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

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ABSTRACT

Do investors rely on work ties, and what organizational structures facilitate workplace information flows? We provide new insights by tracking co-managers outside the focal team and constructing a novel fund-level skill-weighted inter-fund co-manager connections (ICC) measure. We find that funds with a higher ICC exhibit portfolio holdings that are more similar to those of connected funds. A higher ICC is also associated with better fund performance. We use plausibly exogenous superstar manager departures to pin down causality. Value-relevant information is transmitted via such connections: ICC funds profit more from trading on overlapped hard-to-research stocks and non-local stocks than non-ICC funds. Finally, we present the first evidence of the evolution of workplace networks in the mutual fund industry.

Delegated investment managers earn economic rent based on their informational advantages. Previous work shows that connections with other informed economic agents play an important role in explaining mutual fund portfolio decisions and performance. For instance, extant evidence links fund performance to educational connections with corporate board members (Cohen, Frazzini, and Malloy, 2008) and social connections with financial analysts and firm auditors (Gu et al., 2019; Chen et al., 2022). Previous work also attributes fund portfolio overlaps to social connections with other portfolio managers due to geographical proximity (Hong, Kubik, and Stein, 2005; Pool, Stoffman, and Yonker, 2015). Relatively little is known about whether and how professional managers benefit from their social connections at the workplace in terms of their portfolio performance.

Fund managers' work ties are naturally developed within their fund companies. On the one hand, being a member of a fund family helps mutual funds deliver better performance via economies of scale and more information sharing (e.g., Chen, et al., 2004; Brown and Wu, 2016). On the other hand, managers within the same family have incentives to compete as well as cooperate (e.g., Evans, Prado, and Zambrana, 2020). It is unclear how fund managers engage in most effective interactions within a fund family. In this study, we build on these two disparate literatures—connections-based information sharing and fund family affiliation—to investigate the impact of workplace information sharing through the lens of intra-family social connections. To this end, we draw on the management structure of mutual funds to construct a connection measure and explore its portfolio and performance implications.

Mutual fund management has transitioned to a team sport in the last two decades.[1] It is well recognized that teams often manage multiple funds, it is less widely known that some managers serve on multiple teams simultaneously.[2] For instance, within a given fund family, managers A

[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.

and B manage fund 1; A and C manage fund 2 and 3, C (alone) manages fund 4, and D manages funds 5 and 6. The cross-team managerial linkages create a critical condition for workplace information sharing to happen across different fund management units including funds managed by both 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 hinges on both the (1) strength and (2) scale of connections. The scale of connections is intuitive, as more connections imply a potentially larger information set. The strength of connections depends on both incentives to share information and the informational advantage of information sources per se.

In the above hypothetical fund managerial structure, A is a comanager connection to fund 4, just as B is to fund 2 and 3 and C is to fund 1. Funds 5 and 6 do not have any connections, because manager D is not connected to fund 1, 2, 3, and 4. In this case, there is a greater incentive for A to share information with B (C) because AB (AC) comanages fund 1 (2 and 3). While it is possible that A (or B, C) may share the information with D, we hypothesize they are less likely to do so for two reasons. First, they do not comanage funds 5 and 6 and therefore are not rewarded for the performance of these two funds (5 & 6). Second, comanagers (e.g., AB or AC) are likely to spend much more of their time together and hence build a stronger personal relationship than with D. Figure 1A outlines three manager-connected funds (MCFs), which are defined as funds with at least one comanager connection. For example, fund A has both Dylan and Evan as its comanagers connections. We show in Figure 1B that MCFs have become increasingly prevalent in the past three decades and over half of active equity mutual funds have at least one manager serving on other teams starting 2005.

The second part of connection strength is the extent to which a comanager has information. Thus, We introduce the manager skill element into the interfund comanager connection (ICC) measure. Specifically, we follow Berk, Van Binsbergen, and Liu (2017) and apply the skill weight of 1 for each comanager connection if the aggregated assets under management for each manager is within the top tercile, and 0 otherwise.[3] Using the example in Figure 1A, if Dylan is a top-AUM

[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 my results.

manager while Evan is not, the ICC measure for focal fund A would be 1 after applying the skill weight, as is depicted in figure 2A (Section 3.2 provides additional details). In sum, we develop a new fund-level measure of interfund comanager connections (ICC) by counting the number of top-AUM managers connected via common managers.[4]

We hypothesize that interfund comanager connections share valuable information that is transmitted to focal funds and result in superior fund performance. This hypothesis is tested in two steps. The first step is to determine whether the ICC measure indeed captures an information sharing channel that is operating in the workplace. To validate this measure, we examine whether ICC funds exhibit higher portfolio similarity to their connected funds compared to non-ICC funds.[5] By comparing the average portfolio similarity for funds with and without ICC, we show that a higher ICC leads to greater holdings overlap, with an average ICC fund exhibiting three times higher portfolio similarity to connected funds than a matched non-ICC control fund. Using this propensity-score-matched sample, we further run fund-level regressions of average portfolio similarity on ICC along with the same set of control variables in obtaining the propensity scores and a variety of fixed effect structures. The results show that a one-standard-deviation increase in ICC induces 12% higher average portfolio similarity in ICC funds relative to control funds. Both the univariate comparison and the multivariate regression test on portfolio similarity speak to this ICC measure's eligibility in capturing a plausibly operating channel of workplace information sharing.

The second test examines if the information is valuable by estimating panel regressions of fund abnormal performance measures on ICC controlling for both variables that are known to affect fund performance and potential confounders. In the baseline regression, we start by exploiting the within-fund variation by using the fund fixed effect specification, which eliminates the effect of time-invariant fund heterogeneities from the interfund connection story. This specification is

[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.

robust to the addition of time fixed effect, style fixed effect, and family fixed effect and my results maintain both statistical significance and economic magnitude. Consistent with my hypothesis that connections with skilled other-fund comanagers help focal funds garner better abnormal performance, the baseline result shows that a one-standard-deviation increase in ICC leads to a performance improvement by up to 30 bps per year in terms of Fama-French-Carhart four factor alphas.

A central step of analyzing the ICC-performance relation is to evaluate whether the performance gains can be attributed to connections with other-fund comanagers or own-fund managerial ability. The use of within-fund specification in the baseline test mitigates the omitted variable bias by explicitly controlling for all permanent fund characteristics including unobserved manager skill, but this specification is also subject to a finite-sample bias. [6] In a similar spirit to Pástor, Stambaugh, and Taylor (2015), since better-performing managers are more likely to be more connected, other-fund comanager connections may be positively related to own-fund performance through focal manager skill.

To address such endogeneity concerns, we exploit changes in ICC that arise from departures of superstar managers that serves as comanager connections for other funds. In this quasi-experiment, the plausibly exogenous variation in ICC stems from the fact that the departure decisions of superstar managers from the connected funds are deemed as independent from focal fund performance. Such departures cause decreases in manager connections for focal funds but do not impact focal manager abilities. More importantly, to ensure that their departure decisions are less likely to be performance-driven, we classify superstars as those long-tenured managers who are in charge of a significant share of total family assets in large fund companies.[7] Chen, Du, and Sun (2023) uses Bill Gross's departure from PIMCO as a shock to fund size, because Bill Gross

[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.

[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.

is a seasoned and influential bond fund manager to his company. In a similar spirit, the basic intuition for focusing on these senior key managers who are affiliated with influential fund families is that they generally have an interdependent relation with their respective investment companies, where they are typically perceived by fund investors as a unique fund brand and will incur outflows if investors know they are leaving the company. In this case, their departure decisions are least likely to be an ex-ante arrangement of fund families, thus ruling out the potential confounding links with ICC funds' managerial ability.

To exploit the exogenous variation in ICC due to superstar managers' departures, we identify treated funds as ICC funds with superstar manager connections, and control funds as non-ICC funds matched to ICC funds via propensity scores throughout the sample period (never-treated units). The key identifying assumption is that absent the departures of superstar comanagers in connected funds, ICC funds and their matched control funds would have had similar performance evolution. Using the difference-in-difference specification with the same vector of covariates and the same set of fixed effects as in the baseline regression, we find that the departure-induced decreases in the ICC measure result in abnormal performance declines, confirming the positive ICC-performance relation in the baseline finding. Moreover, the performance effects in this DiD setting are both statistically significant and economically sizable. Specifically, a one-standard-deviation decrease in ICC leads to an annual decline of 240 bps in terms of Carhart-four-factor alphas. Further examination of the dynamic relation between ICC and fund performance affirms the non-existence of any pre-trend, further lending support to the validity of causal inference. One may also argue that superstar departures may worsen focal fund performance by making focal managers busier in non-focal funds. Section 7 further discusses a diagnostic test to rule out this channel and validates this exogenous shock. Taken together, these results give us higher confidence to draw causal inferences about the effect of interfund comanager connections on fund performance in this study.

After documenting the significant 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 by interfund comanager connections, a natural task is to see how well the focal management unit (team versus solo) processes such information. To answer this follow-up question, we develop a set of competing sub-hypotheses that are motivated by the behavioral tradeoff that is inherent in the management design. The first hypothesis is that team-managed funds benefit more from the performance effect of ICC due to lower information capacity constraint relative to solo-managed funds (Peng (2005)). The second hypothesis is that Solo-managed funds benefit more from the performance effect of ICC due to lower coordination costs relative to team-managed funds (Chen et al. (2004)). The results from the subsample analyses show that the positive performance impact of ICC is concentrated in team managed funds, consistent with the first hypothesis regarding lower information capacity constraint associated with team management. We also reveal stronger performance effects of ICC for funds from small fund families, possibly due to small families' greater reliance on interfund comanager connections.

To show the robustness of our findings, we identify portfolio-leader managers as an alternative source of information to the focal funds and build an alternative ICC measurement based on the manager's portfolio-leader identity. We collect the portfolio-leader information of sample funds, generate the portfolio-leader-based ICC, and re-estimate previous models. The findings still hold: funds with higher ICC have higher holding similarity with connected portfolios, have better risk-adjusted performance, and the performance effect of ICC is driven by team-managed funds and funds from smaller families.

We further investigate whether the documented ICC-performance relation is value driven. The results are not consistently strong but still point to the fact that connections improve the trade performance based on some overlapped stocks. Both hard-to-research stocks and local stocks are shown to be performance-enhancing for mutual fund portfolios (Pool et al., 2015; Coval and Moskowitz, 1999). By constructing portfolios of such overlapped stocks, we find that ICC funds mainly profit from selling overlapped local stocks compared to non-ICC funds.

Furthermore, to tease out the comanager connection story from non-information-based herding behavior, we utilize an approach that is based on focal funds' reveal preferences and attributes the focal funds' actual choices to information flows facilitated by comanager connections. We find

that when focal funds initiate new positions following connected funds, the SEC search volume for such stocks (but not for similar ones in the connected fund portfolio) is also higher, providing suggestive evidence against simply copycatting connected funds.

The remainder of the paper proceeds as follows. In Section 2, we discuss the related literature and my paper's contribution. In Section 3, we describe the data, the construction of the ICC measure, and summary statistics. In Section 4, we present evidence on the relation between ICC and portfolio similarity. In Section 5, we discuss empirical strategies and test results on the ICC-performance relation. Section 6 contains tests of underlying economic mechanisms through the lens of focal funds' management structure and fund family size. Section 7 provides evidence on whether ICC-related trades are informed, i.e., the trade performance based on overlapped stocks of ICC funds. Section 8 provides a battery of robustness test results on alternative measures of workplace information sharing, a shock validation test, and a placebo test. Section 9 concludes.

2 Related Literature

My paper contributes to several strands of literature. First, this paper adds to the literature regarding the implications of connections for portfolio managers' investment decisions and performance. Cohen, Frazzini, and Malloy (2008) show that educational connections with board members of portfolio firms play a part in mutual fund performance. Gu et al. (2019) find that mutual fund managers exploit their social connections with analysts to generate superior returns. Chen et al. (2022) document that mutual fund managers' social ties with firm auditors also matter for their portfolio decisions. Hong et al. (2005) and Pool et al. (2015) show that word-of-mouth communication has portfolio implications for fund managers when they reside in the same city and same neighborhood, respectively. Rossi et al. (2018) examine peer-type network connections in the UK pension fund industry and find that more centrally connected pension fund managers deliver superior risk-adjusted performance.[8] We advance this connection literature on asset

[8] Both invoking the co-management setting notwithstanding, my 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

management by introducing an intuitive and important work tie, where a focal manager brings in connections from her or his comanagers when concurrently working on non-focal funds. For a given fund that has comanager connections enabled by focal shared managers, we construct a count measure that aggregates all the other-fund skilled comanagers to the focal fund and then evaluate its performance impact. We show that more comanager connections lead ICC funds to yield better performance.

Second, this paper is also related to studies on the effectiveness and implications of workplace information sharing. Sandvik et al. (2020) show that management practices that facilitate information diffusion among coworkers improve sales productivity. Jarosch et al. (2021) documents information spillover effects of skilled coworkers on wage growth. We know little about the implications of workplace information sharing for professional money managers. By concentrating on the mutual fund industry, this paper first echoes this literature on the importance of management practice in creating information spillovers in the workplace: mutual fund managers share valuable information or profitable ideas that have positive externalities in manager-sharing funds.[9] Besides shedding light on a novel channel of workplace information sharing via comanager linkages, a major contribution of this study along this line of inquiries is showing that workplace information sharing has positive performance implications. Since fund performance is linked to both fund managers' productivity and compensation, this is an unstudied but important outcome variable to add to the literature.

More broadly, this study also advances the studies on fund managerial structure. Given the growing trend of team management, there is mixed evidence regarding the performance impact of team management structure. Although some argue in favor of the team approach (See, e.g. Patel and Sarkissian, 2017; Adams, Nishikawa and Rao (2018); Harvey et al. 2021), others cast doubt

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.

[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 my 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.

on the efficacy of team management because team-managed funds cannot outperform their solo-managed counterparts (Prather and Middleton (2002); Bliss, Potter and Schwarz (2008)), or even underperform (Chen et al. (2004); Bar, Kempf and Ruenzi (2011)). Instead of directly weighing in the discussion of performance implications of team management, this paper starts by uncovering a growing trend of managers serving multiple teams at the same time, which is beyond the well-known organizational dichotomy of team versus solo.[10] Being the first to document the prevalence of cross-team manager-overlap designs, this study aims to shed 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 in operating as a channel for workplace information sharing and as a driving factor in fund performance. Clearly, the manager overlap design is enabled by team-based portfolio management. To the extent that the interfund comanager connections are intensified by team management, my results also indicate a potential performance-related driver of the increasing popularity of the group management design. Further subsample analyses conclude that team-managed funds are the main beneficiaries of the informational advantages brought about by interfund comanager connections, consistent with teams being subject to lower information capacity constraint. 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

We compile my data from several sources. We use Morningstar Direct mutual fund database for information on fund managers. This database provides rich and precise managerial information that allows me to identify the manager (s) responsible for the day-to-day management of each 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.

in a given month.[11] We exclude funds with anonymous managers, such as those tagged as "management team" or "multiple managers". This database allows me to delineate team boundaries (and linkages) so that we can accurately define multi-team managers (common managers), focal managers, and non-focal managers. In doing so, we am able to label each fund as an MCF (manager-connected fund) or a non-MCF based on the composition of managers in these different categories. An MCF is overseen by at least one common manager and has at least one non-focal manager connected via the common manager through the comanager relationship in a non-focal team. A connected fund is defined in tandem with an MCF and consists of at least one common manager and at least one comanager connection. In section 3.2, we will describe how we utilize this setup to construct a novel fund-level connection measure.

We rely on the CRSP survivorship-bias-free mutual fund database to obtain monthly fund returns and fund characteristics including fund size, fund age, fund returns, expense ratios and portfolio turnovers.[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 the direct sum of TNA across all share classes and fund age is determined by the oldest share class. Portfolio holding data are taken from the Thomson Financial CDA/Spectrum Mutual Fund database (S12 holdings). Following Wermers (2000), we then employ MFLINKS to match fund-level data from CRSP with their portfolio holding information from Thomson Reuters. We use fund tickers and fund names to merge the Morningstar manager data with the CRSP fund data. We follow the literature and apply standard sample filters to focus my sample on open-ended U.S. domestic active equity funds only.[13] We also remove incubated fund suspects following Evans (2010). All the data screening

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

[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) and others, we exclude fixed income, index, international, money market, and sector funds from my 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

processes end up with a final sample comprising 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 embodies both the quantity and quality of cross-team managerial connections. On the one hand, the size (or cardinality) of the connected manager set matters. This quantity dimension is intuitively linked to both the focal team size and the number of common managers' multiple team memberships. The implicit assumption behind this measure is that manager heterogeneity, meaning that each manager is an independent information source. We also introduce an alternative measure of such connections on a team basis instead of an individual basis and include this control variable in the full specification for testing the ICC-performance relation.

On the other hand, since the quality of connection also matters, we design a skill-weighted connection measure. We follow Berk, Van Binsbergen, and Liu (2017) and identify skilled managers as those in the top third of manager AUM.[15] Manager AUM as the sum of all assets under a manager's management. In figure A2, we utilize a hypothetical fund structure and illustrate in two examples how this variable is computed.

Incorporating both the quantity and quality of the connections in the ICC measure, we summarize it into a simple expression as follows.

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

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)).

[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 my 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.

where j denotes the focal manager; k denotes a connected manager at other funds.[16] To gather a pool of the unique interfund comanager connections, double counting is avoided if a non-focal manager is connected to more than one focal (common) manager. The skill weight is controlled by $I_{j,k,t}$, which equals to 1 when k is a top-AUM manager with its manager AUM belonging to the top tercile, and 0 otherwise. An important merit of this fund-level measure is that it does not impose any condition on the focal fund management structure, meaning both team-managed funds and solo-managed funds have values loaded on this connection measure. We further list two examples of applying this count measure to get a numerical value of ICC in Figure 2A and Figure 2B. Both team-managed funds and solo-managed funds can have a valid ICC value.

3.3 Summary Statistics

Table 1 lists the variable definitions and summary statistics of the main variables used in this paper. Panel A lists the summary statistics of the main variables. An average fund has more than one comanager connection (1.5), with a typical team-managed fund connected to more than two managers (2.2).[17] The median of within-fund average ICC is slightly greater than 0 (0.08), which means that more than 50% of funds experience at least one ICC change in my sample period. Conditioning on being connected, an average fund is connected to more than five non-focal managers (5.5).[18] Panel B shows the correlation matrix for ICC and various fund, team, and family characteristics. With the exception of team size, ICC is highly independent of the existing variables that are documented as fund performance correlates. The correlation between ICC and team size is intuitive (0.485), larger teams are more likely to have managers managing other funds with non-focal managers.

To fully describe all the characteristics that are associated with cross-team managerial connections, we also develop two other measures including the number of busy managers

[16] The connected manager k works with focal manager j in a team outside focal management unit J^i in month t.
[17] 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 my sample period.
[18] See Table A1 for more subsample summary statistics.

(Busyness), and team connections (NumTeam), with the former designed to capture the competing effects of ICC and the latter as an alternative connection measure based on the same organizational structure. Although a higher ICC may capture information sharing, ICC is also measured for funds with managers that manage more funds across different teams. As such, ICC funds are associated with busy managers that may be unable to fully focus on the focal fund(s). As a result of the adverse impact of manager busyness, the performance effect of ICC may be a net effect, which can be purged by including the busyness variable in the performance regression. Also, one may argue that individual connections do not matter as much as team-level connections do, because team members have a great deal of overlap in the information set. Taken to the extreme, there is no manager heterogeneity along the information dimension within a team. Thus, the information set is directly represented by the unit of a fund management team as a whole. To test this story, we construct a team connection measure (NumTeam) by counting the number of non-focal teams that are connected to focal managers. This alternative measure has a correlation coefficient of 0.748 with ICC, which is not surprising in that the more non-focal teams connected, the more likely the focal fund has access to non-focal top-AUM managers. Interestingly, to give a preview of the baseline performance test in Section (4.1), we show that the use of the team connection measure alone indeed is successful in picking up positive performance implications as expected, but its performance effect is completely subsumed by ICC when incorporated together into the regression.

4 ICC and Portfolio Similarity

In this section, we explicitly test whether the measure of interfund comanager connection reasonably describes a channel of workplace information sharing. We hypothesize that if ICC captures information transmission, ICC funds should exhibit greater portfolio overlap with their connected funds. To examine this hypothesis, we first follow the standard in the literature and measure portfolio overlap by computing the cosine similarity between the vector of portfolio active

weights in focal fund and those in connected funds.[19] We will present some univariate comparisons followed by the multivariate regression framework to directly get at the effect of ICC on portfolio similarity.

The investigation of the link between ICC and portfolio similarity entails using non-ICC funds as control funds, which are matched to ICC funds based on the propensity scores obtained from the regressions of likelihood of becoming an ICC fund on a series of fund-related characteristics. More importantly, these control funds are not connected to the same group of connected funds as ICC funds do. Hence, the information sharing effect due to ICC is teased out by comparing the portfolio similarity between ICC funds and their connected funds as opposed to that between control funds and the same connected funds. For each ICC fund (fund with at least one top-AUM manager connections), its corresponding connected funds are a group of funds that have at least one common manager with the focal fund and at least one top-AUM manager. Since there are one-to-many mappings between ICC funds and their connected funds, for ease of direct comparison between ICC funds and matched funds, we follow Girardi et al. (2021) and compute the average portfolio similarity of an ICC fund with all its connected funds expressed in eq. (2).

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

Where j is the number of connected funds for focal fund i, and $Similarity_{i,j,t}$ is bounded between 0 and 1, because it denotes the cosine similarity between fund i and fund j's vectors of portfolio active weights at quarter-end t, respectively. The results are reported in Table 2. By comparing the means of average portfolio similarity across ICC funds and that across matched non-ICC funds, we show that ICC funds have more similar holdings to their connected funds than their control funds do, with an average ICC fund exhibiting three times higher portfolio similarity (Panel A).

[19] 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.

We next estimate a regression of fund average portfolio similarity on ICC along with the same set of control variables in obtaining the propensity scores and a variety of fixed effect structures (eq. (3)). The results (Table 2 Panel B) show that a one-standard-deviation increase in ICC induces 12% higher average portfolio similarity to connected funds (Panel B). Moreover, this higher portfolio similarity of ICC funds relative to control funds is due to comanager connections, rather than shared managers. Combining the descriptive statistics and regression test on portfolio similarity, this ICC measure well represents the organizational channel of workplace information sharing.

$$\begin{aligned} Similarity\_Avg_{i,t} = {} & \alpha + \beta_1 * ICC_{it} + \beta_2 * Log(TNA)_{i,t-1} + \beta_3 * Log(Age)_{i,t-1} + \beta_4 * Expense_{i,t-1} \\ & + \beta_5 * Turnover_{i,t-1} + \beta_6 * Activeness_{i,t} + \beta_7 * Ret_{t-12,t-1} + \beta_8 * Vol_{t-12,t-1} \\ & + \beta_9 * Flow_{t-12,t-1} + \beta_{10} * Log(FamilyAum)_{i,t-1} + \beta_{12} * Teamsize_{i,t} \\ & + FE + \varepsilon_{i,t} \end{aligned} \quad (3)$$

Where FE refers to a varied combination of fixed effects across different specifications, including fund fixed effects, time fixed effects, style fixed effects, and family fixed effects. Standard errors are clustered at the fund level.

5 ICC and Fund Performance

5.1 Baseline Performance Results

The results in Table 2 suggest that comanagers share information across funds. The remaining question is whether the information has value. To examine this hypothesis, we regress fund alpha on ICC and control variables:

$$\begin{aligned} Alpha_{i,t}^{4F} = {} & \alpha + \beta_1 * ICC_{it} + \beta_2 * Log(TNA)_{i,t-1} + \beta_3 * Log(Age)_{i,t-1} + \beta_4 * Expense_{i,t-1} \\ & + \beta_5 * Turnover_{i,t-1} + \beta_6 * Activeness_{i,t} + \beta_7 * Ret_{t-12,t-1} + \beta_8 * Vol_{t-12,t-1} \\ & + \beta_9 * Flow_{t-12,t-1} + \beta_{10} * Log(FamilyAum)_{i,t-1} + \beta_{11} \\ & * Log(TeamAum)_{i,t-1} + \beta_{12} * Teamsize_{i,t} + \beta_{13} * NumTeam_{i,t} + \beta_{14} \\ & * Busyness_{i,t} + FE + \varepsilon_{i,t} \end{aligned} \quad (4)$$

where $\alpha_{i,t}$ is the risk-adjusted return of fund i in month t with the factor loadings estimated by past 12-month rolling regressions; $ICC_{i,t}$ is the interfund comanager connection of fund i in month t; A series of fund time-varying characteristics are added as control variables including the log of fund size, the log of fund age, expense ratios, fund turnover ratios, fund activeness, cumulative net fund returns in the past year, return volatility over the prior twelve months and net fund flows normalized by TNA in the previous twelve months. FE indicates different types and combinations of fixed effects in different specifications, with fund FE specification used as a baseline.

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. The detailed descriptions of these variables can be referred to in Appendix Table 1. In line with the consensus in the literature, fund performance declines with fund size, expenses ratios, and turnovers and increases with fund age and fund activeness.

The results reveal that ICC is positively related to fund performance. A one-standard- deviation increase of ICC leads Fama-French-Carhart four factor alphas to go up by 30.17 bps per year, based on model (5) of Panel A. After adding additional controls including family assets, team assets, and team size in model (2), the positive ICC-performance relation is unaltered. Model (3) of Panel shows the explanatory power of the competing connection measure designed at the manager team level instead of the individual manager level, and model (4) represents the outperformance of the original comanager measure of ICC relative to the team connection measure of NumTeam in the horse race. Model (5) further adds the number of busy managers, which does not display explanatory power itself but boosts the coefficient of interest, possibly due to the potential negative performance impact are separated away from ICC. In the last model of Panel (A), we use a predictive version of the baseline specification (eq. (4)) substituting lagged ICC, the presence of common manager, and busyness for corresponding terms. This specification is employed to mitigate reverse causality concerns that underlie the relation between comanager connection and performance. We find that ICC exhibits its predictive power both statistically and

economically. In sum, the results in Panel A of Table 3 reveal that the relation between ICC and fund performance remains fully intact in all these alternative specifications.

Panel B of Table 2 reports the sensitivity of the results to fixed effects. The results in the first column reveal no evidence of a meaningful relation between ICC and fund performance when fund FEs are removed from the model. Figure A3 shows that the within fund variation in ICC accounts for 61% of that in the pooled sample.[20] In this case, it is not surprising to see no power in detecting the ICC-performance relation if within-fund variation is obscured by other data noises. Results in the last two models show the robustness of the specification to alternative performance measures of Fama-French three-factor alphas and Fama-French five-factor alphas as opposed the main performance metric of Carhart four-factor alphas throughout the paper. Taken together, a greater number of skilled comanager connections for a given fund can significantly translate into better performance.

5.2 A Quasi-experiment and DiD Estimations

The baseline results suffer from endogeneity issues. For example, it could be that better managers are more likely to be assigned to multiple teams, thus acquiring non-focal comanager connections for focal funds. In this case, the ICC-performance relation is plagued with unobserved focal manager ability. To better pin down the causal effect of ICC on performance, we exploit a quasi-experiment of superstar departures that create plausibly exogenous variation in ICC. To begin with, we identify a series of superstar departure events. The superstars are senior key managers with influential fund families. Specifically, superstars should have at least 12 years' firm tenure (90Pctl.), and their management share of family assets should fall in the inter-quartile range, and their affiliated family size should be found in the top tercile. Following the spirit of Chen, Du, and Sun (2023), superstars classified in this way generally have flow consequences. As such, we ensure that the departure decisions are least likely to be driven by fund families' arrangement. We report the yearly frequency of departure events in Table 4. Next, we classify treated funds as those who

[20] The standard deviation of ICC is 4.12 in the pooled sample. The within-fixed-effect standard deviation of ICC is 2.51. In terms of R-squared, fund fixed effects explain roughly 60% of the variation in ICC.

have superstars as comanager connections 2 months before they leave the company.[21] The departures are identified at the fund company level, meaning that once the company affiliation stops, it never appears in the Morningstar database.[22] Due to the staggered nature of such departure events and potential issues with two-way fixed effect methods[23], we adopt the stacked regression approach proposed in Baker, Larcker, and Wang (2022). Specifically, the control group is constructed through three-to-one propensity score matching and only includes funds that never have been connected to a top-AUM manager throughout the sample period and the event window is three months before and after the departure. We estimate the following DiD model on a sample of treated and control funds:

$$\alpha_{i,t} = \beta_0 + \beta_1 * Treat_i * Post_t + Controls_{i,t} * \Gamma + FEs + \varepsilon_{i,t} \quad (5)$$

Where i denotes firm and t denotes month. Treated_i is a dummy variable that equals 1 for funds in the treatment group, Post_t is a dummy variable that equals 1 when a superstar departure event occurred. Γ is a vector of regression coefficients on the controls, which are defined the same as in specification (4). FEs include fund fixed effect and time fixed effect. $\varepsilon_{\text{i,t}}$ is the error term.

My coefficient of interest is β_3, which captures the difference in performance between ICC funds (treated) and Propensity-Score-matched non-ICC funds before and after the departures of superstar managers. My main hypothesis states a positive ICC-performance relation that predicts a negative β_3 in the diff-in-diff model (see Eq. 5), meaning that an exogenous decreases in ICC will result in performance declines due to the loss of access to important information sources. We confirm this prediction in the data. Table 5 outlines the results from the DiD specifications with different fixed effect structures. Panel A show that following superstar departures from fund companies (and thus the connected funds), focal funds experience a huge performance decline that is significant at 1% level with a large economic magnitude of as high as 240 bps per year measured by Fama-French-Carhart four factor alphas. The key identifying assumption in a DiD framework

[21] In untabulated results, the pre-event monthly window could be shortened to one month or extended to 3 months.
[22] 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.
[23] Goodman-Bacon (2021) points out that it is problematic to compare late-treated units to early-treated units when treatment effects are time-varying.

is the classic parallel trend assumption, which states that with the absence of the occurrence of superstar departures, treated funds and control funds would have evolved the same way. Panel B estimates the DiD model with pre-event indicators added, which specifies the dynamic relationship between ICC and fund performance. It shows that the performance effect of ICC only appears post superstar departures, suggesting that there is no pre-trend that could contaminate the DiD estimator. Besides, the results in Panel B also show that the findings in Panel A are robust to different performance metrics including Fama-French three-factor alphas and Fama-French five-factor alphas. The findings shown in Table 5 give us confidence about the causal inferences of the performance impact of ICC.

6 Underlying Channels of the ICC-Performance Relation

6.1 Does the Team Approach Matter?

Given ICC improves fund performance, a natural follow-up question is which fund management structure benefits more from comanager connection? We propose two novel competing hypotheses. On the one hand, team-managed funds may be better equipped to capitalize on comanager connections than their solo peers due to lower information capacity constraints (Peng, 2005); on the other hand, solo-managed funds may take in the information transmitted from cross-team comanagers more efficiently than team-managed ones due to lower coordination costs (Chen et al., 2004). Does team trump solo in assimilating the performance benefit of ICC? This is essentially an empirical question.

We begin by partitioning the sample into team-managed funds and solo-managed funds and redo the tests in Equation (4). Following the prior literature, we classify funds as solo (team) managed when we can identify one (at least two) unique manager(s). The test results are reported in Table 6. The main finding is that ICC is beneficial for the risk-adjusted returns of team-managed funds' while being neutral to the risk-adjusted returns of solo-managed funds. For team-managed funds, the estimation of coefficient estimation of ICC is positive and significant at 1%. The economic magnitude also gets bigger: a one-standard deviation increase in ICC causes annualized

Fama-French-Carhart four factor alphas to rise by 33.69 bps in team-managed funds. The results in Panel A of Table 6 suggest that the previous findings are driven by team-managed funds. Given the popularity of team management and the accompanying trend of managers serving multiple teams at the same time, the findings here further suggest that fund companies may strategically allocate human resources to improve fund performance.

6.2 Does Family Size Matter?

In this section, we sort the ICC-performance relation on fund family size. We also have two competing hypotheses regarding the potential role of family size. For one thing, large fund families naturally breed more work ties for a given fund, thus intensifying the performance impact of interfund comanager connections within a family. In this case, we expect to see a positive conditioning effect of family size on the previously documented ICC-performance relation. For another, small fund families rely more on the comanager type of connection due to limited human capital supply within the organization. Hence, funds with small fund families exhibit stronger performance betterment in response to increases in skilled comanager connections. This second hypothesis predicts a negative conditioning impact of family size.

To formally test the idea of family size being an important cross-sectional driver of ICC's performance impact, we add to the baseline benchmark model a large family indicator together with an interaction term of ICC by the large family indicator, which equals to 1 if the aggregated assets of the fund family associated with a given fund is above the median, and 0 otherwise. The coefficient of interest is on the interaction term. Panel C of Table 6 reports the estimates from this interaction test. The results across different specifications conform to the second hypothesis: The performance impact of ICC is weakened conditioning on being affiliated with a large fund family. Put differently, funds that belong to small families benefit more from ICC. Interestingly, after controlling for the conditioning impact of family size, we now observe a cross-sectional pattern that high-ICC funds tend to outperform low-ICC funds.

7 Further Portfolio Evidence

7.1 Do ICC Funds Make Profitable Trades based on Their Overlapped Holdings?

Section 3.2 described how the skill element of the ICC measure is incorporated, which is to ensure the connections are valuable information sources. In this section, to further test whether the ICC-induced performance enhancement is value-driven, we investigate ICC funds' trading decisions and outcomes by focusing on their overlapping holdings with their connected funds.

First, Pool et al. (2015) show that hard-to-research stocks are more likely to be value-enhancing.[24] Building on their insight, we form portfolios based on the connectedness status of the fund, and the trades of the hard-to-research stock holdings in each quarter t. For connected funds, "Buy" portfolios include stocks with overlapped increased holdings, and "Sell" portfolios include stocks with overlapped decreased holdings. For funds without comanager connections, "Buy" portfolios include stocks with increased holdings, and "Sell" portfolios include stocks with decreased holdings. Stocks in both "Buy" and "Sell" portfolios are weighted by the transaction value. A long-short portfolio is built based on both "Buy" and "Sell" portfolios. All the portfolios are rebalanced quarterly. Following Pool et al. (2015), we set the dependent variable as portfolio DGTW-adjusted extra returns in quarter t, and the included independent variables have the same description as in Table 1. Panel A of Table 7 shows that hard-to-research stocks do not significantly benefit ICC funds more.

Second, Coval and Moskowitz (1999) show that mutual fund managers rely on soft information when trading local stocks and garner abnormal returns from local investments. If connections facilitate soft information transmissions, trades made in overlapping local stocks should generate large profits. Following the same portfolio strategy as in hard-to-research stocks, Panel C of Table 7 shows that ICC funds mainly profit from selling overlapped local stocks compared to non-ICC funds. CiCi (2012) shows the prevalence of the disposition effect in mutual funds but no performance implications. The result that ICC funds are able to sell losing local stocks suggests

[24] We follow the spirit of Pool et al. (2015) and hard-to-research stocks are identified using stocks with advertising expenses or sales less than the yearly medians.

that comanager connections may help alleviate the disposition effect and thus enhance performance.

7.2 Evidence against Naïve Copycatting

One may argue that the performance impact of comanager connections could also be explained by managers simply copycatting their connected funds, especially when skilled managers are present. In this case, without the information sharing from connected funds, focal fund portfolios may also exhibit similarity to the connected funds. Essentially, herding can be information driven as well. To some extent, my results can be viewed as comanager connections inducing more information-based herding behavior. Since information flows are unobservable, which is widely acknowledged in the social connection literature, we can only provide some indirect evidence against alternative explanations. To rule out the possibility of naïve copycatting driving my results, we exploit SEC downloads to link the unobservable connection-driven information sharing to measurable information acquisition activities. We aggregate SEC's daily downloading activities that span from 2003 to 2017 to month level.[25] The test logic follows the spirit of a reveal-preference approach and attributes the focal funds' actual choices to information flows facilitated by comanager connections.

Specifically, we hypothesize that if a focal fund initiates a new position by simply observing connected funds' portfolio stocks, then given the new stock A observed in the focal fund's portfolio, the focal fund should have done research on stock A and all similar stocks (e.g. B and C) held by connected funds. But if the focal fund is informed by a manager in a connected fund that A is a more profitable choice than B and C, it is mostly like to pay attention to stock A only. Since SEC downloads' is an aggregate attention measure, meaning that we cannot track the downloading activity to a specific fund (at most at fund family level through IP address identification), we identify ICC-related new positions like stock A first, and then get the number of all funds tracking such stocks. Similarly, we get the number of all funds tracking matched

[25] Loughran and McDonald (2017) point out that there are some data issues in SEC log datasets in 2003 and 2005. My results are robust to only including the downloads data from 2006 onwards.

control stocks like B and C that do not appear in focal funds' portfolios as a result of connections. In table 7.2, we show that only ICC-related new positions in focal fund portfolio are searched more, which also implies that information acquisition is complementary to information sharing. However, matched stocks that are not followed by focal funds do not have high search activities. Interestingly, the focal funds' other buys also see greater SEC downloads, plausibly due to connection relaxing focal funds' information capacity constraints.

8 Robustness Tests

8.1 Portfolio-leader-based Connection Measure

We argue that managers can benefit from coworking with talented fund managers in outside teams. To provide further evidence, we re-estimate the previous models with another identification of talented fund managers: the portfolio-leader fund managers reported in SEC mutual fund prospectus filings.

In October 2004, the SEC required mutual funds to provide a brief description of each member's role on the management team (e.g., lead member) in prospectus filings. Since team leaders are arguably skilled fund managers, we collect each fund manager's role in the sample funds and computed the number of connected portfolio-leader managers in the spirit of (1), as shown in (6).

$$ICC_{it} = \sum_{k \in K} \max_{j \in J^i} \left(I_{j,k,t}^{lead} \right) \tag{6}$$

where j denotes the focal manager; k denotes a connected manager at other funds. To gather a pool of the unique interfund comanager connections, double counting is avoided if a non-focal manager is connected to more than one focal (common) manager. The skill weight is controlled by $I_{j,k,t}$, which equals to 1 when k is a portfolio-leader manager as reported in SEC mutual fund prospectus filings, and 0 otherwise.

Using the alternative, portfolio-leader-based identification of ICC as in (6), we re-estimate the models specified in (3) and (4), as well as the subsample tests in Section 6. The results are reported

in Table 8. We can see that ICC identified by connected outside team leaders is still associated with higher portfolio holding similarities to connected portfolios and higher fund performance. The economic magnitudes are also comparable to previous findings: a one-standard deviation of portfolio-leader-based ICC is associated with an increase in holding similarity among connected funds as high as 6.87% (56% of the unconditional mean), and with a maximum increase in annual 4-factor alpha of 20 bps. The results also show the same pattern shown in the subsample results in Section 6 – the performance effect of alternative ICC is more pronounced in funds with team-management and from smaller fund families.

8.2 Alternative Connection Measure: Team Affiliation or Family Affiliation?

In addition, one may argue that workplace information sharing does not need to be existent conditional on team connectedness, and as long as fund managers are affiliated with the same fund family, they are engaged in information sharing (Brown and Wu (2016)). To explicitly test this possibility, we also design another alternative measure that satisfies both the same family condition and the same style condition, and the ICC measure wins the horse race between these two measures in my robustness tests. Even if there are some other forms of workplace information sharing that is not captured by either measure, the measurement error issue would have just attenuated my results so that the magnitude based on my measure is more likely to be a lower bound of the true effects.

The test results are reported in Table 9. We find that ICC wins the horse racing with FIS, and even without ICC, FIS alone shows no significant relationship with fund performance. The findings support that connections through shared managers facilitate information flows among manger teams, while loose connections that are not built on day-to-day coworking cannot induce significant information sharing.

8.3 Shock Validation: Lower Connections or Busier Managers?

Empirical results in 5.2 show that superstar departures have an impact on ICC and hence cause worse fund performance. But it is also possible that the leaving of superstars increases the burden

of remaining fund managers and hence the performance of impacted funds gets compromised. In this case, the shock may not be valid to prove the effect of connections on fund performance.

To show the validity of the shock of superstar departures, we redo the test identified in Equation (5) with a new set of dependent variables: ICC and Busyness. The validity of superstar departures as a shock on connection is built on two aspects. First, superstar departures should significantly reduce ICC, and second, superstar departures should not significantly increase Busyness. The results of Table 10 find the two situations are both satisfied: the leaving of attached superstars causes a highly significant drop in ICC for focal funds, which implies no quick replacement of managers for attached funds and hence further justifies the exogeneity of the shock, while the Busyness of focal funds do not change, which means that the leaving of attached superstars do not induce higher work burden on focal fund managers.

8.4 Placebo Tests on Index Fund Sample

My last set of robustness tests focuses on the marginal value of shared information. If ICC improves fund performance through better information sharing, then its effect on performance should disappear for funds where information collection has no marginal effects. Along this line, the index fund would provide an excellent setting to conduct a placebo test. ICC should have nothing to do with index fund performance since there is no active information collection in the fund management. We redo the test specified as in equation (4) with the index fund sample and report the results in Table 11. We find that there is no significant relationship between ICC and fund performance in the sample of index funds. In unreported results, we also find that turnover has no significant impact on fund performance, either. This is consistent with the passive strategies applied among index funds. So, the insignificant estimation of the coefficient of ICC provides further evidence that ICC improves fund performance via the channel of better information sharing.

9 Conclusion and Limitation

This paper delineates the comanager linkages in the mutual fund industry and examines the performance implications of such peer connection. Exploiting a novel setting where mutual fund

managers for one team also work with managers from other teams, this paper starts by providing the first evidence on the prevalence of (co)manager-connected funds. We develop a fund-level measure by incorporating both quantity and quality of the connections to quantify a novel channel of workplace information sharing and examine its performance impact. We hypothesize that interfund comanager connections play a key role in information transmission and influences fund performance. Consistent with my hypothesis, we find that ICC is associated with higher portfolio similarities between ICC funds and their connected funds. In the baseline test, we exploit within-fund specification and show that higher ICC translates into greater fund performance. Relying on a quasi-experiment of departures of superstar connected managers in non-focal funds, we show that the positive ICC-performance relation is likely to be causal and is not driven by unobserved focal managerial ability. Specifically, exogenous decreases in ICC due to superstar departures result in an annual abnormal performance decline of 240bps.

In examining the importance of workplace peer connections in mutual fund performance, this paper also sheds light on underlying economic mechanisms. First, we show the aforementioned performance effect of ICC mainly exists in team-managed funds, consistent with group managers having lower information capacity constraint than solo managers. Second, we show that interfund comanager connections improve fund performance by sharing and transmitting valuable information between involved funds. The positive relation between ICC and the profitability of funds' purchases based on overlapped value-enhancing stocks indicates that comanager connections share value-relevant information that can be passed onto ICC funds. Third, the affiliation with small fund family strengthens the ICC-performance relation, which is plausibly explained by small families' higher reliance on this comanager type of connection. All in all, my findings suggest that work ties facilitate workplace information sharing in the mutual fund industry and benefit fund performance.

The main limitation in this paper is that we cannot observe the information flows, which is also a universal concern for most studies in the connection literature. In this study, we argue that comanagers naturally establish work ties, along which valuable information is transmitted. However, this is only a lower bound for information transmission in the workplace. Coworkers

that do not share an explicit work tie can build up other connections through their educational ties, ethnicity ties, employment ties, or social ties either through serendipitous interactions in the workplace or attending social events outside the workplace. We leave these fruitful areas to future research endeavors.

References

Agarwal, V., Ma, L. and Mullally, K., 2023. Managerial multitasking in the mutual fund industry. Financial Analysts Journal 79(2):65–75.

Adams, J.C., Nishikawa, T. and Rao, R.P., 2018. Mutual fund performance, management teams, and boards. Journal of Banking & Finance 92:358–368.

Asriyan, V., Fuchs, W. and Green, B., 2017. Information spillovers in asset markets with correlated values. American Economic Review 107(7):2007–2040.

Bär, M., Kempf, A. and Ruenzi, S., 2011. Is a team different from the sum of its parts? Evidence from mutual fund managers. Review of Finance 15(2):359–396.

Berk, J.B. and Green, R.C., 2004. Mutual fund flows and performance in rational markets. Journal of Political Economy 112(6):1269–1295.

Berk, J.B. and Van Binsbergen, J.H., 2015. Measuring skill in the mutual fund industry. Journal of Financial Economics 118(1):1–20.

Berk, J.B., Van Binsbergen, J.H. and Liu, B., 2017. Matching capital and labor. The Journal of Finance 72(6):2467–2504.

Bliss, R.T., Potter, M.E. and Schwarz, C., 2008. Performance characteristics of individually–managed versus team–managed mutual funds. Journal of Portfolio Management 34(3), p.110.

Brown, D.P. and Wu, Y., 2016. Mutual fund flows and cross-fund learning within families. The Journal of Finance 71(1):383–424.

Chen, J., Hong, H., Huang, M. and Kubik, J.D., 2004. Does fund size erode mutual fund performance? The role of liquidity and organization. American Economic Review 94(5):1276–1302.

Chen, Y., Huang, J., Li, T. and Pittman, J., 2022. It's a Small World: The Importance of Social Connections with Auditors to Mutual Fund Managers' Portfolio Decisions. Journal of Accounting Research 60(3):901–963.

Choi, D., Kahraman, B. and Mukherjee, A., 2016. Learning about mutual fund managers. The Journal of Finance 71(6):2809–2860.

Christoffersen, S.E. and Sarkissian, S., 2009. City size and fund performance. Journal of Financial Economics 92(2):252–275.

Cici, G., 2012. The prevalence of the disposition effect in mutual funds' trades. Journal of Financial and Quantitative Analysis 47(4):795–820.

Cici, G., Jaspersen, S. and Kempf, A., 2017. Speed of information diffusion within fund families. The Review of Asset Pricing Studies 7(1):144–170.

Cohen, L., Frazzini, A. and Malloy, C., 2008. The small world of investing: Board connections and mutual fund returns. Journal of Political Economy 116(5):951–979.

Coval, J.D. and Moskowitz, T.J., 1999. Home bias at home: Local equity preference in domestic portfolios. The Journal of Finance 54(6):2045–2073.

Evans, R.B., Prado, M.P. and Zambrana, R., 2020. Competition and cooperation in mutual fund families. Journal of Financial Economics 136(1):168–188.

Genc, E., Shirley, S. E., Stark, J. R., & Tran, H., 2023. Finding information in obvious places: Work connections and mutual fund investment ideas. Journal of Financial Markets 63, Article 100767.

Girardi, G., Hanley, K.W., Nikolova, S., Pelizzon, L. and Sherman, M.G., 2021. Portfolio similarity and asset liquidation in the insurance industry. Journal of Financial Economics 142(1):69–96.

Gu, Z., Z. Li, Y. Yang, and G. Li. 2019. Friends in Need are Friends Indeed: An Analysis of Social Ties between Financial Analysts and Mutual Fund Managers. The Accounting Review 94(1):153–181.

Harvey, C.R., Liu, Y., Tan, E.K. and Zhu, M., 2021. Crowding: Evidence from fund managerial structure. (https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3554636)

Hong, H., Kubik, J.D. and Stein, J.C., 2005. Thy neighbor's portfolio: Word-of-mouth effects in the holdings and trades of money managers. The Journal of Finance 60(6):2801–2824.

Kacperczyk, M., Sialm, C. and Zheng, L., 2005. On the industry concentration of actively managed equity mutual funds. The Journal of Finance 60(4):1983–2011.

Pástor, Ľ., Stambaugh, R.F. and Taylor, L.A., 2015. Scale and skill in active management. Journal of Financial Economics 116(1):23–45.

Patel, S. and Sarkissian, S., 2017. To group or not to group? Evidence from mutual fund databases. Journal of Financial and Quantitative Analysis 52(5):1989–2021.

Patel, S. and Sarkissian, S., 2021. Portfolio pumping and managerial structure. The Review of Financial Studies 34(1):194–226.

Peng, L., 2005. Learning with information capacity constraints. Journal of Financial and Quantitative Analysis 40(2):307–329.

Pool, V.K., Stoffman, N. and Yonker, S.E., 2015. The people in your neighborhood: Social interactions and mutual fund portfolios. The Journal of Finance 70(6):2679–2732.

Prather, L.J. and Middleton, K.L., 2002. Are N+ 1 heads better than one?: The case of mutual fund managers. Journal of Economic Behavior & Organization 47(1):103–120.

Rossi, A.G., Blake, D., Timmermann, A., Tonks, I. and Wermers, R., 2018. Network centrality and delegated investment performance. Journal of Financial Economics 128(1):183–206.

Sandvik, J.J., Saouma, R.E., Seegert, N.T. and Stanton, C.T., 2020. Workplace knowledge flows. The Quarterly Journal of Economics 135(3):1635–1680.

Stein, J.C., 2002. Information production and capital allocation: Decentralized versus hierarchical firms. The Journal of Finance 57(5):1891–1921.

Stein, J.C., 2008. Conversations among competitors. American Economic Review 98(5):2150–2162.

Wermers, R., 2000. Mutual fund performance: An empirical decomposition into stock-picking talent, style, transactions costs, and expenses. The Journal of Finance 55(4):1655–1695.

Table 1 Summary Statistics

Table 1 presents the summary statistics for fund, team, and family characteristics. Panel A reports the summary statistics of the time-series averages of the fund characteristics. Panel B reports the correlation between ICC and other fund characteristics. Panel C reports the correlation among ICC, team characteristics and other measures. ICC is defined as the number of non-focal top-AUM managers connected via shared managers. α^{4F} (%) is the fund's Fama-French-Carhart four factor alphas with factor loadings estimated on rolling past 12-month windows. Log (TNA) is the log of the total net assets under the fund's management (TNA) (in $ millions) at the beginning of each month. Age (years) is the years since fund's inception. Expense ratio (%) is the percentage total investment that investors pay as expenses. Turnover (%) (annual) is the minimum of aggregate purchases or sales of securities during the year, divided by the average TNA. α^{4F} activeness (%) is 1 minus the fund R^2 from a time-series regression of fund excess returns on Carhart four factors over the previous 12 months. $\text{Ret}_{t-12,t-1}$ (%) is the cumulative fund return over the past 12 months. $\sigma_{t-12,t-1}$ (%) is the return volatility of a fund measured by the standard deviation of fund monthly return over the prior 12 months. $\text{Flow}_{t-12,t-1}$ (%) is the prior 12-month normalized net flow into a fund and defined as $(\text{TNA}_{i,t} - \text{TNA}_{i,t-12}(1 + \text{Ret}_{t-12,t-1}))/\text{TNA}_{i,t-12}$. Log (Family TNA) is the log of fund family's TNA at the beginning of each month. Team size is the number of managers that manage the fund. Log (Team TNA) is the log of the aggregate of Manager AUMs of the managers of the fund, where Manager AUM is defined as the sum of TNA/(Team size) for all funds overseen by the manager. NumTeam is the number of non-focal teams that fund managers work in. Busyness is the number of busy managers sitting on the focal fund, where the busy manager indicator is one if the number of funds currently managed by the manager is within the top quintile, and zero otherwise. The sample period spans January 1992 to September 2018.

Panel A Summary Statistics

Variable	Nobs.	Mean	Std. Dev.	25th Pctl.	50th Pctl.	75th Pctl.
ICC	312,310	1.49	4.08	0	0	1
ICC_positive	84,572	5.50	6.29	1	3	7
ICC_withinfund	2,214	1.44	3.33	0	0.08	1.15
ICC_lead	312,310	0.02	0.15	0	0	0
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 ratio (%)	300,029	1.17	0.39	0.93	1.14	1.39
Turnover (%) (annual)	294,925	75.51	60.93	33	60	99
α^{4F} activeness (%)	302,989	8.52	8.23	2.93	5.90	11.13
$\text{Ret}_{t-12,t-1}$ (%)	301,423	9.01	18.24	0.08	10.72	19.65
$\sigma_{t-12,t-1}(\%)$	303,210	4.42	2.05	2.88	3.99	5.48
$\text{Flow}_{t-12,t-1}$ (%)	296,336	17.35	82.58	-14.08	-3.78	15.53
Log (Family TNA)	282,758	9.92	2.48	8.40	10.39	11.73
Log (Team TNA)	312,310	7.71	2.10	6.32	7.85	9.26
Team size	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 ratio	Turnover	α^{4F} activeness	$Ret_{t-12,t-1}$	$\sigma_{t-12,t-1}$	$Flow_{t-12,t-1}$
α^{4F}	-0.0015									
Log (TNA)	0.1203	-0.0040								
Age	0.0542	-0.0182	0.5808							
Expense ratio (%)	-0.1568	-0.0002	-0.3264	-0.1929						
Turnover	-0.0545	0.0028	-0.1466	-0.1488	0.1866					
α^{4F} 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			
$\sigma_{t-12,t-1}$	-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 (Family TNA)	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 Other Measures

	ICC	NumTeam	Log (Team TNA)	Team size
NumTeam	0.7476			
Log (Team TNA)	0.1200	0.0923		
Team size	0.4852	0.5415	0.0856	
Busyness	0.3565	0.5313	0.1928	0.3078

Table 2 ICC and Portfolio Similarity

This table provides the univariate and multivariate evidence on portfolio similarity between ICC funds (treated) and their connected funds. Control funds are identified through one-to-one propensity score matching and should have no ICC in the matched fund-quarter. Panel A directly compares the means of average portfolio similarity across ICC-treated funds and that across matched control funds. Panel B shows the results from the multivariate regression analysis. The dependent variable is the average holding cosine similarity for each fund in each quarter on a matched sample that consists of ICC-treated funds and control funds. All the independent variables are described in Table 1. The variables used for PSM are Log (TNA), Log (Age), Expense ratio, $\sigma_{t-12,t-1}$, Flow, $\text{Ret}_{t-12,t-1}$ Log (Family TNA), Log (Team TNA), Team size, α^{3F}, α^{3F} activeness, α^{4F}, α^{4F} activeness, α^{5F}, and α^{5F} activeness. Time fixed effects are calendar year-month fixed effects. Style fixed effects are based on nine Morningstar investment styles. Fund families are identified by CRSP management company codes. The t-statistics are reported in parentheses. *, **, *** indicates significance level at 10%, 5%, and 1%, respectively.

Panel A The univariate difference in average portfolio similarity for fund with and without ICC

Similarity_Avg	Fund_month Obs.	Mean	Std. Dev.
Treated Funds	32,385	0.15	0.21
Matched Control Funds	32,385	0.02	0.05
Difference		0.13	
[p-value]		[0.00]	

Panel B Multivariate regression of ICC on average portfolio similarity

	(1)	(2)	(3)
	$\text{Similarity\_Avg}_{i,t}$	$\text{Similarity\_Avg}_{i,t}$	$\text{Similarity\_Avg}_{i,t}$
$\text{ICC}_{i,t}$	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]
$\text{Expense ratio}_{i,t-1}$	-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]
α^{4F} $\text{activeness}_{i,t}$	-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]
$\sigma_{i,t-12,i,t-1}$	-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]
$\text{Log (Family TNA)}_{i,t-1}$	-0.0059**	-0.0053*	-0.0035
	[-2.09]	[-1.94]	[-1.09]
$\text{Log (Team TNA)}_{i,t-1}$	-0.0122***	-0.0124***	-0.0131***
	[-4.29]	[-4.49]	[-4.57]
$\text{Team size}_{i,t}$	-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 Baseline Results

This table reports results from panel regressions of fund performance on contemporaneous interfund comanager connections (ICC) and covariates that are at the fund level, team level as well as family level. The construction of our ICC measure is described in Section 3.2. Description of control variables including other fund characteristics, team characteristics, and family characteristics are stated in Table 1. α^{4F} are fund returns obtained by estimating Fama-French Carhart four factor model for each fund using a 12-month rolling regression with monthly returns. $\alpha^{3F}$and α^{5F} are risk adjusted fund returns using Fama-French 3-factor model, and Fama-French five-factor model, respectively. The fund fixed effects specification is adopted across the six models in Panel A. All control variables except TeamSize and Busyness are lagged one month. In model (6), the last three control variables with * superscripts will use lagged terms (t-1) in accordance with the lagged ICC measure. Panel B contains results from contemporaneous panel regressions that use the same set of control variables as in model (5) of Panel A. The first model with time fixed effects added shows the motivation for the within-fund specification as our baseline. Using model (5) of Panel A as a benchmark model, we add time (year-month) fixed effects, (Morningstar) style fixed effects, and fund family fixed effects in turn from model (2) to model (4). The last two models substitute α^{3F} and α^{5F} for α^{4F} based on the full specification on the left hand side. The sample period spans Jan. 1992 to Sep. 2018. The t–statistics are reported in parentheses. $*$, $**$, and $***$ represent significance levels of 10%, 5%, and 1%, 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 $ratio_{i,t-1}$	-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]
α^{4F} $activeness_{i,t}$	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]
$\sigma_{i,(t-12,t-1)}$	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 $(Family\ TNA)_{i,t-1}$		0.1962	0.2165	0.1913	0.2167	0.2183
		[0.30]	[0.33]	[0.29]	[0.33]	[0.33]
Log $(Team\ TNA)_{i,t-1}$		-0.5421	-0.4999	-0.5169	-0.5650	-0.5621
		[-0.73]	[-0.67]	[-0.70]	[-0.76]	[-0.76]
$Team\ size^{*}_{i,t}$		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 Robustness to Different Specifications and Alternative Performance Measures

	(1) $\alpha^{4F}_{i,t}$	(2) $\alpha^{4F}_{i,t}$	(3) $\alpha^{4F}_{i,t}$	(4) $\alpha^{4F}_{i,t}$	(5) $\alpha^{3F}_{i,t}$	(6) $\alpha^{5F}_{i,t}$
$ICC_{i,t}$	0.0454	0.4790***	0.4965***	0.4703***	0.4110**	0.3742**
	[0.52]	[3.30]	[3.40]	[3.16]	[2.32]	[2.53]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	No	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Style FE	No	No	Yes	Yes	Yes	Yes
Family FE	No	No	No	Yes	Yes	Yes
Adj. R-squared	0.093	0.093	0.093	0.093	0.090	0.080
Fund-month Obs	261,583	261,577	257,152	257,019	257,019	257,019

Table 4 Annual Frequency of Superstar Departure Events

This table reports the number of superstar departure events. The identified superstar departure events start from 1997 and end in 2018. Superstars are fund managers who work for a fund company with TNA above the 30th percentile (21,185 million dollars) with the share of family assets under management falling between 25th and 75th percentile, and whose tenure is above 90th percentile (141 months).

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

Table 5 The ICC-performance Relation around Superstar Departures

This table reports the results from estimating the DiD model specified in Eq. (3). The identification of superstars is as described in Table 4. Treat_i is one for ICC funds with superstars leaving connected funds within the event window and zero, otherwise. The control funds are non-ICC funds selected through three-to-one propensity score matching for each treated fund. Post_t is one for all the time periods after the occurrence of superstar departures. The variables for conducting propensity score matching are Log (TNA), Log (Age), Expense ratio, $\sigma_{t-12,t-1}$, Flow, $\text{Ret}_{t-12,t-1}$ Log (Family TNA), Log (Team TNA), Team size, α^{3F}, α^{3F} activeness, α^{4F}, α^{4F} activeness, α^{5F}, and α^{5F} activeness. The control variables are the same as in Table 2. Time fixed effects are calendar year-month fixed effects. Style fixed effects are based on nine Morningstar investment styles. Fund families are identified by CRSP management company codes. The t-statistics are reported in parentheses. *, **, *** indicates significance level at 10%, 5%, and 1%, 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) $\alpha_{i,t}^{4F}$
$\text{Treat}_i * \text{Post}_t$	-0.0022**	-0.0026***	-0.0027**	-0.0025**	-0.0026**
	[-2.31]	[-2.60]	[-2.55]	[-2.55]	[-2.55]
Window	[-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 Subsample Tests

This table reports results on the cross-sectional differences in the ICC-performance relation. Panel A reports results from estimating Eq. (4) with the full sample split into two subgroups: team-managed funds and solo-managed funds. Panel B report results from estimating Eq. (4) with the full sample split into two subgroups: large fund family (fund family with above-the-median size) and small fund family. The dependent variables are Fama-French-Carhart four factor alpha with factor loadings estimated on rolling past 12-month windows. All the independent variables are as described in Table A1. The variable of interest is ICC and the control variables are the same as the regressions in Table 2. Time fixed effects are calendar year-month fixed effects. Style fixed effects are based on nine Morningstar investment styles. Fund families are identified by CRSP management company codes.

Panel A ICC-Performance Relation within Team-managed/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 within Large/Small Fund Family

	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

This table presents further portfolio evidence on the ICC-performance relation. Panel A reports results on whether and how ICC funds profit from their trades in local stocks (non-local stocks), the investment returns from which can benefit from soft(hard) information transmission via comanagement linkages. Local stocks are companies located near an investment fund's headquarter. In each quarter t, we form portfolios based on the connection status of the fund, and the trade of the local stock holdings. For connected funds, "Buy" portfolios include stocks with overlapped increased holdings, and "Sell" portfolios include stocks with overlapped decreased holdings. For funds without connections, "Buy" portfolios include stocks with increased holdings, and "Sell" portfolios include stocks with decreased holdings. Stocks in both "Buy" and "Sell" portfolios are weighted by the transaction value. "Diff." is the long-short portfolio. All the portfolios are rebalanced quarterly. The dependent variables are portfolio DGTW-adjusted extra returns in quarter t, and the independent variables are as described in Table 1. ICC_{t-1}, Log $(\text{Family TNA})_{t-1}$, Log $(\text{Team TNA})_{t-1}$, and Team size_{t-1} are scaled by 100. Fund fixed effect is the fixed effect of the fund whose transactions are used to form the portfolio. Panel C reports the results on interaction tests. IsLargeFamily is an indicator that equals 1 for funds that belong to a fund family whose TNA is above the median, and 0 otherwise. Time fixed effects are calendar year-month fixed effects. Style fixed effects are based on nine Morningstar investment styles. Fund families are identified by CRSP management company codes. Similar to Panel A, Panel B reports the performance of portfolios based on trades in hard-to-research versus easy-to-research stocks by ICC and non-ICC fund managers. Hard-to-research stocks are stocks with advertising expenses or sales less than the yearly medians, following Pool et al. (2015). Panel C further provides suggestive evidence against the alternative story of naïve herding. The sample period of the SEC downloading data is from January 2003 to June 2017. Log (# Followers to ICC-related New Positions) refers to the number of funds newly buy the stock by following their connected funds. Log (# Funds holding matched Stocks in connected fund portfolio) is the number of connected funds that buy control stocks. Log (# Funds holding remaining stocks in focal fund portfolio) is the number of focal funds that buy the stocks that are not ICC-induced new positions. The t-statistics are reported in parentheses. *, **, *** indicates significance level at 10%, 5%, and 1%, respectively.

Panel A DGTW-adjusted returns to portfolio trades in local stocks

	Local Stocks			Non-Local Stocks		
	Buy	Sell	Diff.	Buy	Sell	Diff.
ICC fund portfolio	1.72***	-0.29*	2.01***	2.07***	-0.1	2.17***
	(0.14)	(0.16)	(0.17)	(0.17)	(-0.11)	(0.15)
Non-ICC fund portfolio	1.85***	0.17	1.69***	1.75***	-0.06	1.81***
	(0.18)	(0.19)	(0.17)	(0.12)	(0.08)	(0.09)
Diff. - Diff.	-0.13	-0.46*	0.32	0.32	-0.04	0.36**
	(0.23)	(0.25)	(0.25)	(0.21)	(0.13)	(0.18)

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**
	(0.09)	(0.07)	(0.08)	(0.31)	(0.07)	(0.15)
Non-ICC fund portfolio	0.78***	-0.07	0.84***	0.9***	0.00	0.9***
	(0.06)	(0.05)	(0.04)	(0.07)	(0.05)	(0.006)
Diff. - Diff.	0.18	0.02	0.21**	-0.14	0.00	-0.14
	(0.11)	(0.08)	(0.10)	(0.32)	(0.08)	(0.32)

Panel C Connection-based information acquisition activities

	Log (#SEC Downloads)
Log (# Followers to ICC-related new positions)	0.0115***
	[2.62]
Log (# Funds holding matched Stocks in connected fund portfolio)	-0.0012
	[-0.36]
Log (# Funds holding remaining stocks in focal fund portfolio)	0.0516***
	[17.59]
Time_FE	Yes
Stock_FE	Yes
Adj. R-squared	0.806
Stock-month Obs	1,060,828

Table 8 Portfolio-leader-based ICC

This table reports results based on the portfolio-leader-based identification of ICC. The portfolio-leader managers are hand collected from the SEC fund prospectus filings, and the ICC is computed as in (6) and divided by 10000. Panel A provides multivariate evidence on portfolio similarity between ICC funds (treated) and their connected funds. The specification and control variables are as in Table 2. Panel B reports results from panel regressions of fund performance on contemporaneous portfolio-leader-based ICC and covariates that are at the fund level, team level as well as family level, as in Table (3). Panel C reports the results of the subsample tests in Table 6. All the independent variables are as described in Table A1. Time fixed effects are calendar year-month fixed effects. Style fixed effects are based on nine Morningstar investment styles. Fund families are identified by CRSP management company codes.

Panel A Portfolio-leader-based ICC and Fund Average Portfolio Similarity Score

	$Similarity\_Avg_{i,t}$	$Similarity\_Avg_{i,t}$	$Similarity\_Avg_{i,t}$
$ICC\_leader_{i,t}$	387^{**}	395.10^{**}	385.61^{**}
	[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

	$\alpha_{i,t}^{4F}$	$\alpha_{i,t}^{4F}$	$\alpha_{i,t}^{4F}$	$\alpha_{i,t}^{4F}$
$ICC\_leader_{i,t}$	11.27^{***}	7.46^{***}	7.32^{***}	6.65^{***}
	[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
	$\alpha_{i,t}^{4F}$	$\alpha_{i,t}^{4F}$	$\alpha_{i,t}^{4F}$	$\alpha_{i,t}^{4F}$
$ICC\_leader_{i,t}$	7.22^{***}	-5.25	19.76^{***}	2.82
	[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 Performance Effect of Alternative Work Ties

This table reports the results of the performance effect between family information sharing (FIS) and ICC. FIS is the number of top-AUM managers from the same-style funds within the same fund family. Panel A reports the key summary statistics of FIS. Panel B reports the results for regression as identified in (2). Control variables are the same as in Table 3. Time fixed effects are calendar year-month fixed effects. Style fixed effects are based on nine Morningstar investment styles. Fund families are identified by CRSP management company codes. The t-statistics are reported in parentheses. *, **, *** indicates significance level at 10%, 5%, and 1%, respectively.

Panel A Summary Statistics of FIS

FIS	Fund_month obs.	Mean	Std. Dev.	25th Pctl.	50th Pctl.	75th Pctl.
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

	(1) $\alpha_{i,t}^{4F}$	(2) $\alpha_{i,t}^{4F}$	(3) $\alpha_{i,t}^{4F}$
$ICC_{i,t}$	0.425**		0.412**
	[2.49]		[2.39]
$FIS_{i,t}$		0.224	0.159
		[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

This table reports the results of a validation test for the DiD estimations. The identification is in (3) with changed dependent variables. The dependent variable of the first four models is ICC, and the dependent variable of the last two models is Busyness. $\text{Treated} = 1$ means that there are superstars leaving attached funds within the event window. The identification of superstars is as described in Table 4. The control funds are selected through three-to-one propensity score matching and have $\text{ICC} = 0$. The variables for PSM are Log (TNA), Log (Age), Expense ratio, $\sigma_{t-12,t-1}$, Flow, $\text{Ret}_{t-12,t-1}$ Log (Family TNA), Log (Team TNA), Team size, α^{3F}, α^{3F} activeness, α^{4F}, α^{4F} activeness, α^{5F}, and α^{5F} activeness. $\text{Post}_t = 1$ means that the superstar departure events have happened. The control variables are the same as in Table 2. Time fixed effects are calendar year-month fixed effects. Style fixed effects are based on nine Morningstar investment styles. Fund families are identified by CRSP management company codes. The t-statistics are reported in parentheses. *, **, *** indicates significance level at 10%, 5%, and 1%, respectively.

	(1) $\text{ICC}_{i,t}$	(2) $\text{ICC}_{i,t}$	(3) $\text{ICC}_{i,t}$	(4) $\text{ICC}_{i,t}$	(5) $\text{Busyness}_{i,t}$	(6) $\text{Busyness}_{i,t}$
$\text{Treat}_i * \text{Post}_t$	-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]
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

This table reports the results of placebo tests. The specification is as described in (2), and the sample is index funds. The dependent variables are the fund Fama-French three factor alpha, Fama-French-Carhart four factor alpha, and Fama-French five factor alpha, with factor loadings estimated on rolling past 12-month windows. Controls are the same as in Table 3. Time fixed effects are calendar year-month fixed effects. Style fixed effects are based on nine Morningstar investment styles. Fund families are identified by CRSP management company codes. The t-statistics are reported in parentheses. *, **, *** indicates significance level at 10%, 5%, and 1%, respectively.

	(1) $\alpha_{i,t}^{3F}$	(2) $\alpha_{i,t}^{4F}$	(3) $\alpha_{i,t}^{5F}$
$\text{ICC}_{i,t}$	-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 1A Illustration of Interfund Comanager Connection

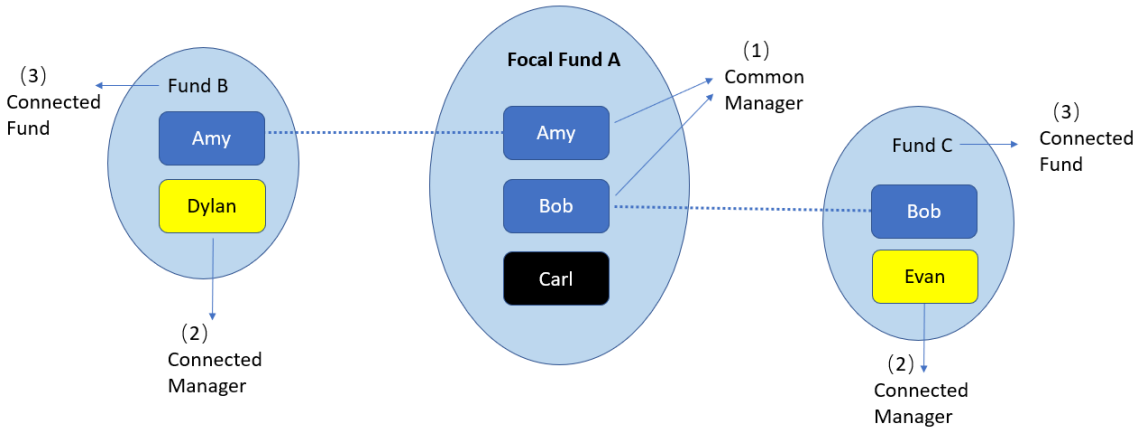


Figure 1B Prevalence of Manager-Connected Funds (MCFs)

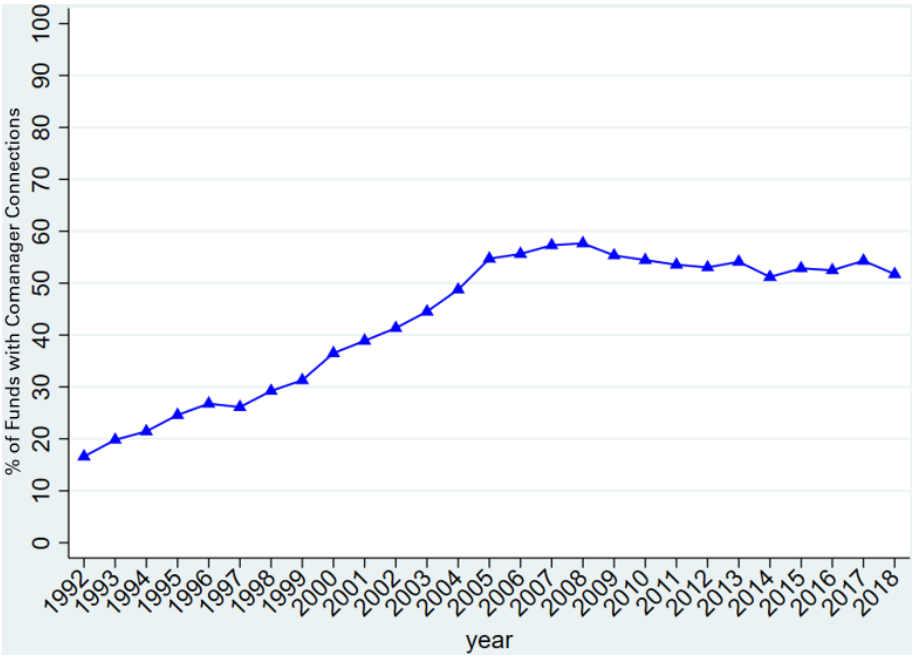


Figure 2A Illustration of ICC Computation for a team-managed MCF

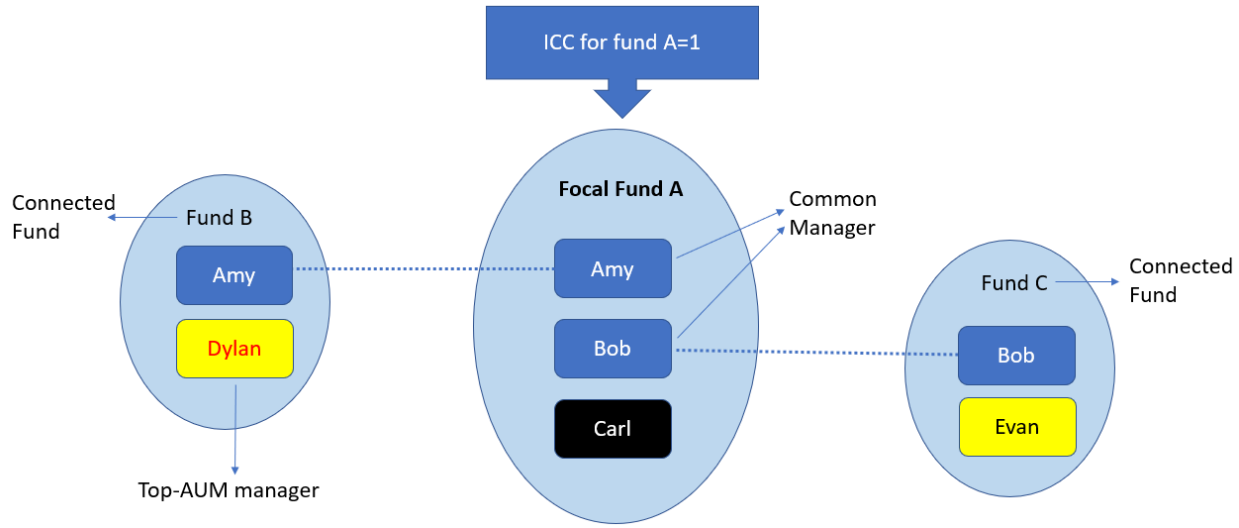
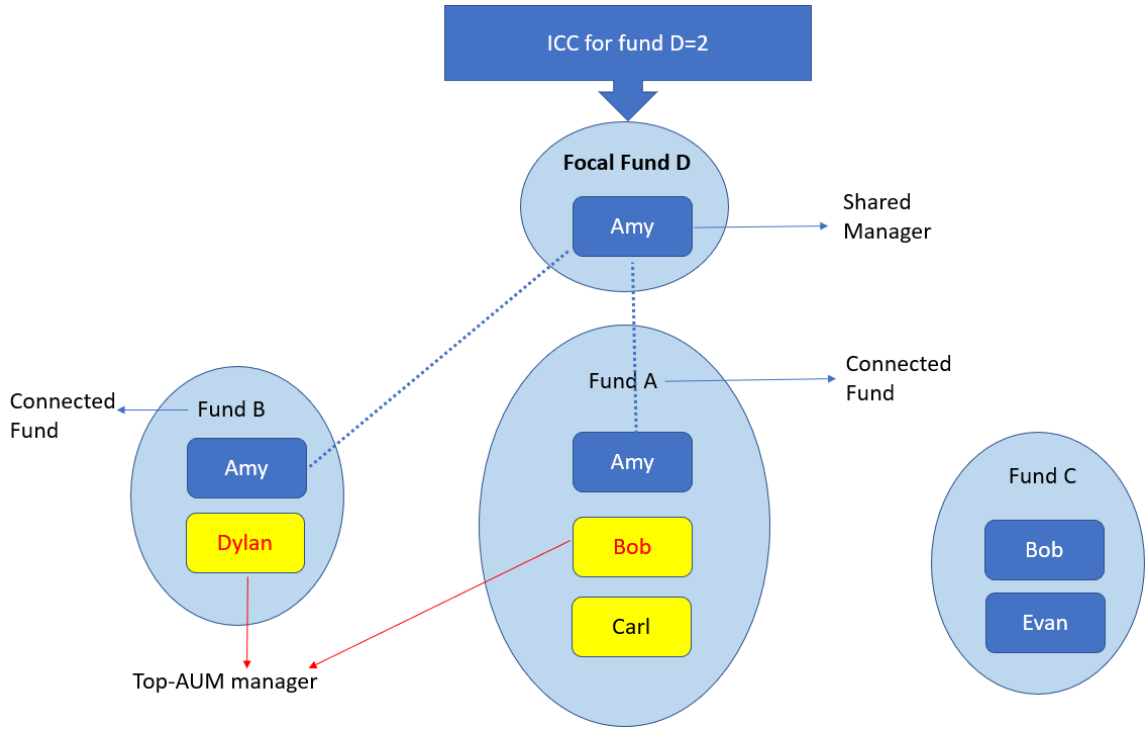


Figure 2B Illustration of ICC Computation for a solo-managed MCF



Appendix

Table A1 Variable Definitions

This table contains a description of all variables used in my 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_lead	Number of team leader fund managers connected to a fund via common managers.	MS, SEC
alpha_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 ratio (%)	Fund total expense.	CRSP
Turnover (%) (annual)	Fund annual turnover.	CRSP
alpha_4f activeness (%)	1 – R-squared of the Fama-French-Carhart four-factor model. Estimation is based on past 12-month rolling windows.	CRSP
Ret_t-12_t-1	Past 12-month fund accumulative return.	CRSP
Sigma_t-12_t-1	Past 12-month fund return volatility.	CRSP
Flow_t-12_t-1	Past 12-month fund flow.	CRSP
Log (Family TNA)	Log of fund family TNA.	CRSP
Log (Team TNA)	Log of a manager team's TNA.	CRSP
Team size	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
#SEC Downloads	Number of SEC file downloading.	SEC
# Followers to ICC-related new positions	Number of funds newly buy the stock by following ICC-related funds.	SEC, MS, Refinitiv
# Funds holding matched Stocks in connected fund portfolio	Number of connected funds that buy control stocks.	SEC, MS, Refinitiv
# Funds holding remaining stocks in focal fund portfolio	Number of focal funds that buy the stock not through following their ICC-related funds	SEC, MS, Refinitiv

Table A2 Subsample distribution of ICC

All	Fund_month Obs	Mean	Std Dev	25th Pctl.	50th Pctl.	75th Pctl.
ICC	312,310	1.49	4.08	0	0	1
ICC_pos	84,572	5.5	6.29	1	3	7
ICC_[1,4]	55,122	1.87	1.03	1	2	3
ICC_[5,8]	11,458	6.14	1.09	5	6	7
ICC_[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 A1.1 Team-managed funds versus manager-connected funds (MCFs)

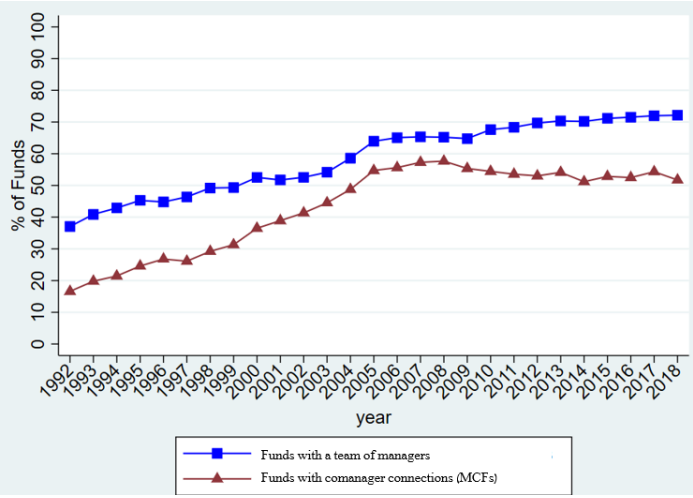


Figure A1.2 MCFs versus ICC funds

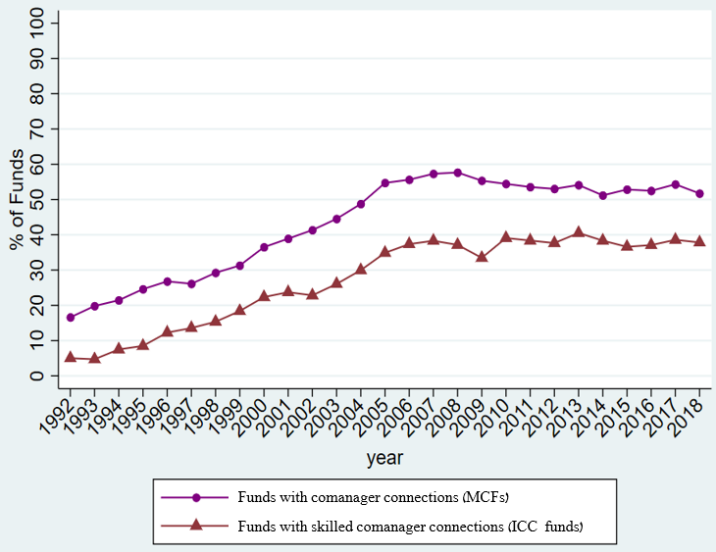


Figure A1.3 MCFs versus multi-team-manager fund

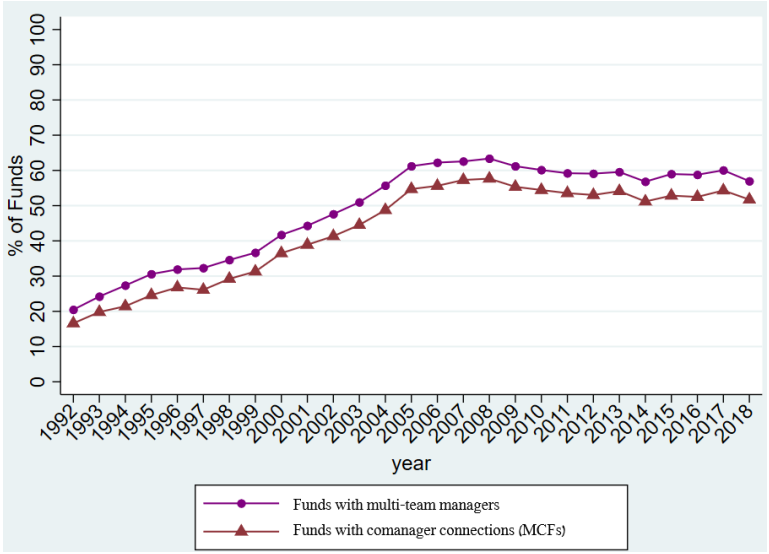
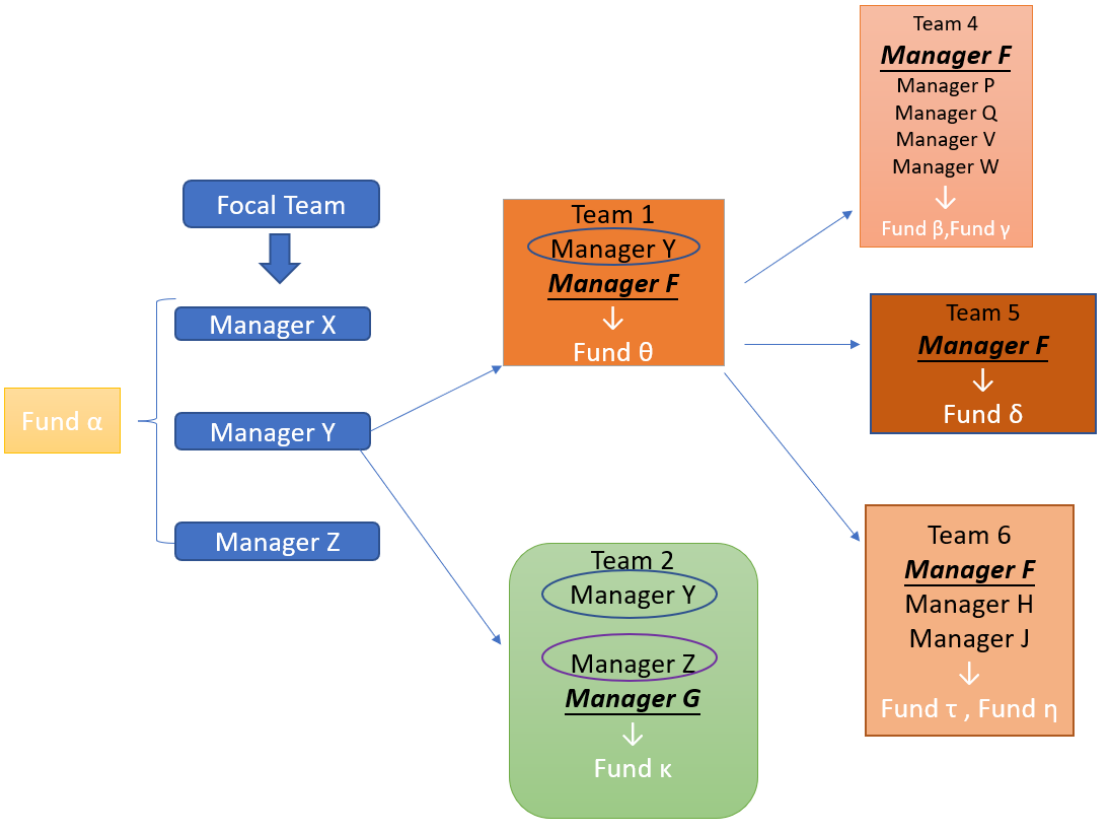


Figure A2. Illustration of computing manager AUM (MgrAUM) for the ICC measure



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

Figure A3. Pooled- and within-fund variation in ICC