fail to outperform their solo-managed counterparts (Prather and Middleton 2002; Bliss, Potter, and Schwarz 2008), or may even underperform (Chen et al. 2004; Bar, Kempf, and Ruenzi 2011). Rather than directly addressing the performance implications of team management, this paper begins by uncovering the growing trend of managers serving on

[9] Genc et al. (2022) also explores the work connections of mutual fund managers, but they adopt a very different setting. Specifically, they exclude all the funds that are involved in manager-overlap situations, which are the exact focus in our study. To the extent that information sharing happens via manager-sharing arrangements, this paper argues that the manager-overlap setting provides more direct evidence of the impact of connected managers on focal fund performance.

multiple teams simultaneously, which is beyond the traditional team-versus-solo organizational dichotomy.[10]

By being the first to document the prevalence of cross-team manager-overlap design, this study sheds light on a new feature of team-connectedness in the mutual fund management structure. We also provide the first systemic evidence on the effectiveness of such a managerial structure as a channel for workplace information sharing and a key driver of fund performance. Clearly, the manager overlap design is enabled by team-based portfolio management. To the extent that interfund comanager connections are intensified by team management, our results indicate that this structure may explain the increasing popularity of the group management design. Further subsample analyses conclude that team-managed funds are the primary beneficiaries of the informational advantage brought about by interfund comanager connections. This result is consistent with the view that teams face fewer information capacity constraints. As such, we provide a supportive rationale for the increasing adoption of team management in the mutual fund industry.

3 Data, ICC Measure, and Summary Statistics

3.1 Data and Sample

The data used in this study is drawn from several sources. We use the Morningstar Direct database to obtain information on fund managers. This database provides precise managerial data that allows us to identify the manager(s) responsible for the day-to-day management of each fund on a monthly basis.[11] Funds with anonymous managers are excluded. The database also allows us to accurately define multi-team managers (common managers), focal managers, and non-focal managers. We categorize each fund as either a manager-connected fund (MCF) or a non-MCF, based on the composition of managers in these various categories. An MCF is defined as a fund

[10] There is a fine line between funds with multi-team managers and funds with comanager connections (MCFs). When only a subset of focal managers oversees another fund, there are no comanager connections brought into the focal fund. However, figure A1.3 shows that the rising trend of MCFs close track the trend of multi-team-manager fund, implying that most multi-team managers bring in comanager connections.

[11] Patel and Sarkissian (2017) show that the Morningstar database provides more precise and larger coverage of manager composition information than CRSP.

overseen by at least one common manager, with at least one non-focal manager connected via the common manager through a comanager relationship in a non-focal team. A connected fund contains at least one common manager and at least one comanager connection. In Section 3.2, we describe how this framework is used to construct a novel fund-level connection measure.

We use the CRSP survivorship-bias-free mutual fund database to obtain monthly fund returns and characteristics including fund size, fund age, expense ratio, and portfolio turnover.[12] Except for fund size (TNA) and fund age, share class characteristics are aggregated at the fund level in a value-weighted manner. Fund size is based on the sum of TNA across all share classes, while fund age is determined by the oldest share class. Portfolio holdings are taken from the Thomson Financial CDA/Spectrum Mutual Fund database (S12 holdings). We employ MFLINKS from Wermers (2000) to match fund-level data from CRSP with their portfolio holdings. We then use fund tickers and names to merge the Morningstar manager data with the CRSP fund data. Applying standard filters, we obtain a sample of open-ended U.S. domestic active equity funds.[13] Following Evans (2010), we exclude incubated fund suspects. After applying these screening procedures, the final sample consists of 2,214 U.S. active equity funds and 309,229 fund-month observations from 1992 to 2018.[14]

3.2 Construction of the ICC Measure

The ICC measure captures both the quantity and quality of cross-team managerial connections. On the one hand, the size (or cardinality) of the connected manager set is important. This quantity

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[12] Details on variable construction is described in Table A1.

[13] Following common filters in studies like Chen et al. (2004), Kacperczyk et al. (2008) and Berk and van Binsbergen (2015), we exclude fixed income, index, international, money market, and sector funds from our sample. We rely on Lipper objectives codes to keep funds with the codes of B, CS, EI, FS, G, GI, H, ID, LCCE, LCGE, LCVE, MC, MCCE, MCGE, MCVE, MLCE, MLGE, MLVE, MR, NR, S, SCCE, SCGE, SCVE, SG, SP, TK, TL, and UT. If Lipper objective codes are not available, Strategic Insights codes and the Wiesenberger Fund Type Code are used in turn: we first choose funds with AGG, ENV, FIN, GMC, GRI, GRO, HLT, ING, NTR, SCG, SEC, TEC, UTI, GLD, or RLE, then select funds with G, G-I, G-S, GCI, IEQ, ENR, FIN, GRI, HLT, LTG, MCG, SCG, TCH, UTL, or GPM. If none of these objective codes are available, a fund is selected when it has a CS policy or holds more than 80% of its value in common shares. Index funds are first filtered out using two variables from CRSP (index_fund_flag, et_flag), and then deleted if the fund names contain keywords of index or ETF, or their variants, or related keywords including S&P and Russell, etc.

[14] The starting year of 1992 is chosen with the aim of acquiring more complete managerial information. (See, e.g. Patel and Sarkissian 2017).

dimension is intuitively linked to both the focal team size and the number of multiple team memberships held by common managers. The underlying assumption of this measure is manager heterogeneity, implying that each manager serves as an independent source of information. We also introduce an alternative measure of these connections at the team level, rather than the individual level, and include this variable as a control in the full specification when testing the ICC-performance relationship.

On the other hand, recognizing that the quality of connections is also crucial, we construct a skill-weighted connection measure. Following Berk, Van Binsbergen, and Liu (2017), we define skilled managers as those in the top tercile of manager AUM, which is calculated as the total assets under a manager's management.[15] Figure A2 illustrates, using a hypothetical fund structure, how this variable is computed in two examples.

Incorporating both the quantity and quality of a fund's connections, we construct the interfund comanager connection measure. For fund i in month t, the ICC is defined as:

$$ICC_{i,t} = \sum_{k \in K^i} \max_{j \in J^i}\left(I_{j,k,t}\right) \tag{1}$$

where j denotes a focal manager of fund i, and J^i is the set of all focal managers for fund i. k denotes a connected manager who works with the focal manager j at other funds, and K^i is the set of all connected managers for fund i. A connection exists if manager k comanages a fund (outside fund i) with focal manager j in month t. The skill weight is controlled by the indicator variable $I_{j,k,t}$ which equals 1 if manager k is a top-tercile manager by AUM in month t, and 0 otherwise. This term weights the connection by manager quality. The max operator ensures that each connected manager k is counted at most once for fund i, even if k is linked to multiple focal managers within the fund. This avoids double-counting and aggregates the fund's team-based connections into a single measure. An important merit of the ICC measure is its applicability to

[15] Using manager AUM to measure managerial skill is also motivated by Berk and Green (2004) and Berk and van Binsbergen (2015). There are two implicit assumptions here: Size is positively related to investment skill and manager skill is additive. The first assumption follows the main spirit behind the value-added measure, and we employ the key TNA element only in our measure to make the cases of multi-fund and multi-team managers tractable. We need the second assumption to invoke the TNA sharing rule so that we can assign the average assets under management to a manager when she works in a team.

both team-managed funds and solo-managed funds. We illustrate the calculation of ICC with two numerical examples in Figure 2.

3.3 Summary Statistics

Table 1 provides summary statistics for the main variables used in this paper. Panel A shows that, on average, a fund has 1.5 comanager connections, with team-managed funds having connections to more than two managers (2.2).[16] The median within-fund average ICC is above zero (0.08), indicating that more than 50% of funds experience at least one ICC change over the sample period. Conditional on having at least one connection, the average fund is connected to more than five non-focal managers (5.5).[17] Panel B displays the correlation matrix for ICC and various fund, team, and family characteristics. Except for team size, ICC is largely uncorrelated with the other variables correlated with fund performance. The correlation between ICC and team size is intuitive (0.485), as larger teams are more likely to include managers who also oversee other funds with non-focal managers.

To capture the characteristics associated with cross-team managerial connections, we develop two additional measures: the number of busy managers (Busyness) and team connections (NumTeam). The former is designed to account for the competing effects of ICC, while the latter serves as an alternative connection measure based on the same organizational structure. Although a higher ICC may reflect greater information sharing, it is also indicative of funds with managers who oversee multiple funds across different teams. Consequently, ICC funds are linked to busy managers who may be unable to devote full attention to their focal funds.

Due to the potential adverse effects of manager busyness, the performance impact of ICC may represent a net effect, which can be mitigated by including the busyness variable in the performance regression. Additionally, one might argue that individual connections are less important than team-level connections, as team members are likely to have significant overlap in

[16] It is not surprising that the ICC distribution is highly right skewed, since funds with multi-team managers have been slowly gaining popularity in the first half of our sample period.
[17] See Table A2 for distributions of ICC variants outside table 1.

their information sets. In the extreme, there is no manager heterogeneity along the information dimension within a team. Thus, the information set is represented by the fund management team as a whole. To test this hypothesis, we construct a team connection measure (NumTeam) by counting the number of non-focal teams connected to focal managers. This alternative measure exhibits a correlation of 0.748 with ICC, which is not surprising given that the more non-focal teams a focal fund is connected to, the more likely it is to have access to top-AUM managers from those teams.

4 ICC and Portfolio Similarity

In this section, we test whether the measure of interfund comanager connections effectively captures a channel for workplace information sharing. We hypothesize that, if ICC facilitates information transmission, funds with higher ICC should exhibit greater portfolio overlap with their connected funds. To test this hypothesis, we follow established practices in the literature and measure portfolio overlap by computing the cosine similarity between the portfolio active weight vectors of the focal fund and those of the connected funds.[18] We begin with univariate comparisons, followed by a multivariate regression analysis to directly assess the effect of ICC on portfolio similarity.

The investigation of the relationship between ICC and portfolio similarity involves using non-ICC funds as control funds. These funds are matched to ICC funds based on the propensity scores derived from regressions predicting the likelihood of a fund becoming an ICC fund, using a set of fund-related characteristics. Importantly, these control funds are not connected to the same group of connected funds as the ICC funds. Thus, the information-sharing effect attributable to ICC is teased out by comparing the portfolio similarity between ICC funds and their connected funds, as opposed to comparing control funds with the same connected funds. For each ICC fund (defined as a fund with at least one top-AUM manager connection), its corresponding connected funds are those with at least one common manager and at least one top-AUM manager. Given the one-to-

[18] Here, the active portfolio weights are computed using CRSP value-weighted market index. Alternatively, portfolio active weights can be computed in excess of those in respective benchmark indices.

many mapping between ICC funds and their connected funds, for ease of comparison between ICC funds and their matched controls, we follow Girardi et al. (2021) to compute the average portfolio similarity between an ICC fund and all its connected funds, as expressed in Equation (2).

$$Similarity\_Avg_{i,t} = \sum_{j=1}^{J^i} \frac{Similarity_{i,j,t}}{J^i} \tag{2}$$

where j is the jth connected fund and J^i is the total number of connected funds for focal fund i. $Similarity_{i,j,t}$, bounded between 0 and 1, is the cosine similarity between fund i and fund j's vector of portfolio active weights in month t. In Panel A of Table 2, we compare average portfolio similarity between ICC funds and their matched non-ICC funds. The results show that ICC funds exhibit significantly higher portfolio similarity with their connected peers than the control funds do. On average, an ICC fund's portfolio similarity is three times higher than that of its matched control, and the difference is significant.

We next estimate a regression of the average portfolio similarity on ICC, incorporating the same set of control variables used to obtain the propensity scores, along with a variety of fixed effects. The panel regression mode is the follows:

$$\begin{aligned} Similarity\_Avg_{i,t} = {} & \beta_1 * ICC_{i,t} + \beta_2 * Log(TNA)_{i,t-1} + \beta_3 * Log(Age)_{i,t-1} \\ & + \beta_4 * Expense_{i,t-1} + \beta_5 * Turnover_{i,t-1} + \beta_6 * Activeness_{i,t} \\ & + \beta_7 * Ret_{t-12,t-1} + \beta_8 * Vol_{t-12,t-1} + \beta_9 * Flow_{t-12,t-1} \\ & + \beta_{10} * Log(FamilyTNA)_{i,t-1} + \beta_{11} * Log(TeamTNA)_{i,t-1} \\ & + \beta_{12} * Teamsize_{i,t} + FEs + \epsilon_{i,t} \end{aligned} \tag{3}$$

where $Similarity\_Avg_{i,t}$ is the average portfolio similarity for fund i in month t, and $ICC_{i,t}$ is the interfund comanager connection of fund i in month t. For fund i, the control variables include the logarithm of total net assets (TNA), the logarithm of fund age (Age), fund total expense (Expense), fund annual turnover (Turnover), 1-R-squared of the Carhart four-factor model (Activeness), past 12-month fund return (Ret), past 12-month fund return volatility (Vol), past 12-month fund flow (Flow), the logarithm of fund family's TNA (FamilyTNA), the logarithm of management team's

TNA (TeamTNA), and the number of managers of the team (Teamsize). Fixed effects (FEs) include fund fixed effects, calendar year-month (time) fixed effects, fund style fixed effects (Morningstar nine categories), and fund family fixed effects (CRSP management company code).

The results, presented in Table 2, Panel B, indicate that the coefficient on the ICC measure is significant (t-statistic = 4.16 in model (1)): a one-standard-deviation increase in ICC is associated with a 12% (0.0025 × 4.08 ÷ 0.085) increase in the portfolio similarity compared to the sample mean. Our results are robust to alternative controls of fixed effects. For example, model (1) controls for fund and time FEs, model (2) adds style FE while the last model in column (3) further controls for family FE. Together, the descriptive statistics and the regression analysis support the conclusion that the ICC measure represents an organizational channel for workplace information sharing.

5 ICC and Fund Performance

5.1 Baseline Performance Results

Having established that comanagers share information across funds, we now turn to the question of whether this information has value. To test this hypothesis, we regress fund alpha on ICC and a set of control variables:

$$\begin{aligned}\alpha_{i,t}^{4F} = {} & \beta_1 * ICC_{i,t} + \beta_2 * Log(TNA)_{i,t-1} + \beta_3 * Log(Age)_{i,t-1} \\ & + \beta_4 * Expense_{i,t-1} + \beta_5 * Turnover_{i,t-1} + \beta_6 * Activeness_{i,t} \\ & + \beta_7 * Ret_{t-12,t-1} + \beta_8 * Vol_{t-12,t-1} + \beta_9 * Flow_{t-12,t-1} \\ & + \beta_{10} * Log(FamilyTNA)_{i,t-1} + \beta_{11} * Log(TeamTNA)_{i,t-1} \\ & + \beta_{12} * Teamsize_{i,t} + \beta_{13} * NumTeam_{i,t} + \beta_{14} * Busyness_{i,t} \\ & + FEs + \epsilon_{i,t} \end{aligned} \tag{4}$$

where i denotes fund i, t refers to month t. $\alpha_{i,t}^{4F}$ is the risk-adjusted return of the fund i in month t. The factor loadings are estimated using rolling regressions over the preceding 12 months and the Carhart four-factor model. $ICC_{i,t}$ is the interfund comanager connection of the fund i in month t. In addition to the eleven control variables from Equation (2), we add two control variables to capture managerial structure: the number of team connections for fund i (NumTeam) and the number of busy managers on the fund (Busyness), where a busy manager is defined as one who manages a top-quintile number of funds. All control variables are defined in the Appendix Table 1. Fixed effects (FEs) are identical to those specified in Equation (3).

Table 3 reports the baseline results. All the models in Panel A include fund fixed effects to control for time-invariant fund characteristics in addition to using a set of classic variables found to influence fund performance outcomes. Appendix Table 1 provides detailed descriptions of these variables. In line with the consensus in the literature, fund performance declines with fund size, expense ratios, and turnovers and increases with fund age and fund activeness.

The results in Panel A of Table 3 indicate a positive association between ICC and fund performance. As shown in Model (1), a one-standard-deviation increase in ICC is associated with an increase in Carhart four-factor alpha of 29 basis points annually (0.588 × 4.08 × 12). This positive relationship remains robust in Model (2) after controlling for family assets, team assets, and team size. Model (3) introduces the alternative connection measure, NumTeam, constructed at the manager-team level. When both measures are included in Model (4), the original comanager-based ICC remains statistically significant, while the team-based measure (NumTeam) becomes insignificant. In line with previous findings in the literature, fund performance declines with fund size, expense ratios, and turnovers and increases with fund age and fund activeness.

We include the number of busy managers as an additional control in Model (5) and find its coefficient to be insignificant. To address concerns of reverse causality between comanager connections and performance, Model (6) replaces contemporaneous ICC with its lagged value. The lagged ICC measure is both statistically significant (t-statistic = 3.43) and economically meaningful: a one-standard-deviation increase predicts a 28-basis-point annual increase in fund alphas (0.581 × 4.08 × 12).

Panel B of Table 3 examines the sensitivity of the results to different fixed effects specifications. We include fund fixed effects to capture the extent to which within-fund variation in ICC is associated with within-fund changes in performance. The results for Models (1) – (3) suggest that, after including time FE, style FE and family FE, the results reported in Panel A of

Table 3 remain unchanged. Finally, the results in the last two models demonstrate the robustness of the specification to alternative performance measures, including Fama-French three-factor and five-factor alphas[19], as compared to Carhart four-factor alphas used throughout the paper.

In summary, the results in Table 3 indicate that the positive relationship between ICC and fund performance is statistically and economically significant, and robust to a variety of alternative model specifications. These findings suggest that a greater number of skilled comanager connections for a fund contribute significantly to better performance.

5.2 A Quasi-Experiment and DiD Estimations

The baseline results may be subject to endogeneity concerns. For instance, it is possible that better managers are more likely to be assigned to multiple teams, thereby acquiring non-focal comanager connections for focal funds. In this case, the observed ICC-performance relationship could be confounded by unobserved focal manager ability. To better pin down the causal effect of ICC on performance, we exploit a quasi-experiment involving the departures of superstar managers, which generate plausibly exogenous variation in ICC.

First, we identify a series of superstar manager departure events. We define a "superstar" as a senior key manager within an influential fund family, meeting the following criteria: at least 12 years of firm tenure (the 90th percentile), a management share of family assets within the interquartile range, and affiliation with a family in the top tercile by size. As in Chen, Du, and Sun (2023), we expect such managers to have significant flow-performance sensitivity. To isolate departures not driven by internal family arrangements, we carefully classify these events. As reported in Table 4, these superstar departures are rare, with fewer than 12 such managers leaving their companies annually.

Next, we classify treated funds as those with superstar comanager connections within two months prior to the manager's departure from the company.[20] Departures are identified at the fund company level, meaning that once a manager leaves, their affiliation no longer appears in the

[19] Activeness is computed using the same factor model that is used to estimate risk-adjusted returns.
[20] In untabulated results, the pre-event monthly window could be shortened to one month or extended to 3 months.

Morningstar database.[21] Given the staggered nature of these departure events and potential issues with two-way fixed effect methods, we adopt the stacked regression approach proposed by Baker, Larcker, and Wang (2022).[22] Specifically, the control group is constructed using three-to-one propensity score matching and includes only funds that were never connected to a top-AUM manager throughout the sample period. The event window spans three months before and after the departure. We estimate the following difference-in-differences (DiD) model using a sample of treated and control funds:

$$\alpha_{i,t}^{4F} = \beta_1 * Treat_i * Post_t + Controls_{i,t} * \Gamma + FEs + \varepsilon_{i,t} \quad (5)$$

where i denotes fund i, t refers to month t. $\alpha_{i,t}^{4F}$ is the risk-adjusted return of the fund i in month t. The factor loadings are estimated using rolling regressions over the preceding 12 months and the Carhart four-factor model. $Treat_i$ is a dummy variable that equals 1 if fund i belongs to the treatment group and 0 otherwise, and $Post_t$ is a dummy variable that equals 1 if an event of superstar manager departure occurs in month t and 0 otherwise. The control variables and fixed effects (FEs) are identical to those specified in Equation (4).

The coefficient of interest, β_1, captures the differential change in performance between treated (ICC) and control (propensity-score-matched non-ICC) funds following superstar manager departures. Given our main hypothesis of a positive ICC-performance relationship, we predict a negative β_1 in the DiD model (Equation (5)). This prediction follows from the logic that the exogenous shock of a superstar's departure reduces a fund's ICC, thereby resulting in performance decline due to the loss of access to value-relevant information sources.

Table 5 presents the results from the DiD specifications with various fixed-effect structures. Panel A shows that following superstar departures from fund companies (and consequently from connected funds), focal funds experience a significant performance decline, with an economic magnitude of up to 312 (-0.0026 × 12) basis points per year, as measured by Carhart four-factor

[21] We manually check on the departure events within the mutual fund observer website, and more than half of the departures are retirement events, which arguably have nothing to do with focal fund performance. Therefore, these departures are more qualified for serving as exogenous shocks to ICC.
[22] Goodman-Bacon (2021) points out that it is problematic to compare late-treated units to early-treated units when treatment effects are time-varying.

alphas. The key identifying assumption in the DiD framework is the parallel trends assumption, which asserts that in the absence of superstar departures, treated and control funds would have evolved similarly.

Panel B of Table 5 estimates the DiD model with pre-event indicators to capture the dynamic relationship between ICC and fund performance. It shows that the performance effect of ICC becomes evident only after superstar departures, suggesting that there is no pre-existing trend that could bias the DiD estimator. Overall, the results presented in Table 5 provide support for the causal inference regarding the performance impact of the ICC measure.

6 Underlying Channels of the ICC-Performance Relation

6.1 Does the Team Approach Matter?

Having shown that ICC enhances fund performance, a natural follow-up question arises: which fund management structure—team-managed or solo-managed—benefits more from these co-manager connections? We propose two competing hypotheses. First, team-managed funds may be better positioned to capitalize on comanager connections due to fewer information capacity constraints (Peng 2005). Second, solo-managed funds might utilize these connections more efficiently, as they face lower internal coordination costs when assimilating external information (Chen et al. 2004). A key empirical question remains: does team or solo management better absorb the performance benefits of ICC?

To answer this question, we begin by partitioning our sample into team-managed and solo-managed funds, and then re-estimate Equation (4). Following the prior literature, we classify a fund as solo-managed if it has one unique manager and as team-managed if it has at least two managers. We present test results in Panel A of Table 6. The main finding is that ICC significantly affects the risk-adjusted returns of team-managed funds, while having no significant impact on the risk-adjusted returns of solo-managed funds. For team-managed funds, the estimated coefficient for ICC is positive and significant, at 0.55 (see model (4)). The economic magnitude is also substantial: a one-standard-deviation increase in ICC leads to a 27 ($0.5543 \times 4.08 \times 12$) basis point increase in annualized Carhart four-factor alphas for team-managed funds. These results suggest that the ICC-performance relationship documented in Table 3 is primarily driven by team-managed funds. Given the growing prevalence of team management and the trend of managers overseeing multiple teams simultaneously, these findings indicate that fund companies may strategically allocate managerial resources to enhance fund performance.

6.2 Does Family Size Matter?

In this section, we examine the ICC-performance relationship with respect to fund family size. We propose two competing hypotheses regarding the potential role of family size. On one hand, larger fund families naturally generate more work ties for a given fund, thereby intensifying the performance impact of interfund comanager connections within the family. In this case, we would expect family size to positively condition the previously documented ICC-performance relationship. On the other hand, smaller fund families are more likely to rely on comanager connections because they have a more limited supply of human capital within the organization. Consequently, funds within smaller families may experience stronger performance improvements in response to increases in skilled comanager connections. This second hypothesis predicts a negative conditioning effect of family size.

To test the role of family size as a cross-sectional driver of ICC's performance impact, we partition our sample into two subsamples: large family and small family funds, and then re-estimate our baseline model. A fund family is defined as a large (small) family if the fund family's TNA is above (below) the median. The results, presented in Panel B of Table 6, support the second hypothesis: the performance impact of ICC is weaker for funds affiliated with large fund families. In other words, funds within smaller families benefit more from ICC.

7 Do ICC Funds Make Profitable Trades Based on Overlapped Holdings?

Section 3.2 describes how the skill element is incorporated into the ICC measure to ensure that the connections represent valuable information sources. In this section, we conduct two tests to examine whether the resulting performance enhancement is value-driven. Specifically, we analyze the trading decisions and outcomes of ICC funds, focusing on their overlapping holdings with connected peers.

First, we examine what type of information is transmitted via workplace networks. If ICC connections facilitate the transmission of soft information, we would expect fund managers to earn abnormal returns on local investments (Coval and Moskowitz 1999). However, given the nature of workplace connections being of the same local area, one may also argue that the relative informational advantage could manifest in non-local investments. To test these opposing predictions, we construct quarterly portfolios segmented by fund connectedness status and trade direction. For connected (ICC) funds, the "Buy" ("Sell") portfolio contains non-local stocks with increased (decreased) overlapping holdings. For unconnected (non-ICC) funds, the "Buy" ("Sell") portfolios contain stocks with increased or decreased holdings, respectively. All portfolios are value-weighted. A long-short portfolio is formed by taking the difference between the "Buy" and "Sell" portfolios, with all portfolios rebalanced quarterly. Following Pool et al. (2015), we assess portfolio performance using the quarterly characteristics-based benchmark-adjusted excess return (DGTW-adjusted return) constructed as in Daniel et al. (1997) and Wermers (2005). Panel A of Table 7 show that the positive DGTW-adjusted returns for ICC funds stem primarily from their *buys* of overlapping non-local stocks, relative to non-ICC funds. This finding suggests that interfund comanager connections reduce the information acquisition costs of non-local investments by focal funds. For local investments where managers within the same workplace do not exhibit relative informational advantages to each other, non-ICC funds perform almost as well as ICC funds.

Second, building on the insight that investments in hard-to-research stocks are more likely to be value-enhancing (Pool et al. 2015), we apply the same portfolio methodology used for non-local stocks to test whether ICC connections convey a particular advantage in trading these stocks. Similar to the results for non-local stocks, the results in Table 7, Panel B, indicate that ICC funds earn significantly higher returns on hard-to-research stocks than non-ICC funds and show no information advantages on easy-to-research stocks.

8 Robustness Tests

8.1 Portfolio-Leader-Based Connection Measure

We argue that fund managers can benefit from collaborating with talented managers in external teams. To provide further evidence, we re-estimate the previous models using an alternative measure of talented fund managers: portfolio-leader fund managers as reported in SEC mutual fund prospectus filings.

In October 2004, the SEC mandated that mutual funds provide a description of each member's role on the management team (e.g., lead member) in their prospectus filings. Given that team leaders are arguably skilled fund managers, we collect information on each fund manager's role in the sample funds and compute the number of connected portfolio-leader managers. Following the approach outlined in Equation (1), we define this alternative ICC measure as the following:

$$ICC\_Leader_{i,t} = \sum_{k \in K^i} \max_{j \in J^i}\left(I_{j,k,t}^{Leader}\right) \tag{7}$$

where j denotes a focal manager of fund i, and J^i is the set of all focal managers for fund i. k denotes a connected manager who works with the focal manager j at other funds, and K^i is the set of all connected managers for fund i. A connection exists if manager k comanages a fund (outside of fund i) with focal manager j in month t. To compile a set of unique interfund comanager connections, we avoid double-counting a non-focal manager who is connected to multiple focal managers. The skill weight is controlled by the indicator variable $I_{j,k,t}^{Leader}$ which equals 1 if manager k is a portfolio-leader in month t according to SEC mutual fund prospectus filings, and 0 otherwise.

Using the portfolio-leader-based ICC measure, we re-estimate the models in Equations (3) and (4), along with the subsample tests from Section 6. The results, presented in Table 8, confirm our primary findings. Panel A shows that ICC_Leader remains positively and significantly associated with portfolio similarity to connected funds. A one-standard-deviation increase in ICC_Leader corresponds to a 6.81% rise in portfolio similarity, compared to the sample mean (0.0386 × 0.15 ÷ 0.085). Panel B demonstrates a positive effect of ICC on fund performance, with an economic magnitude of 20 basis points in annual four-factor alpha. Furthermore, the results in Panel C reveal a pattern similar to that in Table 6: the ICC-performance relationship is stronger for team-managed funds and for funds belonging to smaller families.

8.2 Alternative Connection Measure: Team Affiliation or Family Affiliation?

One might argue that workplace information sharing could occur through channels other than direct manager connections, such as common affiliation with the same fund family (Brown and Wu 2016). To test this alternative channel, we construct a competing measure of family information sharing, FIS, based on same-family and same-style affiliation. In comparison to ICC in equation (1), FIS measure is defined based on the number of top-AUM managers from the same style funds and within the same fund family.

We report results in Table 9. Panel A provides summary statistics and shows that the average family information sharing (FIS) measure is 2.39. This statistic is higher for the ICC funds (3.87) than for the non-ICC funds (1.79). Column (1) of Panel B reproduces our baseline results from Column (4), Panel B of Table 3. Column (2) shows that the coefficient on FIS is insignificant. When both ICC and FIS are included in column (3), ICC is the only significant variable. This result reconfirms that the comanager linkage captures a distinct and significant information channel. Moreover, to the extent that other unobserved forms of workplace information sharing exist, they would constitute the measurement error in our ICC variable. Such measurement error would bias our estimated coefficients downward. Thus, the economic magnitudes we report are likely a conservative lower bound of the true effect of information sharing via manager connections.

Overall, these findings support the notion that connections through shared managers facilitate information flows among manager teams, while more tenuous connections, not grounded in day-to-day collaboration, do not induce significant information sharing.

8.3 Shock Validation: Lower Connections or Busier Managers?

The empirical results in Section 5.2 show that superstar departures affect ICC and lead to a decline in fund performance. However, it is also possible that the departure of superstars increases the workload of remaining managers, thereby compromising the performance of the affected funds. In this scenario, the shock may not be valid for identifying the effect of connections on fund performance.

To validate the shock of superstar-manager departures, we perform tests similar to those in Equation (5) with a new set of dependent variables ($y_{i,t}$): ICC and Busyness. ICC is defined as in Equation (1) and Busyness is defined as in Equation (4).

$$y_{i,t} = \beta_1 * Treat_i * Post_t + Controls_{i,t} * \Gamma + FEs + \varepsilon_{i,t} \tag{8}$$

The indicator variable $Treat_i$ equals 1 if superstar managers leave fund i within a given event window (in months), either [-3, 3] or [-1, 1], and 0 otherwise. Fixed effects (FEs) include fund fixed effects and calendar year-month fixed effects. A valid exogenous shock must satisfy two conditions: (1) superstar departures should reduce the focal fund's ICC, and (2) they should not increase managerial busyness (Busyness).

We report results in Table 10 and confirm both conditions. First, the departure of a connected superstar leads to a significant decline in the focal fund's ICC, suggesting that these connections are not immediately replaced, which supports the exogeneity of the shock. Second, we find no corresponding change in the focal managers' busyness. This result indicates that the departure of superstar managers does not create additional workload for the remaining fund managers, strengthening our earlier argument that superstar-manager departures negatively affect the performance of the connected focal fund by reducing access to valuable information sources.

8.4 Placebo Tests on Index Fund Sample

The final set of robustness tests examines the marginal value of shared information. If ICC enhances fund performance through improved information sharing, its effect should diminish for funds where information collection has no marginal impact. In this context, index funds provide an ideal setting for a placebo test. Since index funds do not involve active information collection, ICC should have no relationship with their performance.

We re-estimate the models specified in Equation (4) using the index fund sample (without fund style fixed effects), with the results reported in Table 11. We find no significant relationship between ICC and fund performance in the index fund sample. Thus, the lack of significance in the ICC coefficients for index funds further supports the conclusion that interfund comanager connections improve fund performance via the channel of enhanced information sharing.

9 Conclusion

This paper explores comanager linkages in the mutual fund industry and examines the performance implications of such peer connections. Leveraging a novel setting in which mutual fund managers from one team also collaborate with managers from other teams, we provide the first evidence on the prevalence of (co)manager-connected funds. We propose a fund-level measure of interfund comanager connection (ICC) that captures both the quantity and quality of these connections. This measure quantifies a new channel of workplace information sharing and allows us to assess its impact on fund performance.

We hypothesize that interfund comanager connections play a crucial role in information transmission and affect fund performance. Consistent with this hypothesis, we find that ICC is positively associated with portfolio similarity between ICC funds and their connected funds. In the baseline test, we utilize a within-fund specification and demonstrate that higher ICC is linked to improved fund performance. Using a quasi-experiment based on the departures of superstar managers from non-focal funds, we establish that the positive ICC-performance relationship is likely causal and not driven by unobserved focal manager ability. Specifically, exogenous decreases in ICC following superstar departures lead to an annual abnormal performance decline of 312 basis points.

In examining the importance of workplace peer connections in mutual fund performance, this paper provides insights into the underlying economic mechanisms. First, we show that the performance effect of ICC primarily exists in team-managed funds, consistent with the hypothesis that group managers face fewer information capacity constraints than solo managers. Second, we show that interfund comanager connections improve fund performance by facilitating the sharing and transmission of valuable information between connected funds. The positive relationship between ICC measure and the positive returns of funds' purchases of overlapping value-enhancing stocks suggests that comanager connections transmit value-relevant information that is passed on to ICC funds. Third, we find that affiliation with a small fund family strengthens the ICC-performance relationship, which is plausibly explained by small families' greater reliance on this type of comanager connection. Overall, our findings indicate that workplace ties facilitate information sharing within the mutual fund industry, ultimately benefiting fund performance.

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Table 1. Summary Statistics

This table presents summary statistics for fund, team, and family characteristics. Panel A reports the summary statistics of fund characteristics. Panel B presents pairwise correlations between the main variable of interest, ICC, and other fund characteristics, and Panel C reports correlations among ICC, team characteristics, and other network measures. All variables are defined in the Appendix Table A1. The sample period spans from January 1992 to September 2018.

Panel A. Summary Statistics

Variable	Nobs.	Mean	Std. Dev.	Q1	Q2	Q3
ICC	312,310	1.49	4.08	0	0	1
α^{4F} (%)	302,983	-0.03	1.87	-1.00	-0.06	0.91
Log(TNA)	312,310	7.29	2.09	5.90	7.41	8.81
Age (years)	312,310	10.63	1.27	6.00	11.83	19.67
Expense (%)	300,029	1.17	0.39	0.93	1.14	1.39
Turnover (%)	294,925	75.51	60.93	33	60	99
Activeness (%)	302,989	8.52	8.23	2.93	5.90	11.13
$\mathrm{Ret}_{t-12,t-1}$ (%)	301,423	9.01	18.24	0.08	10.72	19.65
$\mathrm{Vol}_{t-12,t-1}$(%)	303,210	4.42	2.05	2.88	3.99	5.48
$\mathrm{Flow}_{t-12,t-1}$ (%)	296,336	17.35	82.58	-14.08	-3.78	15.53
Log(FamilyTNA)	282,758	9.92	2.48	8.40	10.39	11.73
Log(TeamTNA)	312,310	7.71	2.10	6.32	7.85	9.26
Teamsize	312,310	2.40	1.97	1	2	3
Busyness	312,310	0.69	0.96	0	0	1
NumTeam	312,310	0.90	1.50	0	0	1

Panel B. Correlation among ICC and Other Fund Characteristics

	ICC	α^{4F}	Log(TNA)	Age	Expense	Turnover	Activeness	$Ret_{t-12,t-1}$	$Vol_{t-12,t-1}$	$Flow_{t-12,t-1}$
α^{4F}	-0.0015									
Log(TNA)	0.1203	-0.0040								
Age	0.0542	-0.0182	0.5808							
Expense	-0.1568	-0.0002	-0.3264	-0.1929						
Turnover	-0.0545	0.0028	-0.1466	-0.1488	0.1866					
Activeness	-0.0920	0.0385	-0.1143	-0.1034	0.1696	0.0623				
$Ret_{t-12,t-1}$	0.0126	0.0215	0.0770	0.0172	-0.0554	-0.0486	0.1489			
$Vol_{t-12,t-1}$	-0.0547	0.0152	-0.0685	-0.1052	0.1798	0.1860	-0.2537	-0.3338		
$Flow_{t-12,t-1}$	-0.0275	0.0142	-0.1046	-0.3415	0.0415	0.0210	0.0708	0.1194	0.0105	
Log(FamilyTNA)	0.1542	0.0017	0.6078	0.2819	-0.3069	0.0095	-0.1405	0.0529	-0.0533	-0.0445

Panel C. Correlation among ICC, Team Characteristics, and Business Measures

	ICC	NumTeam	Log(TeamAUM)	Teamsize
NumTeam	0.7476			
Log(TeamAUM)	0.1200	0.0923		
Teamsize	0.4852	0.5415	0.0856	
Busyness	0.3565	0.5313	0.1928	0.3078

Table 2. ICC Measure and Portfolio Similarity

This table presents univariate and panel regression tests comparing the portfolio similarity of ICC (treated) funds and propensity-score-matched non-ICC (control) funds. Control funds are identified through one-to-one matching and have zero ICC in the matched fund-quarter. Panel A reports the difference in average portfolio similarity between the two groups. Panel B presents panel regression results. We estimate the following regression model:

$$\begin{aligned} Similarity\_Avg_{i,t} = {} & \beta_1 * ICC_{i,t} + \beta_2 * Log(TNA)_{i,t-1} + \beta_3 * Log(Age)_{i,t-1} \\ & + \beta_4 * Expense_{i,t-1} + \beta_5 * Turnover_{i,t-1} + \beta_6 * Activeness_{i,t} \\ & + \beta_7 * Ret_{t-12,t-1} + \beta_8 * Vol_{t-12,t-1} + \beta_9 * Flow_{t-12,t-1} \\ & + \beta_{10} * Log(FamilyTNA)_{i,t-1} + \beta_{11} * Log(TeamTNA)_{i,t-1} \\ & + \beta_{12} * Teamsize_{i,t} + FEs + \epsilon_{i,t} \end{aligned}$$

The dependent variable is the fund-quarter average cosine similarity of portfolio holdings. All independent variables are defined in Appendix Table A1. The propensity score is estimated using the same set of control variables as in the regression. Fixed effects (FEs) include fund fixed effects, calendar year-month (time) fixed effects, fund style (Morningstar nine categories) fixed effects, and fund family (CRSP management company code) fixed effects. Standard errors are clustered at the fund level. p-values are reported in parentheses in Panel A, and t-statistics are reported in parentheses in Panel B. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Average Portfolio Similarity for ICC and Non-ICC Funds

Similarity_Avg	Fund-month Obs.	Mean	Std. Dev.
ICC Funds	32,385	0.15	0.21
Matched Non-ICC Funds	32,385	0.02	0.05
Difference		0.13	
[p-value]		[0.00]	

Panel B. Panel Regression of Average Portfolio Similarity on the ICC measure

	(1) $\text{Similarity\_Avg}_{i,t}$	(2) $\text{Similarity\_Avg}_{i,t}$	(3) $\text{Similarity\_Avg}_{i,t}$
$\text{ICC}_{i,t}$	0.0025***	0.0018***	0.0019***
	[4.16]	[3.26]	[3.57]
$\text{Log(TNA)}_{i,t-1}$	0.0122***	0.0127***	0.0123***
	[3.32]	[3.62]	[3.45]
$\text{Log(Age)}_{i,t-1}$	-0.0234**	-0.0268***	-0.0277***
	[-2.11]	[-2.59]	[-2.69]
$\text{Expense}_{i,t-1}$	-0.0085	-0.0102	-0.0148
	[-0.58]	[-0.73]	[-1.06]
$\text{Turnover}_{i,t-1}$	-0.0041	-0.0036	-0.0041
	[-0.96]	[-0.89]	[-0.99]
$\text{Activeness}_{i,t}$	-0.0072	-0.0047	-0.0090
	[-0.31]	[-0.21]	[-0.41]
$\text{Ret}_{i,t-12,i,t-1}$	0.0202*	0.0198*	0.0186*
	[1.77]	[1.83]	[1.71]
$\text{Vol}_{i,t-12,i,t-1}$	-0.4059**	-0.4251**	-0.4282**
	[-2.17]	[-2.40]	[-2.39]
$\text{Flow}_{i,t-12,i,t-1}$	-0.0001	0.0002	0.0004
	[-0.08]	[0.13]	[0.29]
$\text{Log(FamilyTNA)}_{i,t-1}$	-0.0059**	-0.0053*	-0.0035
	[-2.09]	[-1.94]	[-1.09]
$\text{Log(TeamTNA)}_{i,t-1}$	-0.0122***	-0.0124***	-0.0131***
	[-4.29]	[-4.49]	[-4.57]
$\text{Teamsize}_{i,t}$	-0.0004	-0.0003	-0.0002
	[-0.20]	[-0.17]	[-0.09]
Fund FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Style FE	No	Yes	Yes
Family FE	No	No	Yes
Adj. R-squared	0.554	0.546	0.557
Fund-month Obs	81,773	80,580	80,580

Table 3. Regression of Fund Performance on the ICC and Team Connection Measures

This table reports panel regression results of fund performance on the ICC and Team Connection measures and control variables. We estimate the following panel regression model:

$$\begin{aligned}\alpha_{i,t} = {} & \beta_1\, ICC_{i,t} + \beta_2 \,\mathrm{Log(TNA)}_{i,t-1} + \beta_3\, Log(Age)_{i,t-1} \\ & + \beta_4\, Expense_{i,t-1} + \beta_5\, Turnover_{i,t-1} + \beta_6\, Activeness_{i,t} \\ & + \beta_7\, Ret_{t-12,t-1} + \beta_8\, Vol_{t-12,t-1} + \beta_9\, Flow_{t-12,t-1} \\ & + \beta_{10}\, Log(FamilyAum)_{i,t-1} + \beta_{11}\, Log(TeamAum)_{i,t-1} \\ & + \beta_{12}\, Teamsize_{i,t} + \beta_{13}\, NumTeam_{i,t} + \beta_{14}\, Busyness_{i,t} + FEs + \epsilon_{i,t}\end{aligned}$$

The dependent variable is the fund's monthly alpha (α) from various factor models: the Carhart four-factor model (Panel A and Panel B), the Fama-French three-factor model, and the Fama-French five-factor model (Panel B). Alphas are estimated using rolling 12-month regressions. All control variables are defined in Appendix Table A1 (Activeness is computed using the same factor model that is used to estimate risk-adjusted returns.). Fixed effects (FEs) are identical to those specified in Table 2. The ICC measure is constructed as described in Section 3.2. Standard errors are clustered at the fund level. t-statistics are in parentheses; ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Comanager Connection versus Team Connection

	(1) $\alpha^{4F}_{i,t}$	(2) $\alpha^{4F}_{i,t}$	(3) $\alpha^{4F}_{i,t}$	(4) $\alpha^{4F}_{i,t}$	(5) $\alpha^{4F}_{i,t}$	(6) $\alpha^{4F}_{i,t}$
$ICC_{i,t}$	0.5880***	0.5286***		0.4460**	0.6286***	
	[4.49]	[3.51]		[2.50]	[3.65]	
$ICC_{i,t-1}$						0.5814***
						[3.43]
$NumTeam_{i,t}$			1.1627***	0.4282		
			[2.62]	[0.82]		
$Log(TNA)_{i,t-1}$	-0.0011***	-0.0012***	-0.0012***	-0.0012***	-0.0012***	-0.0012***
	[-18.66]	[-12.89]	[-12.91]	[-12.93]	[-12.88]	[-12.88]
$Log(Age)_{i,t-1}$	0.0001	-0.0004**	-0.0003**	-0.0004**	-0.0004**	-0.0004**
	[0.51]	[-2.39]	[-2.28]	[-2.39]	[-2.36]	[-2.36]
$Expense_{i,t-1}$	-0.0011***	-0.0015***	-0.0015***	-0.0015***	-0.0015***	-0.0015***
	[-3.27]	[-4.11]	[-4.11]	[-4.12]	[-4.13]	[-4.12]
$Turnover_{i,t-1}$	0.8933	-0.7357	-0.6837	-0.7050	-0.7963	-0.7941
	[0.76]	[-0.61]	[-0.57]	[-0.58]	[-0.66]	[-0.66]
Activeness	0.0102***	0.0108***	0.0108***	0.0108***	0.0108***	0.0108***
	[11.75]	[11.46]	[11.46]	[11.46]	[11.46]	[11.46]
$Ret_{i,(t-12,t-1)}$	0.0022***	0.0022***	0.0022***	0.0022***	0.0022***	0.0022***
	[7.28]	[7.15]	[7.20]	[7.17]	[7.12]	[7.13]
$Vol_{i,(t-12,t-1)}$	0.0254***	0.0224***	0.0224***	0.0225***	0.0224***	0.0224***
	[9.02]	[7.92]	[7.91]	[7.92]	[7.90]	[7.90]
$Flow_{i,(t-12,t-1)}$	0.2350	0.0939	0.0945	0.0926	0.0965	0.0965
	[0.35]	[0.13]	[0.13]	[0.13]	[0.13]	[0.13]
$Log(FamilyTNA)_{i,t-1}$		0.1962	0.2165	0.1913	0.2167	0.2183
		[0.30]	[0.33]	[0.29]	[0.33]	[0.33]
$Log(TeamTNA)_{i,t-1}$		-0.5421	-0.4999	-0.5169	-0.5650	-0.5621
		[-0.73]	[-0.67]	[-0.70]	[-0.76]	[-0.76]
$Teamsize_{i,t}$		0.1158	0.1646	0.0579	0.1492	0.1716
		[0.31]	[0.44]	[0.15]	[0.40]	[0.46]
$Busyness_{i,t}$					-0.0001	-0.0001
					[-1.09]	[-0.94]
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.006	0.007	0.007	0.007	0.007	0.007
Fund-month Obs	281,658	261,577	261,577	261,577	261,577	261,577

Panel B. Alternative Specifications and Performance Measures

	(1) $\alpha_{i,t}^{4F}$	(2) $\alpha_{i,t}^{4F}$	(3) $\alpha_{i,t}^{4F}$	(4) $\alpha_{i,t}^{3F}$	(5) $\alpha_{i,t}^{5F}$
$ICC_{i,t}$	0.4790***	0.4965***	0.4703***	0.4110**	0.3742**
	[3.30]	[3.40]	[3.16]	[2.32]	[2.53]
Controls	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Style FE	No	Yes	Yes	Yes	Yes
Family FE	No	No	Yes	Yes	Yes
Adj. R-squared	0.093	0.093	0.093	0.090	0.080
Fund-month Obs	261,577	257,152	257,019	257,019	257,019

Table 4. Annual Frequency of Superstar Manager Departure Events

This table reports the number of superstar manager departure events by year. We classify managers as superstar managers if, in the event month, they meet the following three criteria: (1) work for a fund family with total net assets (TNA) above the 30th percentile ($21,185 million); (2) manage a share of family TNA between the 25th and 75th percentiles; and (3) have a tenure exceeding the 90th percentile (141 months).

Year	Count	Year	Count
1997	1	2008	7
1998	2	2009	6
1999	1	2010	8
2000	7	2011	7
2001	3	2012	9
2002	6	2013	7
2003	6	2014	11
2004	3	2015	10
2005	5	2016	11
2006	7	2017	10
2007	5	2018	7

Table 5. The ICC-Performance Relation around Superstar Departures

This table presents difference-in-differences (DiD) estimates from the following model:

$$\alpha_{i,t}^{4F} = \beta_1\, Treat_i * Post_t + Controls_{i,t} * \Gamma + FEs + \varepsilon_{i,t}$$

The sample consists of treated and matched control funds around exogenous superstar departure events. $Treat_i$ is an indicator equal to one for ICC funds that experience a departure of a superstar from a connected fund within the event window, and zero otherwise. $Post_t$ is an indicator for all periods following the departure (Panel A) or an indicator variable for a month either before or after the departure event month (Panel B). Superstars are identified as described in Table 4. Control funds are selected via three-to-one propensity score matching for each treated fund. The matching variables include Log(TNA), Log(Age), Expense, $\mathrm{Vol}_{t-12,t-1}$, $\mathrm{Flow}_{t-12,t-1}$, $\mathrm{Ret}_{t-12,t-1}$, Log(FamilyTNA), Log(TeamTNA), Teamsize, α^{4F}, and Activeness. All control variables are defined in Appendix Table A1. Fixed effects (FEs) are identical to those specified in Table 2. Standard errors are clustered at the fund level. t-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Diff-in-Diffs Test Results

	(1) $\alpha_{i,t}^{4F}$	(2) $\alpha_{i,t}^{4F}$	(3) $\alpha_{i,t}^{4F}$	(4) $\alpha_{i,t}^{4F}$	(5) $\alpha_{i,t}^{4F}$
$\mathrm{Treat}_i * \mathrm{Post}_t$	-0.0022**	-0.0026***	-0.0027**	-0.0025**	-0.0026**
	[-2.31]	[-2.60]	[-2.55]	[-2.55]	[-2.55]
Window (month)	[-3, 3]	[-3, 3]	[-3, 3]	[-3, 3]	[-3, 3]
Controls	No	Yes	Yes	No	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Style FE	No	No	Yes	Yes	Yes
Family FE	No	No	No	Yes	Yes
Adj. R-squared	0.084	0.086	0.088	0.041	0.046
Fund-month Obs	6,000	5,665	5,552	5,611	5,547

Panel B. Dynamic Model

	$\alpha_{i,t}^{4F}$
$Treated * Window[-2]$	-0.0013
	[-0.78]
$Treated * Window[-1]$	-0.0018
	[-1.00]
$Treated * Window[0]$	0.0000
	[0.02]
$Treated * Window[+1]$	-0.0035**
	[-1.98]
$Treated * Window[+2]$	-0.0050***
	[-2.75]
$Treated * Window[+3]$	-0.0016
	[-0.80]
Controls	Yes
Fund FE	Yes
Time FE	Yes
Style FE	Yes
Family FE	Yes
Adj. R-squared	0.048
Fund-month Obs	5,547

Table 6. How the ICC-Performance Relationship Varies with Management Structure and Family Size?

This table examines how the ICC-performance relationship varies with management structure and family size. Panel A presents results separately for team-managed and solo-managed funds, while Panel B reports results separately for funds belonging to small and large fund families. A family is classified as large if its family TNA is above the sample median. The dependent variable is the fund's monthly Carhart four-factor alpha, estimated using rolling 12-month windows. All control variables are defined in Appendix Table A1. Fixed effects (FEs) are identical to those specified in Table 2. Standard errors are clustered at the fund level. t-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A. ICC-Performance Relation for Team-Managed and Solo-Managed Funds

	Team-Managed				Solo-Managed			
	$\alpha_{i,t}^{4F}$	$\alpha_{i,t}^{4F}$	$\alpha_{i,t}^{4F}$	$\alpha_{i,t}^{4F}$	$\alpha_{i,t}^{4F}$	$\alpha_{i,t}^{4F}$	$\alpha_{i,t}^{4F}$	$\alpha_{i,t}^{4F}$
ICC_t	0.1281	0.1738*	0.5933***	0.5543***	0.1138	0.2434	0.2838	0.2838
	[1.42]	[1.95]	[3.89]	[3.52]	[0.30]	[0.64]	[0.54]	[0.54]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	No	No	Yes	Yes	No	No	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Style FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Family FE	No	No	No	Yes	No	No	No	Yes
Adj. R-squared	0.091	0.091	0.094	0.094	0.088	0.088	0.093	0.093
Fund-month Obs	167,780	164,799	164,783	155,978	113,885	112,262	101,576	101,576

Panel B. ICC-Performance Relation for Funds Belonging to Small and Large Families

	Small Family				Large Family			
	$\alpha_{i,t}^{4F}$	$\alpha_{i,t}^{4F}$	$\alpha_{i,t}^{4F}$	$\alpha_{i,t}^{4F}$	$\alpha_{i,t}^{4F}$	$\alpha_{i,t}^{4F}$	$\alpha_{i,t}^{4F}$	$\alpha_{i,t}^{4F}$
ICC_t	0.2842*	0.3279*	0.7678**	0.7678**	0.0371	0.0555	0.3604**	0.3604**
	[1.65]	[1.94]	[2.57]	[2.57]	[0.37]	[0.55]	[2.15]	[2.15]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	No	No	Yes	Yes	No	No	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Style FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Family FE	No	No	No	Yes	No	No	No	Yes
Adj. R-squared	0.083	0.083	0.086	0.086	0.100	0.101	0.109	0.109
Fund-month Obs	129,015	125,891	125,787	125,787	152,638	151,158	131,555	131,555

Table 7. Portfolio Evidence on Information Channels

This table presents portfolio-based tests of whether ICC funds benefit from specific information channels. Panel A tests whether ICC funds earn higher returns than non-ICC funds by trading non-local stocks, which have higher information acquisition costs. Non-local stocks are defined as companies headquartered in a different state from the fund's management company. For each quarter, we construct value-weighted portfolios based on fund connection status and trade direction. For ICC funds, the Buy (Sell) portfolio contains stocks with an increase (decrease) in overlapping holdings. For non-ICC funds, the Buy (Sell) portfolio contains stocks with an increase (decrease) in total holdings. A long-short portfolio (Diff.) is calculated as Buy minus Sell. Panel B examines trading in hard-to-research versus easy-to-research stocks, where hard-to-research stocks are defined as those with advertising expenses or sales below the annual median. The portfolio construction methodology follows that of Panel A. t-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A. DGTW-Adjusted Returns to Portfolio Trades in Non-Local Stocks

	Non-Local Stocks			Local Stocks		
	Buy	Sell	Diff.	Buy	Sell	Diff.
ICC fund portfolio	2.07***	-0.1	2.17***	1.72***	-0.29*	2.01***
	[12.18]	[-0.91]	[14.47]	[12.29]	[-1.81]	[11.82]
Non-ICC fund portfolio	1.75***	-0.06	1.81***	1.85***	0.17	1.69***
	[14.58]	[-0.75]	[20.11]	[10.28]	[0.89]	[9.94]
Diff. - Diff.	0.32	-0.04	0.36**	-0.13	-0.46*	0.32
	[1.52]	[-0.31]	[2.01]	[-0.57]	[-1.84]	[1.28]

Panel B. DGTW-Adjusted Returns to Portfolio Trades in Hard-to-Research Stocks

	Hard-to-Research Stocks			Easy-to-Research Stocks		
	Buy	Sell	Diff.	Buy	Sell	Diff.
ICC fund portfolio	0.96***	-0.09	1.05***	0.76**	0.00	0.76**
	[10.67]	[-1.29]	[13.12]	[2.45]	[0.00]	[5.07]
Non-ICC fund portfolio	0.78***	-0.07	0.84***	0.9***	0.00	0.9***
	[13.00]	[-1.40]	[21.01]	[12.86]	[0.00]	[15.00]
Diff. - Diff.	0.18	0.02	0.21**	-0.14	0.00	-0.14
	[1.64]	[0.25]	[2.10]	[2.10]	[-0.44]	[0.00]

Table 8. Analysis Using Portfolio-Leader-Based ICC

This table reports robustness tests using an alternative ICC measure, ICC_Leader, that identifies connections specifically to portfolio-leader managers, as designated in SEC fund prospectus filings. The measure is constructed per Equation (7). We hand collected portfolio leader information from SEC fund prospectus filings. Panel A presents multivariate evidence on portfolio similarity between ICC funds and their connected funds. The specification and control variables follow Table 2. Panel B reports panel regressions of fund performance on the portfolio-leader-based ICC and a set of fund-, team-, and family-level controls, following the specification in Table 3. Panel C reports the results of the subsample tests detailed in Table 6. All variables are defined in Appendix Table A1. Fixed effects (FEs) are identical to those specified in Table 2. Standard errors are clustered at the fund level. t-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Portfolio-Leader-Based ICC and Fund Average Portfolio Similarity Score

	$\text{Similarity\_Avg}_{i,t}$	$\text{Similarity\_Avg}_{i,t}$	$\text{Similarity\_Avg}_{i,t}$
$\text{ICC\_Leader}_{i,t}$	0.0387**	0.0395**	0.0386**
	[2.44]	[2.49]	[2.45]
Controls	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Style FE	No	Yes	Yes
Family FE	No	No	Yes
Adj. R-squared	0.529	0.529	0.540
Fund-month Obs	81,773	80,580	80,580

Panel B. Portfolio-Leader-Based ICC and Fund Performance

	$\alpha^{4F}_{i,t}$	$\alpha^{4F}_{i,t}$	$\alpha^{4F}_{i,t}$	$\alpha^{4F}_{i,t}$
$\text{ICC\_Leader}_{i,t}$	0.0011***	0.0007***	0.0007***	0.0007***
	[4.47]	[3.27]	[3.21]	[3.05]
Controls	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Time FE	No	Yes	Yes	Yes
Style FE	No	No	Yes	Yes
Family FE	No	No	No	Yes
Adj. R-squared	0.007	0.093	0.093	0.093
Fund-month Obs	261,577	261,577	257,152	257,019

Panel C. Subsample Tests of Portfolio-Leader-Based ICC-Performance Relationship

	Team	Solo	Small Family	Large Family
	$\alpha_{i,t}^{4F}$	$\alpha_{i,t}^{4F}$	$\alpha_{i,t}^{4F}$	$\alpha_{i,t}^{4F}$
$\text{ICC\_Leader}_{i,t}$	0.0007***	-0.0005	0.0020***	0.0003
	[2.88]	[-1.02]	[4.89]	[1.06]
Controls	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes
Family FE	Yes	Yes	Yes	Yes
Adj. R-squared	0.094	0.093	0.086	0.109
Fund-month Obs	155,978	101,576	125,787	131,555

Table 9. Analysis of Alternative Work Tie Measures

This table presents results comparing the performance effects of family information sharing (FIS) and our main measure, interfund comanager connections (ICC). FIS is the number of top-AUM managers working for same-style funds within the same fund family. Panel A reports summary statistics for the FIS measure. Panel B reports regression results based on the specification in Table 3. Control variables are the same as those in Table 3. All variables are defined in Appendix Table A1. Fixed effects (FEs) are identical to those specified in Table 2. Standard errors are clustered at the fund level. t-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Summary Statistics of FIS

FIS	Fund_month obs.	Mean	Std. Dev.	Q1	Q2	Q3
Full-sample	282,758	2.39	3.38	0	1	3
ICC funds	81,405	3.87	3.82	1	3	5
Non-ICC funds	201,353	1.79	2.99	0	1	2

Panel B. Performance Results with FIS

	$\alpha^{4F}_{i,t}$	$\alpha^{4F}_{i,t}$	$\alpha^{4F}_{i,t}$
$ICC_{i,t}$	0.4246**		0.4121**
	[2.49]		[2.39]
$FIS_{i,t}$		0.2240	0.1592
		[0.94]	[0.66]
Controls	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Style FE	Yes	Yes	Yes
Family FE	Yes	Yes	Yes
Adj. R-squared	0.093	0.093	0.093
Fund-month Obs	257,019	257,019	257,019

Table 10. Shock Validation: The DID Test for ICC and Busyness Measures

We estimate the following panel regression model with two dependent variables, ICC and Busyness:

$$y_{i,t} = \beta_1 * Treat_i * Post_t + Controls_{i,t} * \Gamma + FEs + \varepsilon_{i,t}$$

The indicator variable $Treat_i$ equals 1 if fund i experiences the departure of a superstar manager (as defined in Table 4) from a connected fund within the event window, and 0 otherwise. We consider event windows of [-1, +1] and [-3, +3] months. The indicator variable $Post_t$ equals 1 for all periods after the departure event. Control funds are selected via three-to-one propensity score matching from the pool of non-ICC funds (ICC=0). The matching variables are identical to the control variables used in the regression. Control variables are the same as those in Table 2. Fixed effects (FEs) include fund fixed effects and calendar year-month (time) fixed effects. Standard errors are clustered at the fund level. t-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1) $\mathrm{ICC}_{i,t}$	(2) $\mathrm{ICC}_{i,t}$	(3) $\mathrm{ICC}_{i,t}$	(4) $\mathrm{ICC}_{i,t}$	(5) $\mathrm{Busyness}_{i,t}$	(6) $\mathrm{Busyness}_{i,t}$
$\mathrm{Treat}_i * \mathrm{Post}_t$	-0.9684^{***}	-0.8095^{***}	-1.0877^{***}	-0.9997^{***}	0.0421	-0.0013
	[-4.19]	[-4.30]	[-4.91]	[-5.93]	[0.97]	[-0.03]
Window	[-3,3]	[-3,3]	[-1,1]	[-1,1]	[-3,3]	[-1,1]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	No	Yes	No	Yes	Yes	Yes
Time FE	No	Yes	No	Yes	Yes	Yes
Adj. R-squared	0.354	0.909	0.363	0.910	0.865	0.864
Fund-month Obs	5,816	5,794	2,542	2,508	5,816	2,508

Table 11. Placebo Tests in Index Funds

This table presents placebo test results using the sample of index funds and the specification from Equation (3). The dependent variables are funds' monthly alphas from the Fama-French three-factor, Carhart four-factor, and Fama-French five-factor models, estimated using rolling 12-month windows. Control variables are the same as those used in Table 3 and are defined in Appendix Table A1. Fixed effects include fund fixed effects, calendar year-month (time) fixed effects, and fund family (CRSP management company code) fixed effects. Standard errors are clustered at the fund level. t-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1) $\alpha_{i,t}^{3F}$	(2) $\alpha_{i,t}^{4F}$	(3) $\alpha_{i,t}^{5F}$
$ICC_{i,t}$	-0.0070	-1.2450	-0.0994
	[-0.00]	[-0.67]	[-0.05]
Controls	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Family FE	Yes	Yes	Yes
Adj. R-squared	0.102	0.109	0.099
Fund-month Obs	31,239	31,239	31,239

Figure 1. Illustration and Evolution of Manager-connected Funds

Figure 1A illustrates when a fund is labeled as a manager-connected fund based on the presence of interfund comanager connections. For example, focal fund A qualifies as a manager-connected fund having Dylan and Evan as connected managers via shared managers of Amy and Bob. Figure 1B plots out the year-to-year evolution of the percentage of domestic, active equity mutual funds as manager-connected funds.

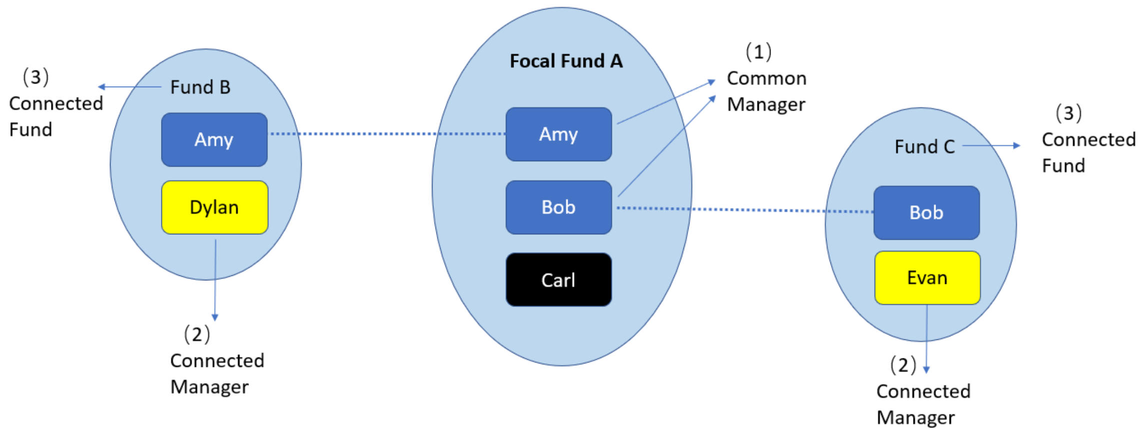


Figure 1A Illustration of Interfund Comanager Connection

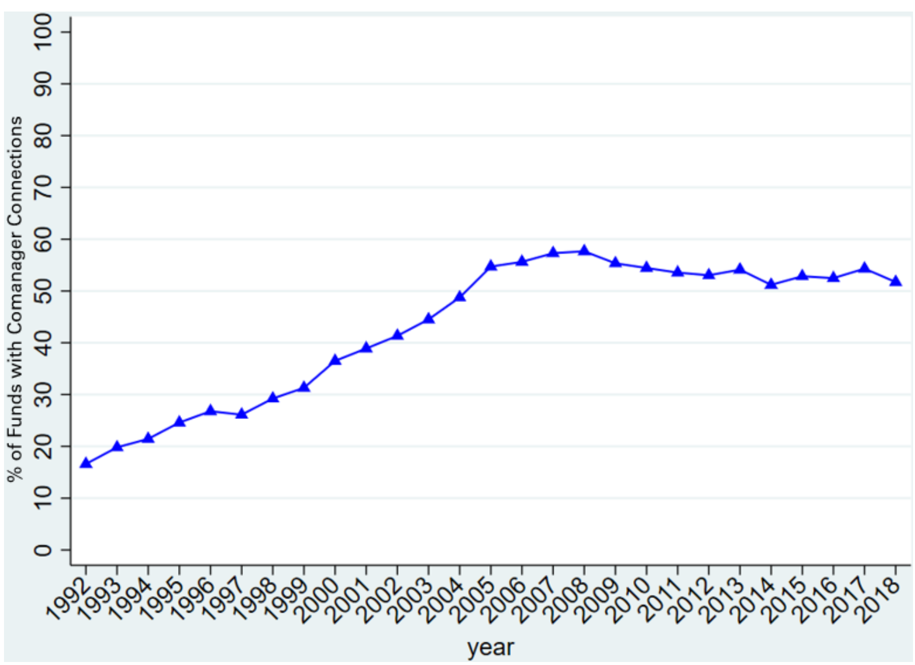


Figure 1B Prevalence of Manager-Connected Funds (MCFs)

Figure 2. Constructing the Interfund Comanager Connections (ICC) Measure

Figure 2 shows the process of computing the number of interfund comanager connections (ICC) for a given team-managed fund and a given solo-managed fund in figure 2A and figure 2B, respectively. Figure 2A uses the same example in figure 1A and shows the value of the ICC measure for team-managed focal fund A after considering the skilled (top-AUM/portfolio leader) manager status. Figure 2B shows the value of the ICC measure for solo-managed focal fund D.

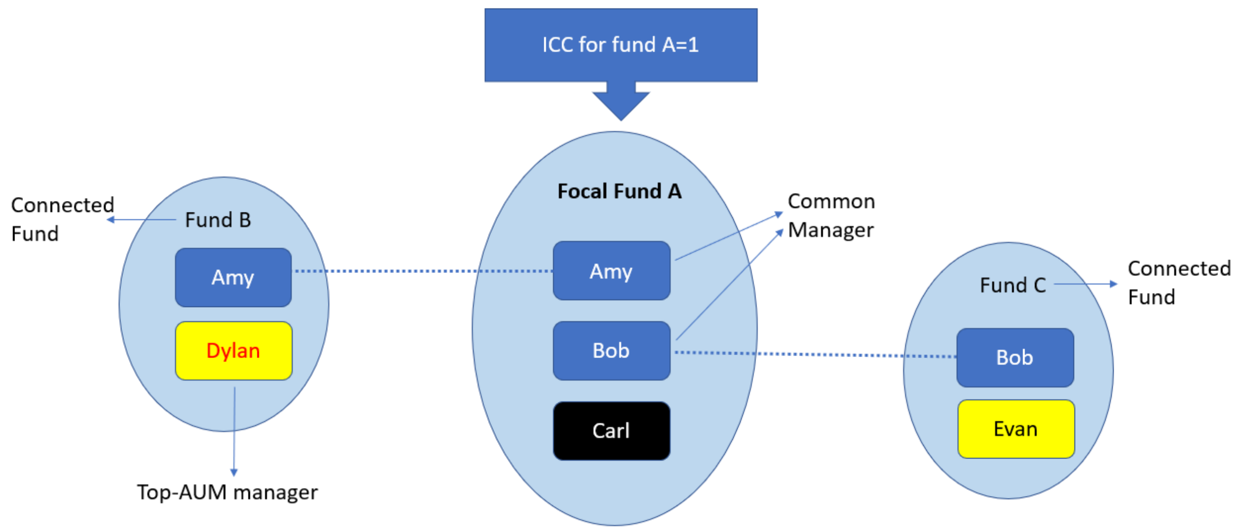


Figure 2A Illustration of ICC Computation for A Team-Managed MCF

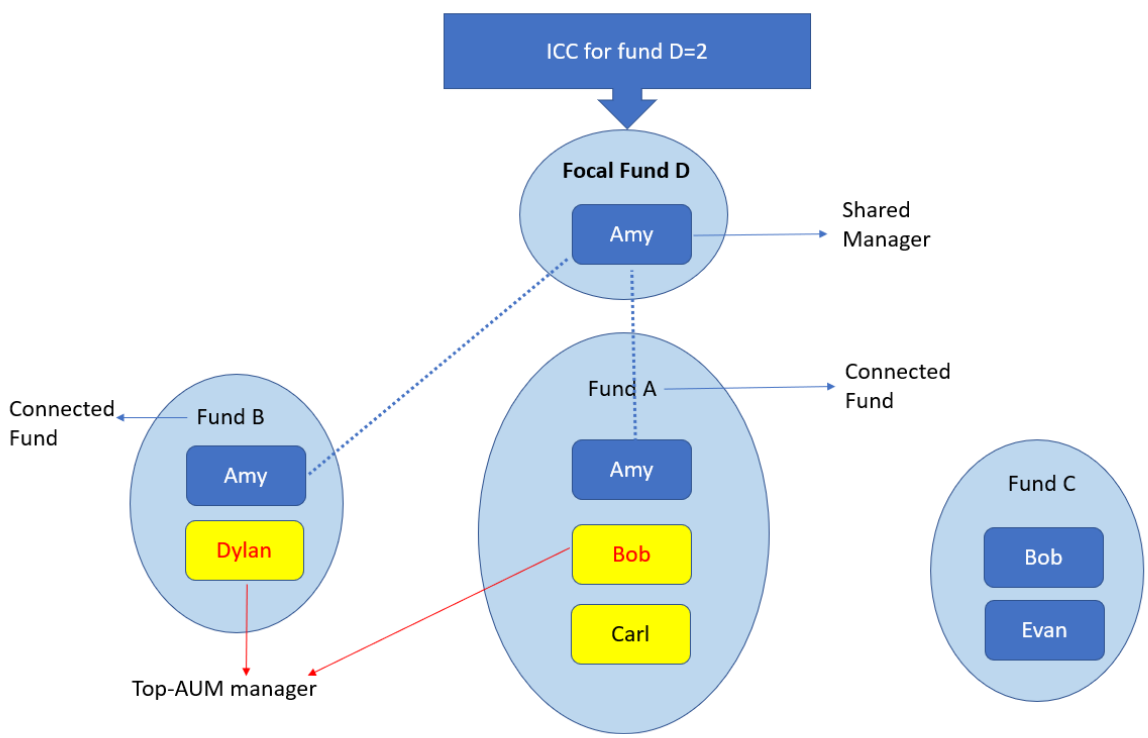


Figure 2B Illustration of ICC Computation for A Solo-Managed MCF

Appendix

Table A1. Variable Definitions

This table contains a description of all variables used in our empirical analyses. Data sources are as follows:
1. CRSP: CRSP Survivor-Bias-Free Mutual Fund Database
2. MS: Morningstar historical holdings
3. Refinitiv
4. SEC: SEC EDGAR (Electronic Data Gathering, Analysis, and Retrieval system)

Variable name	Description	Data source
ICC	Number of Top-AUM fund managers connected to a fund via common managers.	MS, CRSP
ICC_Leader	Number of team leader fund managers connected to a fund via common managers.	MS, SEC
α^{4F} (%)	Fama-French-Carhart four-factor alpha. Factor loadings are estimated based on past 12-month rolling windows.	CRSP
Log(TNA)	Log of mutual fund TNA (total net assets)	CRSP
Age (Years)	Fund age (in years).	CRSP
Expense (%)	Fund total expense.	CRSP
Turnover (%) (Annual)	Fund annual turnover.	CRSP
Activeness (%)	1 – R-squared of the Fama-French-Carhart four-factor model. Estimation is based on past 12-month rolling windows.	CRSP
$\mathrm{Ret}_{t-12,t-1}$ (%)	Past 12-month fund accumulative return.	CRSP
$\mathrm{Vol}_{t-12,t-1}$ (%)	Past 12-month fund return volatility.	CRSP
$\mathrm{Flow}_{t-12,t-1}$ (%)	Past 12-month fund flow.	CRSP
Log(FamilyTNA)	Log of fund family's TNA.	CRSP
Log(TeamTNA)	Log of a manager team's TNA.	CRSP
Teamsize	Number of managers of a manager team.	MS
Busyness	The number of busy managers in a manager team. Busy manager is a manager who manages top-quintile number of funds.	MS
NumTeam	The total number of teams of the managers managing a fund.	MS
Simlarity_Avg	The cosine similarity between two funds in terms of active holdings. Active holding is the difference between the fund holding and the weight of the stock in the whole market.	Refinitiv

Table A2. Distributions of ICC Variants

This table presents more distributions of variants of the ICC (Interfund Comanager Connection) measure, including within-fund distribution of ICC, ICC based on portfolio leader status, positive ICC, ICC above different thresholds, and ICC among team-managed/solo-managed funds.

	Fund-month Obs	Mean	Std Dev	Q1	Q2	Q3
			All Funds			
ICC	312,310	1.49	4.08	0	0	1
ICC (within fund)	2,214	1.44	3.33	0	0.08	1.15
ICC_Leader	312,310	0.02	0.15	0	0	0
ICC ($>$ 0)	84,572	5.5	6.29	1	3	7
ICC ($\in$ [1,4])	55,122	1.87	1.03	1	2	3
ICC ($\in$ [5,8])	11,458	6.14	1.09	5	6	7
ICC ($\geq$ 9)	17,992	16.21	5.17	12	15	21
			Team-managed Funds			
ICC	183,782	2.23	5	0	0	2
			Solo-managed Funds			
ICC	128,528	0.43	1.69	0	0	0

Figure A1. Evolution of Manager-connected Funds, ICC funds, and Other Funds

Figure A1 plots out and compares different time trends for the percentage of domestic, active equity mutual funds as team-managed funds, manager-connected funds (MCFs), funds with multi-team managers, and funds with skilled interfund comanager connections (ICC funds). Manager-connected funds and ICC funds are illustrated in figure 1 and 2, respectively. Funds with multi-team managers are defined as funds with at least one fund manager concurrently working on different portfolio management teams.

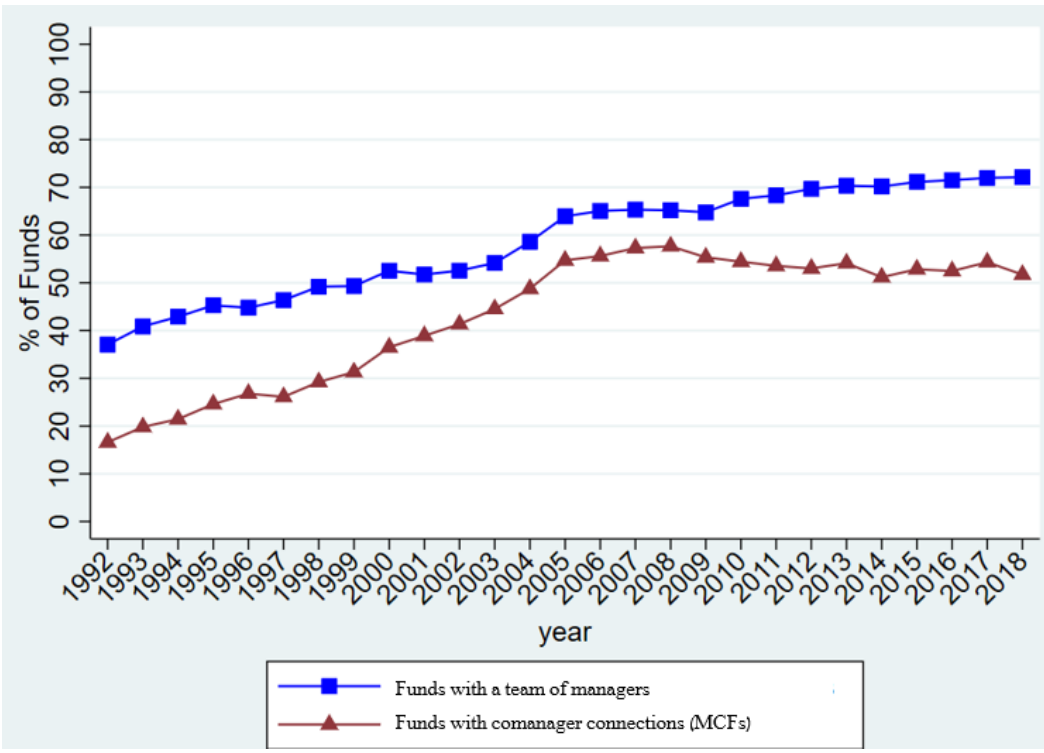


Figure A1.1 Team-Managed Funds versus Manager-Connected Funds (MCFs)

Figure A1—Continued

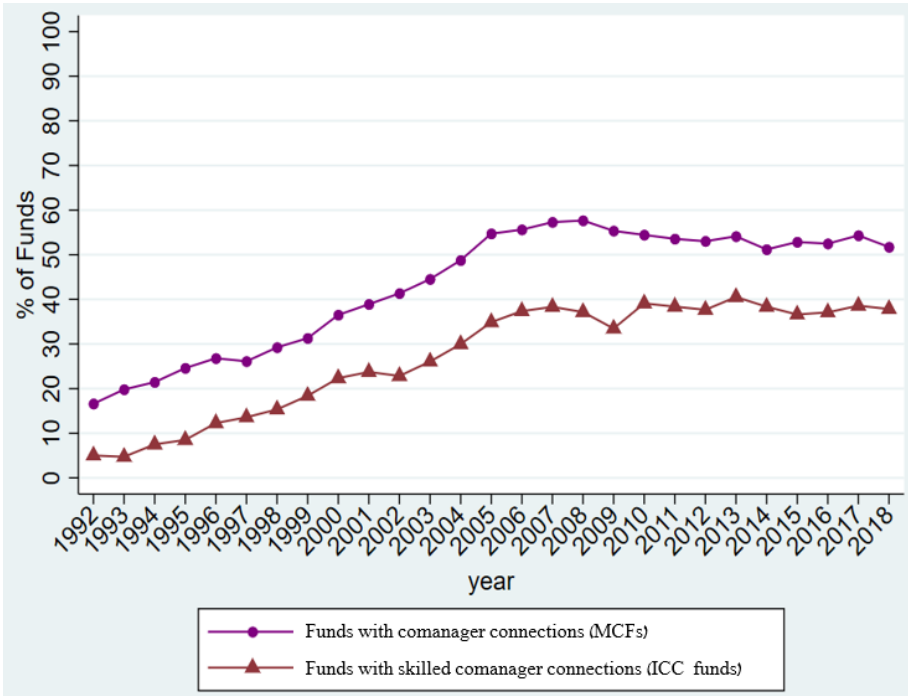


Figure A1.2 MCFs versus ICC Funds

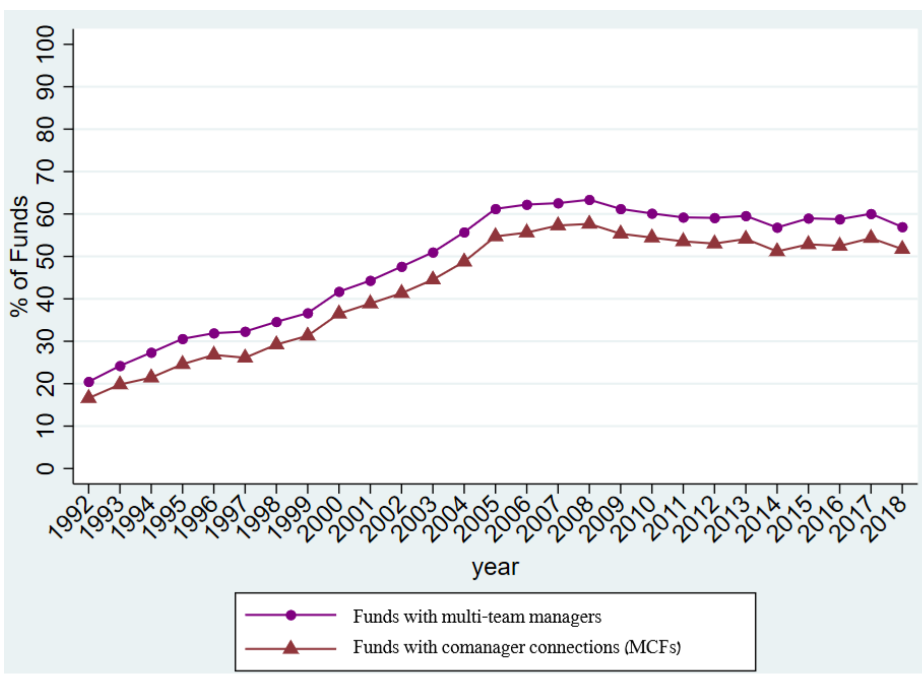
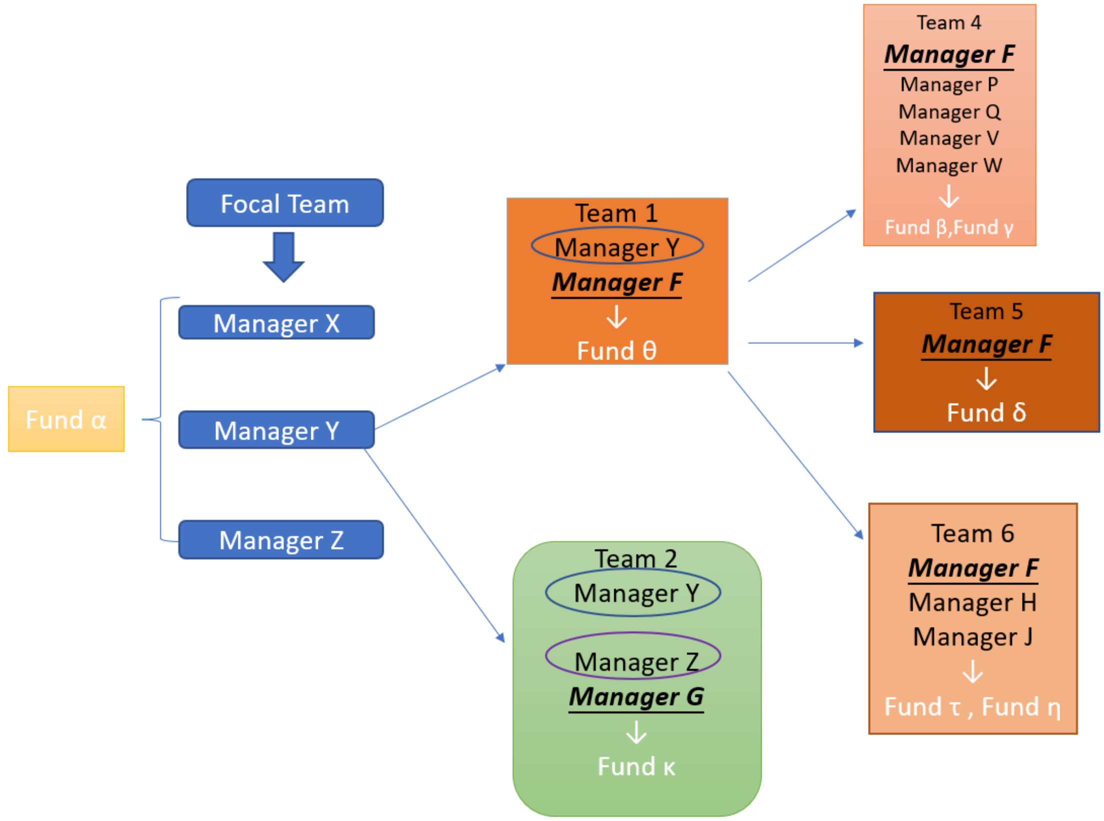


Figure A1.3 MCFs versus Multi-Team-Manager Funds

Figure A2. Illustration of Computing Manager AUM (MgrAUM) for the ICC Measure



Information sharing sources for fund α in month t: {F, G}

$MgrAUM_{k,t} = \sum_{i^k \in I^k} (\frac{FundAsset_{i^k,t}}{\#FundMgr_{i^k,t}})$;

Manager F's average team contribution across all teams with hypothetical fund sizes (measured in millions):

TNA for Team 1=fund θ=1m → team contribution= 1m/2=0.5m

TNA for Team 4= fund β + fund γ=5m → team contribution= 5m/5=1m

TNA for Team 5= fund δ=3m → team contribution= 3m/1=3m

TNA for Team 6= fund τ + fund η=3m → team contribution= 3m/2=1.5m

Manager F's skill measure is his MgrAUM variable, which sums all the average team contribution values: 0.5+1+3+1.5=6m

Manager Y's average team contribution across all teams with hypothetical fund sizes:

TNA for Focal Team=fund α=0.9m → team contribution= 0.9m/3=0.3m

TNA for Team 1=fund θ=1m → team contribution= 1m/2=0.5m

TNA for Team 2= fund κ=6m → team contribution= 6m/3=2m

Manager F's skill measure is his MgrAUM variable, which sums all the average team contribution values: 0.3+0.5+2=2.8m