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ABSTRACT

This paper explores how informal information channels impact the investment performance of mutual funds. We measure the strengths of two specific information channels linked to the geographical location of fund managers: information transfers among managers (fund-fund links), and between fund managers and the companies in which they invest (fund-company links). We analyze the marginal impact of these information channels on abnormal returns generated from stock holdings. We find that each channel increases investment performance in the absence of the other. Investment performance is reduced when the two information channels act in combination, an effect that appears to be driven by "crowded trades" that reduce profitability. The stock selections that are associated with the presence of one information channel but the absence of the other earn positive future returns. Overall, our results show that the economic benefits of informal information channels depend critically on the nature of their interactions.

1. Introduction

In financial markets where significant frictions exist in the dissemination of information, investors may acquire differential information through unobserved informal channels. Though these channels are typically opaque to outside observers, researchers have begun to theoretically and empirically characterize channels that might impact investors' belief formation and decision-making. In particular, recent studies on mutual funds provide growing evidence on the presence of informal communication among market participants who are "neighbors", i.e. located in social and geographical proximity.[2] For example, fund managers could have easier access to information about local companies as they can readily visit the operations, talk to employees, or collect information through their friends, acquaintances and associates in the local community, giving them information advantages over managers in distant locations (see Coval and Moskowitz (2001)).[3] Similarly, Hong, Kubik and Stein (2005) posit that fund managers could obtain information about asset prices by "word-of-mouth" from their professional peers located in geographical proximity, resulting in correlated strategies among managers in the same city.[4]

Building on the existing literature, we focus our attention on two informal information channels known to be associated with mutual fund managers' portfolio decisions: (1) *fund-fund* links, which transfer information between fund managers about potential investment opportunities; and (2) *fund-company* links, where the fund's geographical proximity to the company's headquarters facilitates the acquisition of information about the company. Like several prior studies, we use measures based on geographical distance to proxy for the existence of informal information channels. The main departure of

[2] For empirical evidence on informal communication in financial markets, see Garmaise and Moskowitz (2003), Shiller (2000), Hong, Kubik and Stein (2004), and Duflo and Saez (2002, 2003). For theoretical studies drawing attention to the impact of social communication on asset prices, see Ozsoylev (2005), and Colla and Mele (2009).

[3] Ivković and Weisbenner (2005), Massa and Simonov (2006), and Ivković, Sialm, and Weisbenner (2008) also find similar evidence. Also see Parwada (2008) who uses a sample of entrepreneurial fund managers to show that the managers tend to locate near their former employers, perhaps to access professional, social, and family networks.

[4] Some other studies also uncover effects of informal communication in investment decisions. Ivković and Weisbenner (2007) find word-of-mouth communication among individual investors as reflected in the trades of neighbors. Ng and Wu (2010) find similar evidence for investors in the same trading room. Duflo and Saez (2002,

our study from existing studies is that we use an empirical setting that accounts for more than one information channel simultaneously, thereby allowing us to disentangle the performance implications of each information channel in isolation and in combination with other channels. We argue that it is important to analyze the effects of these information channels in an integrated setting because, as we further discuss below, various strands of research suggest that the economic impact of informal information channels varies depending on the volume and nature of communication. In addition, our main aim is to infer the performance implications of informal information channels in financial markets, whereas several related studies (e.g. Hong, Kubik, and Stein (2005)) have mainly focused on documenting the existence of such informal communication.[5]

The economic value of informal communication remains an ambiguous issue in the literature. Empirical studies such as Coval and Moskowitz (2001) suggest that certain types of informal communication enhance investment performance. Stein's (2008) model shows that communication among competitors (e.g. mutual fund managers) can increase the value of investment ideas. Bala and Goyal (1998) develop models of information transmission and, under certain conditions, predict that agents arrive at optimal decisions in the presence of communication. Overall, these studies predict that investment performance increases with informal communication.

In contrast, Stein (2009) posits that "crowded trades" may reduce performance when too many investors act on similar information. Along similar lines, Colla and Mele (2009) and DeMarzo, Vayanos, and Zweibel (2001) predict that information exchanges have a detrimental impact on the informed traders' profitability when the information signals transmitted to the traders have positive correlations. Ellison and Fudenberg's (1995) model of word-of-mouth communication concludes that boundedly rational agents who communicate via word-of-mouth achieve efficient outcomes only if they each receive little information, suggesting a negative relationship between the quantity of communication and the

2003) document the impact of social interactions on individuals' retirement plan decisions. Feng and Seasholes (2004) document correlated trading among investors in the same region.

efficiency of outcomes.[6] To summarize therefore, these papers predict that more informal communication received by portfolio managers can diminish investment performance.

Given the ambiguity in the literature, the economic value of informal communication is an empirical issue that this paper addresses by focusing on mutual funds' investment performance. Using a large sample of holdings of actively managed equity mutual funds in the U.S., we show that stronger informal information links have a significant impact on the fund manager's stock selection ability.[7] However, whether an informal information channel enhances or diminishes the profitability of investments depends critically on the nature (i.e. presence or absence) of other informal channels. We show that the investments associated with stronger fund-fund (fund-company) communication channels generate an *outperformance* of about 2.91% (3.02%) in annualized characteristic-adjusted returns in the absence of the other information channel. These findings are consistent with the value-added effects of informal channels on investment decisions documented by studies like Coval and Moskowitz (2001). In striking contrast, fund-fund (fund-company) information links are associated with a substantial *underperformance* of about -3.74% (-3.63%) in annualized characteristic-adjusted returns when they act in combination with the other informal communication channel.

To further investigate the mechanism behind the finding that investment performance decreases with the volume of information, we calculate two measures, the absolute dollar-ratio trade imbalance and the herding measure, to capture the propensity of correlated trades using the methodology in Lakonishok et al. (1992) and Wermers (1999). Our results based on these two measures provide evidence that "crowded trades" could explain the underperformance when strong fund-fund and fund-company channels aggregate, since Stein (2009) suggests that profitability dissipates when crowded-trades occur. Consistent

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[5] As stated in Hong, Kubik, and Stein (2005),"…[our approach] does not allow us to determine whether fund managers are passing along "irrationally exuberant" sentiment to their nearby colleagues, or real information about fundamentals."

[6] This notion is also consistent with cognitive studies showing that human beings find it difficult to combine a lot of information simultaneously (Tversky and Kahneman (1974), Hogarth (1980), Abdel-Khalik and El-Sheshai (1980)). Some other related studies on informal communication include Bikchandani, Hirshleifer, and Welch (1992) and Cao, Han, and Hirshleifer (2011), which posit that it is possible for economic outcomes to be suboptimal when communication occurs.

with less reputed fund managers having less access to valuable informal communication, the marginal benefits of both fund-company and fund-fund information links are smaller for funds from small families than for those from large families. Results are similar across subsamples based on fund size. The effect of the concentration of funds in geographical clusters that facilitate fund-fund information channels is not subsumed by the "big city effects" (i.e., effect of population concentration) documented by Christofferson and Sarkissian (2009). Our results are robust to multivariate analyses which include a variety of model specifications and control variables.

Overall, we find that the holdings with ex-post superior performance are those associated with (1) strong fund-company information links in the absence of fund-fund channels, and (2) strong fund-fund information links in the absence of fund-company channels. Based on these stylized results, we conduct an initial examination of possible information that can be inferred about future asset prices from the investment choices of fund managers. Using fund holdings reported at the end of a quarter (which is stale information for all subsequent quarters), we construct a hypothetical portfolio of stocks associated with the two information settings that generate superior characteristic-adjusted returns. We call this the Best Information Portfolio (or BIP). The BIP replicates the equal-weighted holdings of the two superior information portfolios from the previous quarter, and holds it in subsequent quarters. For a wide range of holding periods, we find significant average monthly returns ranging from 1.35% to 1.81% for the BIP, and the returns remain significant even after adjusting for risk attributes. These results suggest that the stock selections made by fund managers among stocks associated with certain informal communication channels predict the future performance of those stocks.

This study broadly contributes to the literature on informed trading and informal communication in financial markets. We offer fresh empirical evidence on the effects of informal information channels on investment performance, an area where empirical evidence remains scarce. To the best of our knowledge, this study is the first to examine multiple information channels linked to the geographical location of

[7] Throughout the paper, we use the notion of "strength" of information flows in the context of volume (or quantity) of information flows, while remaining agnostic about the quality implications.

mutual funds in a unified empirical setting, and to provide empirical evidence on the effects of the aggregation of informal communication. The results point to the important distinction between volume versus quality of informal communication− an aspect of information channels that is little understood in the context of financial markets. Overall, our findings characterize the conditions under which information channels related to geographical location add value for fund managers, but also reveal more complexity in information settings than acknowledged in previous empirical papers.

The paper is organized as follows. Section 2 describes the data and methodology. Results are presented in section 3. Section 4 ends with concluding remarks.

2. Data and Methodology

A. Sample Description

The primary data source used in this study is the CRSP Survivor-bias Free U.S. Mutual Fund Database (MFDB), supplemented by data collected from other publicly available sources. CRSP MFDB added data on the location of management companies starting in 2000, with the availability of this data increasing in more recent years. For each fund listed in CRSP MFDB, we identify the fund's location as the city and state provided for the fund's management company. Our initial sample consists of U.S. mutual funds investing in domestic stocks for which we were able to find location information in our sample period from the last quarter of 2003 to that of 2010. As is standard in the literature, we exclude index, sector, international and bond funds, and funds that are not run by the same management company as the majority of funds in the same fund family.

In addition, we apply several other selection criteria to form our final sample. First, we only choose equity funds primarily investing in domestic equity having "growth", "aggressive growth", "growth and income", or "balanced" as stated objective categories.[8] We exclude the funds with less than $5 million

[8] The main results remain materially unchanged if we exclude balanced funds from the sample.

total net assets. Our final sample consists of 2,931 unique equity funds spanning 571 fund families for which we have the headquarter location.[9]

Next, we obtain the holdings data for the mutual funds in our final sample from the CRSP Holdings database. The CRSP Holdings database, introduced in 2005, gathers details of quarterly holdings dating back to July 2003 and uniquely maps to other CRSP fund data via ICDI codes. Portfolio holdings in a quarter are disclosed some time during the three months in the next quarter. For the stocks in the holdings database, we obtain the headquarter location of the company from the COMPUSTAT database.

The CRSP Holdings database assigns a portfolio code to each unique portfolio. We consolidate multiple ICDI codes representing different share classes of the same fund to the unique portfolio code, if the underlying portfolios are identical. We then merge portfolio data with fund characteristics data like monthly total net assets and management company. Finally, we obtain stock price and returns data for the portfolio companies from CRSP monthly stock files. The U.S. Census Bureau's Gazetteer geographical data provides the latitude and longitude coordinates of the cities where the funds and companies are headquartered, where these coordinates are then used to calculate the geographical distances between each pair of cities.

Table I presents summary statistics on the sample of funds and the characteristics of the stocks they hold. The median fund size (i.e. total net assets) in the sample is \$226.1 million and fund age (based on the first offer date) is 10 years. Since our metrics of informal information links are based on geography, we report a summary geographical distribution of the portfolio companies and funds in Table I as well. In the median fund portfolio, 5.41% of the total amount invested in domestic equity holdings is concentrated in stocks of companies less than 100 km away from the fund location. Over half (66.72%) of the total amount invested is in companies more than 1000 km from the fund. For the median fund in the sample, 10.23% of funds are located within 100 km distance of each other, while 60.03% are located more than

[9] The main fund identifier in CRSP is the ICDI code. However, CRSP assigns multiple ICDI codes to different share classes of the same fund. We prevent erroneous counting of funds by merging information of multiple ICDI codes representing the same fund into one unique fund. We only include stock holdings of publicly traded companies

1000 km apart.[10] While the mutual fund industry may be concentrated in a few cities, there is substantial dispersion in the data to allow for an examination of differences in location characteristics.

Table I also reports summary statistics on the stocks held in mutual fund portfolios during the sample period. The median fund portfolio holds 74 stocks, with a median company age of 37 years. We report the characteristics of the stocks along the three style dimensions in Daniel, Grinblatt, Titman and Wermers (henceforth DGTW) (1997), namely, size, book-to-market ratio and momentum. The median stock holding in a value-weighted DGTW size quintile is 4.21, indicating that mutual funds on average concentrate their portfolios in larger companies. The median value-weighted DGTW book-to-market (B/M) quintile of stocks held is 2.50, suggesting that mutual funds in the sample have dispersed investments across growth and value stocks. The median fund shows a preference for stocks having higher past returns by investing in stocks slightly above the third DGTW momentum quintile.

B. Methodology

This section describes the empirical methodology used in this study. We first outline a method for measuring information channels and then the framework to test their performance implications.

B.1. Measuring information channels

Ideally, data on real information channels via which each fund manager receives communication about investment opportunities would be employed to study the impact of informal communication on performance. However, it is extremely hard to pinpoint specific information sources with available data. Researchers have used various proxies for unobservable communication channels, like shared educational backgrounds (see Cohen, Frazzini and Malloy (2008)), neighborhood effects, and geographical proximity.

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headquartered in the U.S. and have stock returns data available from CRSP, and exclude other assets held in the portfolios.

[10] Note that the geographical distribution of mutual funds is reported in terms of frequency, and not as aggregated dollar amounts managed by the universe of funds. This is because in order to operationalize the metrics of information flows among fund managers, each fund manager is considered a potential network link and can transfer information, irrespective of the size of the funds they manage.

In this paper, we use measures of the *likelihood* of strong information channels based on geographical proximity.

(i) Fund-Fund (FF) Links

We first consider information channels between a fund manager and other managers investing in similar asset classes (in this case, domestic stocks). Hong, Kubik and Stein (2005) show proximately located mutual fund managers are more likely to engage in informal communication. We focus on information channels between fund managers from different fund families and explore the issues of intra-family information exchanges separately in later sections.

Based on this premise, we measure the likelihood of fund-fund (hereafter *FF*) information links between fund manager *j* and fund manager *i* as

$$L^{FF}(Links)_{j,i} \quad = \quad \frac{1}{(1 \,+\, Distance_{j,i})} \tag{1}$$

Here, $Distance_{j,i}$ is the natural logarithm of the geographical distance between the city locations of fund *j* and fund *i*, plus one. The likelihoods of *FF* information channels between a fund manager and all other fund managers who do not belong to the same fund family are then aggregated for each fund in the sample. This provides an estimate of the quantity (or density) of communication a fund manager *j* has with other fund managers as

$$(Links)_j^{FF} = \sum_{i=1}^{N} L^{FF}(Links)_{j,i} = \sum_{i=1}^{N} \frac{1}{(1+Distance_{j,i})} \tag{2}$$

Here, $i=1,\ldots,N$ are all funds in the sample that do not belong to the same fund family as fund *j*.

Finally, we sort all funds in each quarter by the measure of *FF* information links ($Links^{FF}$) and rank them into quartiles. The funds in the lowest quartile in a quarter are considered to be the funds with weak *FF* information links ($Q^{FF,weak}$), while funds in the highest quartile are considered to be the funds with strong *FF* information links ($Q^{FF,strong}$). Note that the notion of "strength" is based on density of information links, and we do not make any assumptions about the precision or quality of the communication.

A few caveats are in order regarding the measure of fund-fund information links used in this study. This measure includes only the funds in our sample, which is restricted based on various criteria like active management and predominantly domestic equity investments, among others. It does not account for all information links involving managers in the universe of mutual funds. For example, while a sector fund manager is excluded from the sample, she may be an information source for a manager included in the sample. However, we believe that the above measure of fund interactions is highly correlated with a similar measure derived from the universe of money managers, since the geographical cluster patterns are unlikely to change significantly. Likewise, the relative comparison of location-based interactions is also unlikely to change substantially.[11]

A second confounding effect that may impact the precision of measuring the information linkages is the issue of relocation and manager turnover. If information links arise out of a manager's networks and interactions, it is possible that they remain with the manager after she relocates. In that case, a manager "carries" the links wherever she goes. For instance, if a fund manager relocates to Iowa after many years as a Boston-based manager, it is possible that she continues to have access to information links in the Boston area that are not accounted for by the measures used. In fact, Parwada (2008) finds evidence indicating that fund managers who relocate continue to exhibit a preference for the formerly local stocks. Two crucial factors mitigate this problem in our empirical setting. First, our relatively shorter sample period makes the issue of relocation and turnover unlikely to be a substantial oversight. More importantly, while relocation or turnover may create noisy measures of information linkages, these events increase the similarity across information settings of managers in different locations. Similar to the effect of a fund's research houses not located in the fund's city, this likely causes a bias against finding systematic differences in the effect of geography-based information channels.

[11] We calculated an alternative fund-fund (*FF*) link measure including sector funds. The alternative measure has a correlation close to one with the *FF* measure used in the study.

(ii) Fund-Company (FC) Links

The second type of informal communication considered in this paper is that between fund managers and companies in which they invest. We measure these fund-company (hereafter *FC*) information links for each stock in a fund's portfolio in a given quarter. The likelihood of a *FC* information channel existing between fund manager *j* and the stock *n* held in *j*'s portfolio is

$$L^{FC}(Links)_{j,n} = \frac{1}{(1+Distance_{j,n})} \tag{3}$$

Here, $Distance_{j,n}$ is the natural logarithm of the geographical distance between the city locations of fund *j* and company *n*, plus one.

Next, we sort the stocks in each fund's portfolio in each quarter by measures of *FC* information links ($L^{FC}(Links)$) and rank them into quartiles. Within each fund's portfolio, the lowest *FC* quartile is considered the information portfolio with the weakest fund-company links ($Q_j^{FC,weak}$). On the other hand, the holdings in the highest *FC* quartile are considered to be the portfolio of stocks with the strongest fund-company information links ($Q_j^{FC,strong}$). We rescale to sum to one the portfolio weights of the holdings within each quartile, thus creating four portfolios for each fund manager in each quarter. We also consider alternative rankings, like deciles and quintiles, which generate qualitatively similar results.

Our main metric of the strength of fund-company links has a continuous range as opposed to Coval and Moskowitz's (2001) dichotomous local versus non-local status of holdings.[12] The main distinction of our setting is that a part of each fund's portfolio is guaranteed to be regarded as relatively proximate by definition, while Coval and Moskowitz (2001) allow for managers to not have any local stock holdings. For example, a fund manager located in Alaska may have the nearest holding in a company headquartered 500 km away and this holding may be categorized in the nearest *FC* quartile in our setting. In contrast, a New York manager's nearest *FC* quartile may only be comprised of companies located within 100 km.

While we consider the dichotomous measure for robustness checks, we retain the continuous measure of $L^{FC}(Links)$ as our main metric for two reasons. First, the dichotomous measure of localness, by definition, is likely to be a restrictive measure when used to proxy for the intensity of information channels in geographical proximity. In contrast, our continuous variable can better measure the potential information links attributable to geographical proximity beyond the threshold of "localness". Specifically, regional externalities like public transportation, regional educational and business networks, among other factors may facilitate an elevated level of information exchanges and interactions beyond the customary 100-kilometer (km) threshold for the dichotomous variable. For example, Amtrak's Northeast Corridor (NEC) is a well-developed high-speed train system connecting Boston, New York City, Washington D.C., etc. in the region. While most of these cities are more than 100 km apart in geographical distance, they are well-connected by public transportation and facilitate frequent travel for business meetings and conferences. The pairwise likelihood of economic interactions between two fund managers located in the NEC coverage area may be substantially higher than between a manager from these areas and one from the West Coast, either due to ease of transportation, commonalities in economic networking events (like asset management conferences), or shared educational backgrounds. Second, our continuous measure allows for the fact that managers who do not have enough investment opportunities within 100 km may increase their effort in acquiring information on the relatively proximate holdings.

B.2. Measuring marginal impacts of information channels

Based on the empirical metrics of information channels discussed previously, we develop a framework of studying marginal impact of informal information channels (fund-fund and fund-company) on fund performance. Our goal is to empirically disentangle the impact and investigate the interactions between these two informal information channels in the context of investment performance.

[12] In unreported robustness checks, we use Coval and Moskovitz's binary measure and the results are qualitatively similar.

Figure 1 presents the outline of our information metric in a univariate setting. We form four groups of investments by assigning them to portfolios *P1, P2, P3* and *P4.* The funds having strong (weak) fund-fund links form the quartile group $Q^{FF,strong}$ ($Q^{FF,weak}$). Here, $Q^{FF,strong}$ is the highest quartile, Q_4^{FF}, ranked by measures of *FF* links, and $Q^{FF,weak}$ is the lowest quartile Q_1^{FF} ranked by measures of *FF* links. Within each fund *j*'s portfolio, the stocks with strong (weak) fund-company links form the quartile group $Q_j^{FC,strong}$ ($Q_j^{FC,weak}$). Here, $Q_j^{FC,strong}$ is the highest quartile Q_4^{FC} ranked by measures of *FC* links, and $Q_j^{FC,weak}$ is the lowest quartile Q_1^{FC} ranked by measures of *FC* links.

In Figure 1, the main portfolios of interest ranked based on *FF* and *FC* information links are:

- Portfolio *P1:* Portfolio of funds with weak *FF* links ($Q^{FF,weak}$) investing in stocks with strong *FC* links ($Q_j^{FC,strong}$).
- Portfolio *P2:* Portfolio of funds with weak *FF* links ($Q^{FF,weak}$) investing in stocks with weak *FC* links ($Q_j^{FC,weak}$).
- Portfolio *P3:* Portfolio of funds with strong *FF* links ($Q^{FF,strong}$) investing in stocks with strong *FC* links ($Q_j^{FC,strong}$).
- Portfolio *P4:* Portfolio of funds with strong *FF* links ($Q^{FF,strong}$) investing in stocks with weak *FC* links ($Q_j^{FC,weak}$).

Developing these categories of information channel combinations lays the foundation for disentangling the performance impact of different information channels using empirical data. The manner of construction ensures that each fund in each *FF* quartile has at least one stock holding that can be assigned to the four fund-company quartiles based on *FC* information channels. For example, in Figure 1 the holdings in portfolio *P1* are located relatively close to the fund, and have a higher likelihood of fund-company communication, compared to stocks in portfolio *P2,* which are geographically distant and likely to have fewer information transfers. So, the information processes related to portfolio *P1* may be different from *P2* by the additional fund-company information links that are present in *P1*, but absent in *P2*. Note that the method of disentangling *FC* information channels makes it possible to avoid confounding effects due to heterogeneities in other fund-, manager-, family- and time-specific factors. Similarly, portfolio *P1* is different from *P3* in that *P3* is associated with fund-fund information channels generating an additional informal link, while *P1* is not. While it is necessary to make comparisons across funds to observe the marginal impact of *FF* information links, doing so introduces other confounding fund-specific factors, like managerial skills, to the analysis. Therefore, we later perform further bivariate and multivariate analyses to compare funds that have similar attributes along dimensions other than information channels. It is also interesting to note that in this framework, portfolio *P2* can be viewed as a control group with the lowest density of both forms of informal communication.

Following DGTW (1997), we compute the characteristic-adjusted return (i.e. DGTW return) which measures a fund manager's stock selection ability. We use the DGTW return as the main measure of return in this paper. Our main objective is to uncover the impact of informal communication on fund managers' before-cost investment ability in specific investments, so we do not examine after-cost net returns that mingle the effects of manager skills, fees, and transaction costs. For each fund in quartiles Q_1^{FF} through Q_4^{FF}, we compute the mean monthly raw returns for the quartile subportfolios Q_1^{FC} through Q_4^{FC} in each quarter as

$$\mathrm{R}^{\mathrm{raw}} = (1/3) * \sum_{i=1}^{S} \sum_{t=1}^{3} w_{i,t} R_{i,t} \tag{4}$$

Here, $w_{i,t}$ is the portfolio weight of stock *i* in month *t* in that information portfolio, and *S* is the number of stocks in the portfolio.[13] Similarly, we compute characteristic-adjusted information portfolio returns for each fund in each quarter as

[13] Using equal weight yields qualitatively similar results.

$$R^{adj} = (1/3) * \sum_{i=1}^{S} \sum_{t=1}^{3} w_{i,t} (R_{i,t} - R_i^{bench}) \tag{5}$$

Here, R_i^{bench} is the value-weighted monthly return of stock *i*'s DGTW benchmark portfolio (following Daniel et al. (1997)).[14] The differences in the portfolio returns form the basis of first studying the marginal impact of these information channels in a reduced form setting. The baseline analyses identify the marginal impact of informal information links as follows:

- For holdings with strong *FC* channels, the difference in characteristic-adjusted returns $R^{adj}(P3)$-$R^{adj}(P1)$ between the portfolios *P3* and *P1* reflects the marginal impact of *FF* information links.
- For holdings with weak *FC* channels, the difference $R^{adj}(P4)$-$R^{adj}(P2)$ between the portfolios *P4* and *P2* gives the marginal impact of *FF* information links.
- For the funds with weak *FF* channels, difference $R^{adj}(P1)$-$R^{adj}(P2)$ measures the marginal performance impact of *FC* information links for the fund.
- For the funds with strong *FF* channels, $R^{adj}(P3)$-$R^{adj}(P4)$ measures the marginal impact of *FC* information links for the fund.

Finally, we report the value-weighted average returns (weighted by TNA) across funds in order to provide conservative estimates that avoid results driven by small funds.

3. Results

In this section, we present the empirical results on the relationship between informal information channels and the stock selection ability exhibited by mutual fund managers in specific information settings.

[14] Daniel et al. (1997) construct the benchmark portfolios using the three stock characteristics that best explain the cross-section of stock returns, namely, size, book-to-market equity (BE/ME) and momentum (past 12 months). A three-way sort is done where stocks are first sorted into size quintiles, then stocks in each size quintile are sorted into BE/ME quintiles, and finally stocks in each BE/ME quintile are sorted into momentum quintiles. As a result, 125 value-weighted benchmark portfolios are developed where each stock held by a mutual fund can be assigned to one of the 125 groups based on their size, BE/ME and momentum characteristics in the month prior to the beginning of the quarter in which they are held, and the matched group serves as the benchmark. For more on stock

A. Summary statistics: Portfolio characteristics

Table II reports summary statistics of the funds and stock holdings for a 4x4 matrix of portfolios formed from the two information channels. In Panel A, we report various fund characteristics for the group of funds forming the four *FF* quartiles. Funds with strong *FF* measures (quartile $Q4^{FF}$) tend to be larger and somewhat younger than those with weak *FF* measures (quartile $Q1^{FF}$). However, expenses and turnover are similar across the different *FF* quartiles. The number of funds managed by the fund family is substantially more for funds in $Q4^{FF}$ (median of 59 funds) compared to those in $Q1^{FF}$ (median of 28 funds). Managers of funds in $Q4^{FF}$ tend to have shorter tenures than fund managers in $Q1^{FF}$.

Panel B presents the portfolio characteristics of the stocks that form the *FC* quartiles for the funds in different *FF* quartiles. The overall DGTW size, book-to-market and momentum factors across the portfolios appear comparable. Based on the value-weighted averages reported, most of the portfolios hold stocks around the fourth DGTW size quartile, between the second and third DGTW B/M quartile, and third DGTW momentum quartile. These summary statistics seem to indicate that fund managers on average hold stocks of similar characteristics (on a dollar-weighted basis) across different *FF* and *FC* information portfolios. The percentage of portfolio dollars invested across the different information portfolios are also of similar magnitudes for the overall sample. For instance, funds in the weakest *FF* quartile ($Q1^{FF}$) on average invest 24.67% of the total portfolio amount in companies forming the strong *FC* portfolio ($Q4^{FC}$), while investing 25.79% in the weak *FC* portfolio ($Q1^{FC}$). Funds in the strongest *FF* quartile ($Q4^{FF}$) invest about 26.0% in companies forming the strong *FC* portfolio ($Q4^{FC}$), while investing 24.29% in the weak *FC* quartile ($Q1^{FC}$).

B. Information channels and portfolio performance

B.1. <u>Univariate Results</u>

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characteristics predicting stock returns, see Fama and French (1992, 1993, 1996), Jegadeesh and Titman (1993), Daniel and Titman (1997).

Table III reports the baseline univariate tests on the relation between informal information channels and portfolio returns. We present average annualized returns on quarterly holdings. We compute value-weighted returns for each fund's four *FC* information portfolios in each quarter. The average values reported in the table for $Q1^{FC}$ through $Q4^{FC}$ are portfolio returns weighted by fund total net assets (TNA). First, Panel A of Table III presents raw returns on the portfolios forming the 4x4 matrix of *FF* and *FC* quartiles. We make comparisons between the paired ($Q1^{FF}$, $Q4^{FC}$), ($Q1^{FF}$, $Q1^{FC}$), ($Q4^{FF}$, $Q4^{FC}$) and ($Q4^{FF}$, $Q1^{FC}$) subportfolios outlined in Figure 1 as our main results in these reduced form analyses. For funds in $Q1^{FF}$, the raw returns increase when the *FC* links grow stronger, and are the highest for $Q4^{FC}$. However, the returns across *FC* links show different patterns for funds in stronger *FF* link quartiles (i.e. $Q2^{FF}$, $Q3^{F}$, $Q4^{FF}$). In the presence of strong *FC* links ($Q4^{FC}$), the returns decrease from columns $Q1^{FF}$ to $Q4^{FF}$. In contrast, in the absence of *FC* links ($Q1^{FC}$), the returns increase from columns $Q1^{FF}$ to $Q4^{FF}$. The results of raw returns show significant marginal impacts of the conditional *FF* and *FC* links. Conditional on weak *FF* links (i.e. within the $Q1^{FF}$ column), the marginal impact of *FC* links is 2.63%, and is significant at the 5% level. Conditional on weak *FC* links (i.e. within the $Q1^{FC}$ row), the marginal impact of *FF* links is 3.53%, and is significant at the 1% level. Conditional on strong *FF* links (i.e. within the $Q4^{FF}$ column), the marginal impact of *FC* links is a negative and economically significant -5.12%. Conditional on strong *FC* links (i.e. within the $Q4^{FC}$ row), the marginal impact of *FF* links is a negative and economically large -4.22%. Nonetheless, the raw returns may simply be a reflection of different levels of risk borne by the manager in these portfolios.

In Panel B of Table III, we report characteristic-adjusted returns for the information portfolios as the more appropriate measure for judging stock selection ability due to the presence of style-related fixed effects in returns. A comparison of Panel A and Panel B shows that style-adjusted returns have a pattern qualitatively similar to that of raw returns. The *FC* links have a significantly positive marginal impact on returns in the absence of *FF* links (i.e. funds in $Q1^{FF}$). Funds with weak *FF* links ($Q1^{FF}$) generate positive characteristic-adjusted returns on their holdings with strong *FC* links ($Q4^{FC}$) that exceed the returns on holdings with weak *FC* links ($Q1^{FC}$) by 3.02% per year at the 1% significance level. In contrast, in the presence of strong *FF* links (i.e. funds in $Q4^{FF}$), the *FC* links have a significantly negative marginal impact on portfolio returns. For funds in $Q4^{FF}$, the portfolios with strong *FC* links ($Q4^{FC}$) generate significantly lower characteristic-adjusted returns compared to the portfolios with weak *FC* links ($Q1^{FC}$). For these funds, the marginal impact of *FC* channels on characteristic-adjusted returns is -3.63% and is significant at the 1% level. In other words, when the strong *FF* links act in combination with the strong *FC* links, the result is a reversal in informational benefits and subsequent underperformance.

Using across-fund comparisons (presented in rows), the *FF* links have a significantly positive marginal impact on returns in the absence of *FC* links (i.e. stocks in $Q1^{FC}$). Note that unlike the analyses of marginal impact of *FC* links where within-fund portfolio decompositions are used, studying the marginal impact of *FF* links necessitates across-fund comparisons. This gives rise to the possibility that other heterogeneities between the funds drive performance differences. We explore these issues in later analyses. For the baseline results, we use a means comparison test between the information portfolio returns for each quarter to determine the marginal impact of *FF* information channels, holding the nature of *FC* channels constant. Funds with strong *FF* links ($Q4^{FF}$) *underperform* the funds with weak *FF* links ($Q1^{FF}$) by 3.74% in characteristic-adjusted returns (significant at 1% level), for holdings where strong *FC* links exist ($Q4^{FC}$). Interestingly, in the absence of *FC* links ($Q1^{FC}$), the strong *FF* funds *outperform* the weak *FF* funds by 2.91% annually (at 1% level of significance).

To summarize, the salient feature of the results is that the two information channels, while beneficial when acting in isolation, have a negative impact on the fund manager's stock selection ability when they act in combination. So, an aggregation of information channels has a detrimental effect on the portfolio outcomes of fund managers. These findings may arise due to the value-reducing impact of "crowded trades" discussed by Stein (2009), which reduce returns for fund managers located in areas with high fund manager density investing in local stocks (which are also local to many other investors). In contrast, remotely-located firms that are far from areas with high fund manager density are less likely to attract a high number of correlated trades. The results are also consistent with the theoretical models predicting that people have a poor ability to aggregate information efficiently due to limitations in cognitive capacity (e.g. Ellison and Fudenberg, 1995; Tversky and Kahneman, 1974).

B.2. Crowded Trades Effect

The perhaps puzzling results on the underperformance of the portfolios associated with strong information channels on both *FF* and *FC* dimensions could be attributed to the effect of crowded trades. To explore this issue, we calculate two variables, the absolute dollar-ratio trade imbalance (|*DRatio*|) and the herding measure (*HM*), to measure the likelihood that fund holdings with two strong information channels are associated with elevated correlated trading (e.g. correlated purchases or sales) by mutual fund managers. These two measures, first introduced in Lakonishok et al. (1992) to capture feedback trading or trading in herds among institutional investors, are later used extensively in Wermers' (1999) study of mutual fund herding. The essence of these two measures is to capture the imbalance between the number of buyers and sellers, which increases with crowded trades.

Following Wermers (1999), we define the absolute dollar-ratio trade imbalance measure (|*DRatio*|) for each stock *i* held by a fund in quarter *t* as

$$\left|DRatio_{i,t}\right| = \left|\frac{\$buy_{i,t} - \$sell_{i,t}}{\$buy_{i,t} + \$sell_{i,t}}\right|$$

Here $\$buy_{i,t}$ ($\$sell_{i,t}$) equals the total purchases (sales) by all mutual funds, in dollars, of stock *i* during quarter *t*, applying the average of the beginning- and end-of-quarter prices to aggregate increases (decreases) in share-holdings for that stock quarter. We compute the herding measure (*HM*) for each stock *i* held by a fund in quarter *t* as

$$HM_{i,t} = \left|p_{i,t} - E[p_{i,t}]\right| - E\left|p_{i,t} - E[p_{i,t}]\right|$$

Here $p_{i,t}$ is the proportion of funds trading stock i during quarter t that are buyers. The proxy used for $E[p_{i,t}]$ is the proportion of all stock trades by mutual funds during quarter t that are buys. $E|p_{i,t} - E[p_{i,t}]|$ is calculated under the null hypothesis of herding only by random chance.[15]

In Table IV, we report our empirical tests of the conjecture that crowded trades may be a driver of the underperformance observed when strong information channels act in combination. In general, higher values of |*DRatio*| and *HM* indicate a higher propensity for correlated trades. As shown in Table IV, both Panel A and B present a picture consistent with the possible crowded-trades effect on portfolio performance. For funds with relatively weak *FF* links ($Q1^{FF}$ to $Q2^{FF}$), the difference in |*DRatio*| and *HM* between the strongest ($Q4^{FC}$) and weakest ($Q1^{FC}$) *FC* quartile portfolios are not statistically significant, suggesting that their performance differentials are not driven by the variance in correlated trades. We observe similar patterns for performance differentials between the funds with the strongest ($Q4^{FF}$) and weakest ($Q1^{FF}$) *FF* links for holdings with relatively weak *FC* channels ($Q1^{FC}$ to $Q2^{FC}$). In sharp contrast, the differences of |*DRatio*| and *HM* measures between portfolios $Q4^{FF}$ and $Q1^{FF}$ including stocks with strong *FC* channels are positive and statistically significant at the 1% level. These results show that the stocks held in the $Q4^{FC}$ portfolio of the funds with the strongest *FF* links ($Q4^{FF}$) are associated with more crowded-trades than the $Q4^{FC}$ portfolio of the funds with the weakest *FF* links ($Q1^{FF}$). Similarly, the differences in these two measures between portfolios $Q4^{FC}$ and $Q1^{FC}$ with the strongest *FF* links are also positive and statistically significant at the 1% level. Taken together with the earlier results on returns, these findings are consistent with Stein's (2009) conjecture that crowded-trades reduce performance of investments substantially. They strongly suggest that crowded-trades could explain the negative marginal impact of *FF* and *FC* information channels when they act in combination.

B.3. <u>Fund and Family Size</u>

[15] The readers are referred to Lakonishok et al. (1992) and Wermers (1999) for a more detailed explanation for the measures.

The baseline results support the significant marginal impact of *FC* and *FF* information channels on managers' stock selection ability. However, the strengths of information channels may be proxying for other fund attributes that affect performance. For example, funds with stronger *FF* links may be part of larger family complexes, while those with weaker *FF* links belong to small families. Moreover, family size is likely to be a proxy for the level of intra-family information channels that is available to a fund manager.[16] It may be the case that external *FF* links are only important for managers lacking intra-family information channels. We address the issue of family size by scrutinizing small and large fund families separately. We sort the sample of funds and rank them into terciles by the number of funds within the family for each quarter, independent of prior sorts on *FF* links. We consider other rankings like quartiles, but the ranking method does not have any bearing on our results.

Panel A of Table V presents results for the smallest fund families, and Panel B reports corresponding statistics for the largest families. The fund managers from small families are less likely to gain from the intra-family interactions that facilitate information acquisition. The fund managers from large fund families are likely to have more intra-family information channels, in addition to more internal resources (e.g. research units). On the other hand, fund managers from larger families may also be more reputed among peers with stronger networks with other managers that lead to more information links. So, while fund managers from larger families may have the least need for information from informal external channels, they are likely to have the most informal information channels available to them.

In Panel A of Table V for small families, the marginal impact of *FC* links, while still positive, ceases to be statistically significant for funds with weak *FF* links, which contrasts with the baseline results. The funds in the strong *FF* quartile ($Q4^{FF}$) underperform in their strong *FC* holdings ($Q4^{FC}$) compared to weak *FC* holdings ($Q1^{FC}$) by 3.29% (at 1% level significance), which is consistent with the baseline results. The empirical evidence suggests that, unlike typical funds from the entire sample, fund managers from small families are unable to draw economic benefits from strong *FC* information sources. Interestingly,

[16] To the extent that family size reflects organizational differences, Stein (2002) posits that hierarchical versus decentralized structures that may characterize big versus small complexes, respectively, may hinder or encourage

these findings lend more credence to the word-of-mouth mechanism of information transfer than localized information acquisition. There is no clear reason to expect managers from small fund families to have less access to localized information via, for instance, regional media compared to managers from large fund families. The qualitative results for the marginal impact of *FF* channels are similar to those in the baseline results. Fund-fund links help in the absence of fund-company channels, but not in the presence of strong fund-company links.

In Panel B of Table V, we present the results for the funds belonging to the largest fund families. They broadly echo the baseline results in Table III. For weak *FF* funds from large families, the marginal impact of strong *FC* links on characteristic-adjusted returns is positive and significant (at 5%) with a magnitude of 1.83% annually. In contrast, the strong *FF* funds from large families underperform in their strong *FC* holdings compared to weak *FC* holdings by 2.43%. Additionally, the marginal impact of *FF* channels remains significant even for comparisons between funds from large *FF* families. Therefore, the evidence indicates that intra-family communication channels do not subsume the effects of external information links. For holdings with strong *FC* measures, large family funds with weak *FF* measures outperform large family funds with strong *FF* measures by 2.53%. For these funds, the marginal impact (1.73% and 0.88%) of *FF* on returns from holdings where there are weak *FC* ($Q1^{FC}$ and $Q2^{FC}$) is larger and more significant than those from funds belonging to small families.

Overall, the results suggest that the marginal impact of information links is larger for funds belonging to large families, and intra-family channels do not subsume the effects of external channels. These results suggest that funds from large families are able to leverage their reputation and visibility among their peers to form more advantageous communication channels than those from small families.

Fund size is another potentially critical factor influencing the role of external information links, since it is likely to proxy for various unobservable fund- and manager-specific factors and the impact on informal information links (largely "soft" information that cannot be immediately verified) may differ across funds of different sizes. Theoretical research seems to suggest that smaller funds may be able to

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the collection and use of "soft information" (like the information gathered via informal communications) by m generate better marginal benefits from informal information channels than larger funds (see, for example, Berk and Green (2004) and Stein (2002)).[17] On the other hand, managers of large funds are likely to have more reputational and social capital.[18] In the empirical tests that follow, we investigate the relation between fund size and marginal benefits from informal information channels. Comparisons within fund size categories also act as a robustness check to verify if the baseline results hold across the spectrum of fund sizes.

Table VI presents the analyses of characteristic-adjusted returns from portfolios across fund size terciles. We rank funds into size terciles for each quarter based on TNA in the last month of the previous quarter. Panel A reports the analyses for the subsample of funds forming the smallest fund size tercile. Consistent with the findings so far, the marginal impact of *FC* channels on performance continues to be positive (but insignificant) for weak *FF* funds and significantly negative for strong *FF* funds (-2.16%), supporting the prediction that information advantages are higher for more exclusive *FC* channels. Also, the marginal impact of *FF* channels remains significantly negative (-1.99%) for holdings with strong *FC* information channels, and significantly positive (1.59%) in the absence of *FC* channels.

Panel B of Table VI presents the subsample of funds forming the largest fund size tercile. Again, weak *FF* funds show significant stock selection ability in holdings where they have strong *FC* channels. Strong *FF* funds underperform weak *FF* funds by 2.47% annually when investing in companies associated with strong *FC* measures. On the other hand, the strong *FF* funds outperform the weak *FF* funds by 1.85% annually in investments lacking *FC* channels. Due to space considerations, we omit the

[17] Berk and Green (2004) argue that larger funds have managers with more managerial skills. In their model, one of the explanations for a skilled manager's failure to consistently outperform passive benchmarks is that the manager spreads her information acquisition activities too thin across various assets while managing sufficiently large funds. Also, Stein (2002) relates organizational form to firm size and posits that "soft" or unverifiable information generates better performance in smaller, single-manager, decentralized firms, compared to large hierarchical firms.

[18] Managers of larger funds may be the originators of the information that is being transmitted via fund-fund channels. In this case, these managers are more likely to have taken long positions in stocks before the information diffuses to other managers and results in increases in stock price. This would reflect as higher returns and consequently higher marginal impacts of fund-fund flows for these managers. However, this process cannot clearly explain the relationship between marginal impacts of fund-company channels and fund size, since managers of smaller funds can also develop direct ties with companies.

results for medium sized funds, which are qualitatively similar to those for large funds. Overall, the evidence on the marginal impact of information channels holds across different fund size categories.

B.4. Multivariate Results

So far we have presented our univariate results for the total sample and various sub-samples. These analyses allow a more focused examination of the nature of informal information links for various types of funds and provide a clear demonstration of the salient features of our results. However, the univariate analyses are subject to the concern that information channels proxy for other factors that are underlying drivers of investment performance. Hence, we proceed to multivariate regressions with additional controls related to the portfolio manager's ability and decision-making process.

In the following regressions, we use the value weighted portfolio return of holdings in each *FC* quartile as the dependent variable. As a result, one fund in a quarter accounts for four observations. The choice of this dependent variable achieves several purposes. It reduces the problem of dependence across observations in a large panel data sample, without removing the option of studying performance differences within a fund's portfolio. It makes the multivariate regression results more comparable to the findings in the previous sections, while retaining the validity of a measure that aims to capture the performance generated from a portfolio in a particular information environment.

Table VII presents the results of fixed-effect regressions for various model specifications. Specifically, the value-weighted characteristic-adjusted portfolio returns for quarter *t* are regressed on dummy variables that capture the strength of *FF* and *FC* links (and their interactions) in addition to a variety of control variables. Among the main explanatory variables, *Strong* (*Weak*) *FF Dummy* assumes a value of one if the fund is in the strongest (weakest) *FF* quartiles of the sample of funds in the quarter, and zero otherwise. The strongest (weakest) *FF* quartiles are the third and fourth (first and second) quartiles of funds formed by the sorted and ranked *FF* measure. *Strong* (*Weak*) *FC Dummy* assumes a value of one if the portfolio is the strongest (weakest) *FC* portfolio for the fund-quarter. The strongest (weakest) *FC* portfolios are the third and fourth (first and second) quartiles of holdings formed by the sorted and ranked *FC* measure. *Strong FF x Strong FC* is the interaction term for *Strong FF Dummy* and *Strong FC Dummy* and represents the portfolio where the funds having strong *FF* links invest in stocks with relatively strong *FC* links. *Weak FF x Strong FC* is the interaction term for *Weak FF Dummy* and *Strong FC Dummy* and represents the portfolio where the funds having the weak *FF* links invest in stocks with relatively strong *FC* links.

Model (1) in Table VII is the baseline specification that includes only the information links-related variables as the explanatory variables. Model (1) shows that the coefficient of *Strong FF Dummy* is positive and significant at the 5% level, with an economically significant magnitude of 0.013. This suggests that the strong *FF* links improve the portfolio performance by 1.3% per year, ceteris paribus. The coefficient on *Strong FF x Strong FC* is significantly negative, with an economically significant magnitude of -0.021. Ceteris paribus, strong *FF* and strong *FC* channels, when combined, reduce style-adjusted returns by a net 0.8% per year. The results suggest that the information links among fund managers have a positive marginal impact on stock selection ability independently, but the combination of the two channels has a detrimental impact on portfolio performance. The sign and the significance of the coefficient on the *Weak FF x Strong FC* variable point to a similar interpretation for the marginal impact of *FC* channels, i.e., the *FC* information links have a positive impact on performance in the absence of *FF* channels. Overall, the results from the multivariate regressions are consistent with those from the univariate analyses presented in previous sections.

Model (2) adds a set of fund and family characteristics as control variables. The fund level control variables in model (2) include fund size, expenses, and turnover, among others. In model (2), the magnitude and significance of the *FF* and *FC* measures are qualitatively similar to the baseline regression. Model (3) includes a set of variables that capture the effect of city size based on general population. As shown in Christoffersen and Sarkissian (2009), the urban location of funds significantly affect their performance. It is possible that the *FF* and *FC* measures capture heterogeneities related to city of location instead of the strength of informal communication channels. *Big City Dummy* is a dummy taking a value of one if the fund is headquartered in one of the 20 largest populated cities defined by the

U.S. Census Bureau in the report year, and zero otherwise. Model (3) also includes interaction terms of the city size, *FF* and *FC* dummies. Notably, the variables *Strong FF Dummy, Strong FF x Strong FC* and *Weak FF x Strong FC* remain significant and are not subsumed by the city size dummies. In fact, none of the city size variables are statistically significant. In unreported regressions, we use alternative city size definitions and obtain similar results.[19] This result is interesting because it suggests that portfolio performance is related to the density of mutual fund population but not the density of general population, supporting the theory that the more *relevant* information channels influence performance. Model (4) of Table VII includes another set of control variables measuring local bias exhibited by fund managers, the interactions of local bias with *FF* and *FC* measures. The results for the two information channels are consistent with the baseline regression and all the local bias variables are insignificant.[20] Model (5) includes all the control variables employed in models (2)-(4), and generates results consistent with the sparser specifications.[21] So, after controlling for a variety of factors and various fixed effects in multivariate analyses, the *FF* and *FC* measures continue to be significantly related to stock selection ability. In sum, the multivariate analysis confirms the relation between informal information channels, the nature of their interactions and stock selection ability revealed in the univariate tests.

C. Copycat Portfolios and Future Asset Prices

[19] Alternative measures of city size that were also considered were remote city dummies (as defined by Coval and Moskowitz (2001)) and big city as defined by the top ten cities by population.

[20] In unreported results, the cross-sectional regression methodology outlined in Fama and MacBeth (1973) was also used as an alternative. The results were qualitatively similar to the reported pooled panel data regressions using robust standard errors. Since the magnitude of economic impacts of *FC* and *FF* information flows are difficult to interpret from the Fama-MacBeth methodology, only the pooled panel data regressions are reported and interpreted in this section for brevity.

[21] In an unreported robustness check, we replicate the multivariate regressions reported above for a subsample of large cap stocks (the two largest DGTW size quintiles) to address the possibility that informal communication may not play a significant role in stock holdings of these companies that have the most publicly available information, visibility and analyst following. However, the qualitative results are indistinguishable from the representative regressions, which suggests that public information availability does not preclude the impact of informal information flows.

Our analyses show that the portfolios with ex-post superior performance are associated with (1) strong fund-company information links in the absence of fund-fund links, and (2) strong fund-fund information links in the absence of fund-company links. It is possible that fund investments made based on the information acquired via these channels are indicative of future stock prices, beyond the horizon of the three-month quarterly portfolios of funds. If so, fund holdings that become publicly available information in a report quarter could be used to infer future values of assets based on observing mutual funds' portfolio strategies.

Table VIII presents an initial examination of superior information channels of mutual fund managers and their relationship with future stock returns. At the start of each quarter, using fund holdings reported in the previous quarter, we construct a hypothetical "copycat" portfolio, called the *Best Information Portfolio* (or BIP), including the stock holdings which were part of the two information environments that were (ex-post) identified as beneficial in mutual fund investments. BIP contains the holdings of the two information portfolios with superior performance from reports in the most recently disclosed holdings using equal weights across stocks, and holds it starting the first month of the next quarter for up to one year.

Panel A of Table VIII presents returns for three- to twelve-month holding strategies for equal-weighted BIP portfolios, with three-month increments. We also present the returns for the subsamples of funds that vary in family size and fund size, since these fund attributes have an impact on the relation between returns and information channels. The three-month holding period for the BIP generates statistically significant average monthly returns of 1.63%. The corresponding returns for the six-, nine- and twelve-month holding periods for BIP are positive and have magnitudes of 1.81%, 1.35% and 0.85%, respectively, and remain significant till the nine-month holding period strategy. Moreover, the three- and six-month holding period returns of the BIP strategy are positive and significant for subsamples of funds with varying family and fund sizes. In summary, the overall positive returns from BIP are representative of patterns within fund subsamples, and do not appear to be driven by outliers. The evidence suggests that the information channels that are associated with better quarterly holdings performance for mutual funds seemingly pick stocks that continue to outperform in the future.

While Panel A of Table VIII reports the positive returns from BIP strategies, they may be explained by underlying characteristics of the stocks in the portfolio. Panel B presents the average monthly characteristic-adjusted returns for the BIP. The monthly returns of the BIP are significantly positive for two holding periods, and are similar across fund subsamples, thereby providing similar conclusions as the results based on raw returns. Overall, the evidence suggests potential asset pricing implications of identifying investor information channels that outperform others, where stocks picked by certain information channels are more likely to have superior future returns. Note that we have not factored in the transaction costs or established the feasibility of the strategy. A more comprehensive investigation of these asset pricing implications is beyond the scope of this study and is left for future research.

4. Concluding Remarks

This study broadly contributes to the literature on informed trading that links the geographical location of investors to informal communication channels that influence their investment decisions. Our focus is on two forms of information linkages associated with mutual fund managers that have been documented by previous papers: (1) *fund-fund* information links, which transfer information about potential investment opportunities between fund managers across fund families; and (2) *fund-company* information links, which facilitate a manager's acquisition of differential information about a company via links with the company. Whereas some previous studies have explored the performance impact of informal information channels associated with mutual fund managers by focusing on one type of informal communication (e.g. communication between local companies and fund managers in Coval and Moskowitz (2001)), we make the first attempt to disentangle the performance implications of more than one type of informal communication in a setting that accounts for their interactions. Overall, our results provide several novel empirical insights.

First, strong fund-fund information links have a significantly positive marginal impact on returns in the absence of fund-company information links, and vice versa. So, informal communication via either channel is beneficial for the managers' stock selection ability in isolation. However, when the two types of information channels are present together, they generate substantial underperformance from portfolio holdings and appear distinctly counter-productive in generating economic value. There is some evidence that the "crowded trades" effect can explain this apparently puzzling finding. Multivariate analyses confirm the results after controlling for a multitude of factors like fund size, family size, fund age, manager tenure, degree of local bias, and the size of cities in which the fund is located. We also conduct an initial examination of the link between the information environments that generate superior investment performance and future asset returns. Our findings suggest that investment decisions in stocks associated with certain beneficial information environments may predict asset returns that persist into the future.

The empirical evidence presented in our study raises intriguing questions related to the study of informed trading and suggests some interesting avenues for future research. While our findings provide some insights on how information links related to geographical location can be valuable for fund managers, they also reveal substantial complexity in the informational benefits. As in Coval and Moskowitz (2001), our results seem to suggest that, in equilibrium, fund managers should maximize performance by concentrating their portfolios in holdings located in informationally advantageous environments, perhaps without having to substantially increase risk. Additional research that accounts for alternative informal information channels (e.g. educational networks) and identifies the complexities in the effect of informal communication in financial markets could provide further insights on the economic value of communication in financial markets.

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FF Links / *FC Links*	*Weak Fund-Fund (FF) Links* $(Q^{FF,weak})$	*Strong Fund-Fund (FF) Links* $(Q^{FF,strong})$	*Marginal Impact: FF* Links $(Q^{FF,strong} - Q^{FF,weak})$
Strong Fund-Company (FC) Links $(Q_j^{FC,strong})$	Portfolio P1 $(Q^{FF,weak}, Q_j^{FC,strong})$ Information Links: *Fund-Company*	Portfolio P3 $(Q^{FF,strong}, Q_j^{FC,strong})$ Information Links: *Fund-Fund* *Fund-Company*	Difference: $R^{adj}(P3)$- $R^{adj}(P1)$
Weak Fund-Company (FC) Links $(Q_j^{FC,weak})$	Portfolio P2 $(Q^{FF,weak}, Q_j^{FC,weak})$ Information Links: *None*	Portfolio P4 $(Q^{FF,strong}, Q_j^{FC,weak})$ Information Links: *Fund-Fund*	Difference: $R^{adj}(P4)$- $R^{adj}(P2)$
Marginal Impact: FC Links $(Q_j^{FC,strong} - Q_j^{FC,weak})$	Difference: $R^{adj}(P1) - R^{adj}(P2)$	Difference: $R^{adj}(P3) - R^{adj}(P4)$	

Fig. 1. Marginal Impacts of Informal Information Channels

This figure reports a metric for forming portfolios of stocks held by mutual funds according to information links associated with the holding. The likelihood of *FC* information links existing between fund manager *j* and the company issuing stock *n* that is held in *j*'s portfolio is $L^{FC}(Link)_{j,n} = 1/(1+Distance_{j,n})$ where, $Distance_{j,n}$ is the natural logarithm of the geographical distance between the city where fund *j* is located and the city in which company *n* is headquartered. For each fund *j*, each quarter the holdings are sorted by $L^{FC}(Link)_{j,n}$ and ranked into quartiles, with $Q_j^{FC,strong}$ $(Q_j^{FC,weak})$ being the highest (lowest), i.e. $Q4^{FC}$ $(Q1^{FC})$ quartile and form the portfolios *Strong (Weak) Fund-Company Links* in each quarter. The likelihood of an information channel existing between fund manager *j* and fund manager *i* is $L^{FF}(Links)_{j,i} = 1/(1+Distance_{j,i})$ where $Distance_{j,i}$ is the natural logarithm of the geographical distance between the city where fund *j* is located and the city in which fund *i* is located. The strength of informal information channels a fund manager *j* has with other fund managers is computed as

$$(Links)_j^{FF} = \sum_{i=1}^{N} L^{FF}(Links)_{j,i} = \sum_{i=1}^{N} 1/(1+Distance_{j,i})$$

Here, $i=1,\ldots,N$ are all funds in the sample that do not belong to the same fund family as fund *j*. Each quarter the funds are sorted by $(Links)_j^{FF}$ and ranked into quartiles, with $Q^{FF,strong}$ $(Q^{FF,weak})$ being the highest (lowest), i.e. $Q4^{FF}$ $(Q1^{FF})$ quartile and form the categories *Strong (Weak) Fund-Fund Links*. R^{adj} is the value-weighted characteristic-adjusted return generated from a portfolio of holdings.

Table I
Summary Statistics on U.S. Mutual Funds

Fund age in the holding quarter is computed as the difference between the year of the first month in the quarter and the year of the fund's first offer date. Proximity distribution of a fund's holdings is reported as the percentage of total amount invested in domestic equity in a quarter, in stocks of companies that are 0-100 kilometer (km), 100-500 km, 500-1000 km and more than 1000 km from the location of the fund. Proximity distribution of mutual funds is computed for each fund as the percentage of funds in the universe of funds located 0-100km, 100-500km, 500-1000km and more than 1000km from each specific fund, and reported as an average across all funds. Median number of companies in a fund's portfolio is the average across all quarters. Daniel et al (DGTW) (1997) is followed to compute the size, book-to-market and momentum quintiles for the stocks held and the value-weighted characteristics are reported for the median fund. Company age is the difference between the year of the first month of the quarter and the year in which a company was established, reported in years.

Total number of funds in sample	2,931
Total number of mutual fund families in sample	516
Median total net assets ($ million)	226.1
Median fund age (in years)	10.0
Proximity distribution of fund investments:	
Avg. % invested in stocks: 0-100 km	5.41
Avg. % invested in stocks: 100-500 km	12.56
Avg. % invested in stocks: 500-1000 km	15.31
Avg. % invested in stocks: >1000 km	66.72
Proximity distribution of fund managers:	
Avg. % of funds located 0-100 km	10.23
Avg. % of funds located 100-500 km	20.12
Avg. % of funds located 500-1000 km	9.62
Avg. % of funds located >1000 km	60.03
Portfolio characteristics:	
Median number of companies in portfolio	74
Median value-weighted DGTW Size quintile	4.21
Median value-weighted DGTW B/M quintile	2.50
Median value-weighted DGTW MOM quintile	3.13
Median company age (in years)	37.0

Table II
Summary Statistics on Portfolio Characteristics

The likelihood of a fund-company (*FC*) information channel existing between fund manager *j* and each company issuing stock *n* that is held in *j*'s portfolio is $L^{FC}(Links)_{j,n}$ = 1/(1+ $Distance_{j,n}$). Here, $Distance_{j,n}$ is the natural logarithm of the geographical distance (in km) between the city where fund *j* is located and the city in which company *n* is headquartered. Every quarter, each fund's holdings are ranked into quartiles $Q1^{FC}$ through $Q4^{FC}$ based on $L^{FC}(Links)_{j,n}$, with $Q4^{FC}$ being the *Strong Fund-Company Links* portfolio and $Q1^{FC}$ being the *Weak Fund-Company Links* portfolio. The likelihood of an information channel existing between fund manager *j* and fund manager *i* is $L^{FF}(Links)_{j,i} = 1/(1+Distance_{j,i})$ where $Distance_{j,i}$ is the natural logarithm of the geographical distance between the city where fund *j* is located and the city in which fund *i* is located. The strength of fund-fund (*FF*) informal information links a fund manager *j* has with other fund managers is computed as

$$(Links)_j^{FF} = \sum_{i=1}^{N} L^{FF}(Links)_{j,i} = \sum_{i=1}^{N} 1/(1+Distance_{j,i})$$

Here, $i=1,\dots,N$ are all funds in the sample that do not belong to the same fund family as fund *j*. Every quarter, the funds are ranked into quartiles $Q1^{FF}$ through $Q4^{FF}$ based on $(Links)_j^{FF}$, with $Q4^{FF}$ being the *Strong Fund-Fund Links* portfolio and $Q1^{FF}$ being the *Weak Fund-Fund Links* portfolio. *Fund Age* is computed from the first offer date. *Mgr. tenure* is the length of manager tenure at the fund. *#funds in family* is the number of funds in the family. *Size Q, BE/ME Q, Mom Q* are the value-weighted Daniel et al (DGTW) (1997) size, book-to-market and momentum quintiles for the stocks in the portfolio averaged across all funds. *% invested* is calculated as the portfolio weight of stocks in a *FC* quartile for a fund by market value of holdings, averaged across all funds.

		Weak Fund-Fund (FF) Links $Q1^{FF}$		$Q2^{FF}$		$Q3^{FF}$		*Strong Fund-Fund (FF) Links* $Q4^{FF}$	
		Mean	[Median]	Mean	[Median]	Mean	[Median]	Mean	[Median]
A. Fund characteristics:									
TNA (in $mill)		558.9	[206.32]	1011.2	[274.67]	1084.1	[201.71]	602.2	[285.56]
Fund Age (in years)		13.2	[10.0]	12.7	[10.0]	12.8	[10.0]	12.1	[10.0]
Expenses		0.011	[0.012]	0.012	[0.012]	0.011	[0.012]	0.012	[0.012]
Turnover		0.97	[0.88]	1.41	[0.93]	1.22	[0.94]	0.98	[0.86]
#funds in family		52	[28]	40	[38]	60	[31]	71	[59]
Mgr. tenure (in years)		5.9	[5.0]	6.3	[5.0]	5.8	[5.0]	4.8	[4.0]
B. Portfolio Characteristics:									
Strong Fund-Company (FC) Links									
$Q4^{FC}$	Size Q	3.95		4.13		4.02		4.18	
	BE/ME Q	2.38		2.83		2.84		2.60	
	Mom Q	3.17		3.09		3.12		3.16	
	% invested	24.67		24.40		24.93		26.00	
$Q3^{FC}$	Size Q	4.02		3.82		4.11		4.13	
	BE/ME Q	2.63		3.01		3.02		2.60	
	Mom Q	3.20		3.26		3.29		3.09	
	% invested	25.04		25.78		24.39		24.79	
$Q2^{FC}$	Size Q	3.92		4.13		4.01		3.98	
	BE/ME Q	2.80		2.71		3.02		2.40	
	Mom Q	3.20		3.37		3.41		3.02	
	% invested	25.57		26.02		24.14		24.27	
$Q1^{FC}$	Size Q	3.86		3.98		4.02		4.08	
Weak Fund-Company (FC) Links	BE/ME Q	2.39		2.12		2.71		2.67	
	Mom Q	3.24		3.01		3.33		3.33	
	% invested	25.79		25.01		24.91		24.29	

Table III
Performance of Mutual Funds and Informal Information Channels (Percentage Annualized Returns)

Every quarter, the likelihood of a fund-company (*FC*) information channel existing between fund manager *j* and each company issuing stock *n* that is held in *j*'s portfolio is calculated as $L^{FC}(Links)_{j,n}$ = 1/(1+ $Distance_{j,n}$). Here, $Distance_{j,n}$ is the natural logarithm of the geographical distance (in km) between the city where fund *j* is located and the city in which company *n* is headquartered. Each fund's holdings are ranked into quartiles $Q1^{FC}$ through $Q4^{FC}$ based on $L^{FC}(Links)_{j,n}$, with $Q4^{FC}$ being the *Strong Fund-Company Link*s portfolio and $Q1^{FC}$ being the *Weak Fund-Company Links* portfolio. The likelihood of an information channel existing between fund manager *j* and fund manager *i* is $L^{FF}(Links)_{j,i} = 1/(1+Distance_{j,i})$ where $Distance_{j,i}$ is the natural logarithm of the geographical distance between the city where fund *j* is located and the city in which fund *i* is located. The strength of fund-fund (*FF*) informal information links a fund manager *j* has with other fund managers is computed as

$$(Links)_j^{FF} = \sum_{i=1}^{N} L^{FF}(Links)_{j,i} = \sum_{i=1}^{N} 1/(1+Distance_{j,i})$$

Here, $i=1,\ldots,N$ are all funds in the sample that do not belong to the same fund family as fund *j*. Every quarter, the funds are ranked into quartiles $Q1^{FF}$ through $Q4^{FF}$ based on $(Links)_j^{FF}$, with $Q4^{FF}$ being the *Strong Fund-Fund Links* portfolio and $Q1^{FF}$ being the *Weak Fund-Fund Links* portfolio. For each fund, returns are computed in each quarter for a *FC* links portfolio as

$$\mathrm{R}^{\mathrm{raw}} = (1/3)*\sum_{i=1}^{S}\sum_{t=1}^{3} w_{i,t}R_{i,t}$$

where $w_{i,t}$ is the portfolio weight of stock *i* in month *t*, and *S* is the number of stocks in the portfolio. Characteristic-adjusted *FC* links portfolio returns are computed in each quarter as:

$$\mathrm{R}^{\mathrm{adj}} = (1/3)*\sum_{i=1}^{S}\sum_{t=1}^{3} w_{i,t}(R_{i,t} - R_i^{bench})$$

where R_i^{bench} is the value-weighted monthly return of stock *i*'s DGTW quintile benchmark portfolio (following Daniel et al. (1997)). Reported returns (expressed in annual percentage rates) are value-weighted by fund total net assets (TNA) within each *FF* quartile and averaged across quarters. $^{***, **, *}$ represent significance at 1%, 5% and 10% level respectively.

Panel A: Raw Returns						
	Weak Fund-Fund (FF) Links $Q1^{FF}$	$Q2^{FF}$	$Q3^{FF}$	*Strong Fund-Fund (FF) Links* $Q4^{FF}$	Marginal Impact: *FF Links* $(Q4^{FF} - Q1^{FF})$ [t-statistic]	
Strong Fund-Company (FC) Links						
$Q4^{FC}$	18.43	19.01	15.71	14.21	-4.22***	[-3.57]
$Q3^{FC}$	18.17	17.45	17.20	17.50	-0.67	[-0.83]
$Q2^{FC}$	17.02	17.10	19.01	18.91	1.89**	[2.10]
$Q1^{FC}$	15.80	18.24	18.83	19.33	3.53***	[3.40]
Weak Fund-Company (FC) Links						
Marginal Impact: *FC Links* $(Q4^{FC} - Q1^{FC})$	2.63**	0.77	-3.12***	-5.12***		
[t-statistic]	[2.32]	[1.07]	[-3.10]	[-4.39]		

Panel B: Characteristic-adjusted Return						
	Weak Fund-Fund (FF) Links $Q1^{FF}$	$Q2^{FF}$	$Q3^{FF}$	*Strong Fund-Fund (FF) Links* $Q4^{FF}$	Marginal Impact: *FF Links* $(Q4^{FF} - Q1^{FF})$ [t-statistic]	
Strong Fund-Company (FC) Links						
$Q4^{FC}$	2.34	0.92	-0.40	-1.40	-3.74***	[-3.94]
$Q3^{FC}$	1.33	0.03	-0.26	-0.35	-1.68**	[-2.31]
$Q2^{FC}$	0.11	-0.34	-0.30	0.17	0.06	[0.23]
$Q1^{FC}$	-0.68	1.83	1.40	2.23	2.91***	[2.62]
Weak Fund-Company (FC) Links						
Marginal Impact: *FC Links* $(Q4^{FC} - Q1^{FC})$	3.02***	-0.91	-1.80**	-3.63***		
[t-statistic]	[2.98]	[-1.03]	[-2.42]	[-4.12]		

Table IV

Crowded Trades and Informal Information Channels (Dollar-Ratio Trade Imbalance and Herding)

Every quarter, the likelihood of a fund-company (*FC*) information channel existing between fund manager j and each company issuing stock n that is held in j's portfolio is calculated as $L^{FC}(Links)_{j,n}$ = 1/(1+ $Distance_{j,n}$). Here, $Distance_{j,n}$ is the natural logarithm of the geographical distance (in km) between the city where fund j is located and the city in which company n is headquartered. Each fund's holdings are ranked into quartiles $Q1^{FC}$ through $Q4^{FC}$ based on $L^{FC}(Links)_{j,n}$, with $Q4^{FC}$ being the *Strong Fund-Company Link*s portfolio and $Q1^{FC}$ being the *Weak Fund-Company Links* portfolio. The likelihood of an information channel existing between fund manager j and fund manager i is $L^{FF}(Links)_{j,i} = 1/(1+Distance_{j,i})$ where $Distance_{j,i}$ is the natural logarithm of the geographical distance between the city where fund j is located and the city in which fund i is located. The strength of fund-fund (*FF*) informal information links a fund manager j has with other fund managers is computed as

$$(Links)_j^{FF} = \sum_{i=1}^{N} L^{FF}(Links)_{j,i} = \sum_{i=1}^{N} 1/(1+Distance_{j,i})$$

Here, $i=1,\ldots,N$ are all funds in the sample that do not belong to the same fund family as fund j. Every quarter, the funds are ranked into quartiles $Q1^{FF}$ through $Q4^{FF}$ based on $(Links)_j^{FF}$, with $Q4^{FF}$ being the *Strong Fund-Fund Links* portfolio and $Q1^{FF}$ being the *Weak Fund-Fund Links* portfolio. For each stock i held by a fund in quarter t, the absolute dollar-ratio trade imbalance measure ($|DRatio|$) for the stock-quarter is computed as

$$\left|DRatio_{j,t}\right| = \left|\frac{\$buy_{i,t} - \$sell_{i,t}}{\$buy_{i,t} + \$sell_{i,t}}\right|$$

where $\$buy_{i,t}$ ($\$sell_{i,t}$) equals the total purchases (sales) by all mutual funds, in dollars, of stock i during quarter t (applying the average of the beginning- and end-of-quarter prices to aggregate increases (decreases) in shareholdings for that stock quarter, following Wermers (1999). Panel A reports the time series equal-weighted average of the absolute dollar-ratio trade imbalance measure across all stocks in the fund's portfolio, averaged across all funds in the sample in a quarter. For each stock i held by a fund in quarter t, the herding measure (*HM*) for the stock-quarter is computed following Wermers (1999) as

$$HM_{i,t} = \left|p_{i,t} - E[p_{i,t}]\right| - E\left|p_{i,t} - E[p_{i,t}]\right|$$

where $p_{i,t}$ is the proportion of funds trading stock i during quarter t that are buyers. The proxy used for $E[p_{i,t}]$ is the proportion of all stock trades by mutual funds during quarter t that are buys. $E|p_{i,t} - E[p_{i,t}]|$ is calculated under the null hypothesis of herding only by random chance. Panel B reports the time series equal-weighted average of the herding measure across all stocks in the fund's portfolio, averaged across all funds in the sample in a quarter. $^{***}, ^{**}, ^{*}$ represent significance at 1%, 5% and 10% level respectively.

Panel A: Absolute Dollar-Ratio (|*DRatio*|) Trade Imbalance Measure						
	Weak Fund-Fund (*FF*) Links $Q1^{FF}$	$Q2^{FF}$	$Q3^{FF}$	Strong Fund-Fund (*FF*) Links $Q4^{FF}$	Marginal Impact: *FF* Links ($Q4^{FF} - Q1^{FF}$)	[t-statistic]
Strong Fund-Company (FC) Links						
$Q4^{FC}$	0.113	0.092	0.080	0.142	0.029**	[2.41]
$Q3^{FC}$	0.089	0.085	0.121	0.105	0.016*	[1.99]
$Q2^{FC}$	0.090	0.077	0.103	0.101	0.011	[1.43]
$Q1^{FC}$	0.108	0.084	0.091	0.099	-0.009	[-1.21]
Weak Fund-Company (FC) Links						
Marginal Impact:						
FC Links ($Q4^{FC} - Q1^{FC}$)	-0.005	0.008	-0.011	0.043***		
[t-statistic]	[-0.22]	[0.63]	[-1.29]	[3.43]		

Panel B: Herding Measure (*HM*)						
	Weak Fund-Fund (*FF*) Links $Q1^{FF}$	$Q2^{FF}$	$Q3^{FF}$	Strong Fund-Fund (*FF*) Links $Q4^{FF}$	Marginal Impact: *FF* Links ($Q4^{FF} - Q1^{FF}$)	[t-statistic]
Strong Fund-Company (FC) Links						
$Q4^{FC}$	1.845	3.102	2.830	2.952	1.107**	[1.98]
$Q3^{FC}$	1.566	2.140	2.261	2.551	0.985*	[1.74]
$Q2^{FC}$	2.093	3.092	1.733	2.020	-0.073	[-0.22]
$Q1^{FC}$	2.271	2.834	1.568	1.520	-0.751	[-1.12]
Weak Fund-Company (FC) Links						
Marginal Impact:						
FC Links ($Q4^{FC} - Q1^{FC}$)	-0.426	0.268	1.262*	1.432***		
[t-statistic]	[-0.37]	[0.42]	[1.90]	[2.57]		

Table V

Performance of Mutual Funds and Informal Information Channels (by family size)

Every quarter, the likelihood of a fund-company (*FC*) information channel existing between fund manager *j* and each company issuing stock *n* that is held in *j*'s portfolio is calculated as $L^{FC}(Links)_{j,n}$ = 1/(1+ $Distance_{j,n}$). Here, $Distance_{j,n}$ is the natural logarithm of the geographical distance (in km) between the city where fund *j* is located and the city in which company *n* is headquartered. Each fund's holdings are ranked into quartiles $Q1^{FC}$ through $Q4^{FC}$ based on $L^{FC}(Links)_{j,n}$, with $Q4^{FC}$ being the *Strong Fund-Company Links* portfolio and $Q1^{FC}$ being the *Weak Fund-Company Links* portfolio. The likelihood of an information channel existing between fund manager *j* and fund manager *i* is $L^{FF}(Links)_{j,i} = 1/(1+Distance_{j,i})$ where $Distance_{j,i}$ is the natural logarithm of the geographical distance between the city where fund *j* is located and the city in which fund *i* is located. The strength of fund-fund (*FF*) informal information links a fund manager *j* has with other fund managers is computed as

$$(Links)_j^{FF} = \sum_{i=1}^{N} L^{FF}(Links)_{j,i} = \sum_{i=1}^{N} 1/(1+Distance_{j,i})$$

Here, *i=1,…,N* are all funds in the sample that do not belong to the same fund family as fund *j*. Every quarter, the funds are ranked into quartiles $Q1^{FF}$ through $Q4^{FF}$ based on $(Links)_j^{FF}$, with $Q4^{FF}$ being the *Strong Fund-Fund Links* portfolio and $Q1^{FF}$ being the *Weak Fund-Fund Links* portfolio. For each fund, returns are computed in each quarter for a *FC* links portfolio as

$$R^{raw} = (1/3) * \sum_{i=1}^{S} \sum_{t=1}^{3} w_{i,t} R_{i,t}$$

where $w_{i,t}$ is the portfolio weight of stock *i* in month *t*, and *S* is the number of stocks in the portfolio. Characteristic-adjusted *FC* links portfolio returns are computed in each quarter as:

$$R^{adj} = (1/3) * \sum_{i=1}^{S} \sum_{t=1}^{3} w_{i,t} (R_{i,t} - R_i^{bench})$$

where R_i^{bench} is the value-weighted monthly return of stock *i*'s DGTW quintile benchmark portfolio (following Daniel et al. (1997)). Every quarter the funds are sorted into terciles by number of funds in the family, with the lowest and highest terciles being the small and large fund families respectively. Panel A (Panel B) reports returns for funds in small (large) families. Returns (expressed in annual percentage rates) are value-weighted by fund total net assets (TNA) within each *FF* quartile and averaged across quarters. ***, **, * represent significance at 1%, 5% and 10% level respectively.

Panel A: Small Fund Families						
	Weak Fund-Fund (FF) Links $Q1^{FF}$	$Q2^{FF}$	$Q3^{FF}$	*Strong Fund-Fund (FF) Links* $Q4^{FF}$	Marginal Impact: *FF Links* $(Q4^{FF} – Q1^{FF})$	[t-statistic]
Strong Fund-Company (FC) Links						
$Q4^{FC}$	1.13	-0.37	-0.53	-1.84	-2.97***	[-2.60]
$Q3^{FC}$	1.02	-0.12	-0.72	-0.28	-1.30	[-1.43]
$Q2^{FC}$	0.54	0.45	1.03	0.05	-0.49	[-1.03]
$Q1^{FC}$	0.13	1.13	0.91	1.45	1.32	[1.50]
Weak Fund-Company (FC) Links						
Marginal Impact:						
FC Links $(Q4^{FC} – Q1^{FC})$	1.00	-1.50*	-1.44*	-3.29***		
[t-statistic]	[1.49]	[-1.90]	[-1.84]	[-3.52]		

Panel B: Large Fund Families						
	Weak Fund-Fund (FF) Links $Q1^{FF}$	$Q2^{FF}$	$Q3^{FF}$	*Strong Fund-Fund (FF) Links* $Q4^{FF}$	Marginal Impact: *FF Links* $(Q4^{FF} – Q1^{FF})$	[t-statistic]
Strong Fund-Company (FC) Links						
$Q4^{FC}$	1.86	1.40	-0.93	-0.67	-2.53**	[-2.51]
$Q3^{FC}$	0.82	0.53	-0.76	0.30	-0.52	[0.95]
$Q2^{FC}$	0.14	-0.12	0.41	1.02	0.88	[1.62]
$Q1^{FC}$	0.03	0.23	1.29	1.76	1.73**	[2.34]
Weak Fund-Company (FC) Links						
Marginal Impact:						
FC Links $(Q4^{FC} – Q1^{FC})$	1.83**	1.17	-2.22***	-2.43***		
[t-statistic]	[2.18]	[1.23]	[-2.58]	[2.75]		

Table VI
Performance of Mutual Funds and Informal Information Channels (by fund size)

Every quarter, the likelihood of a fund-company (*FC*) information channel existing between fund manager *j* and each company issuing stock *n* that is held in *j*'s portfolio is calculated as $L^{FC}(Links)_{j,n} = 1/(1+ Distance_{j,n})$. Here, $Distance_{j,n}$ is the natural logarithm of the geographical distance (in km) between the city where fund *j* is located and the city in which company *n* is headquartered. Each fund's holdings are ranked into quartiles $Q1^{FC}$ through $Q4^{FC}$ based on $L^{FC}(Links)_{j,n}$, with $Q4^{FC}$ being the *Strong Fund-Company Links* portfolio and $Q1^{FC}$ being the *Weak Fund-Company Links* portfolio. The likelihood of an information channel existing between fund manager *j* and fund manager *i* is $L^{FF}(Links)_{j,i} = 1/(1+Distance_{j,i})$ where $Distance_{j,i}$ is the natural logarithm of the geographical distance between the city where fund *j* is located and the city in which fund *i* is located. The strength of fund-fund (*FF*) informal information links a fund manager *j* has with other fund managers is computed as

$$(Links)_j^{FF} = \sum_{i=1}^{N} L^{FF}(Links)_{j,i} = \sum_{i=1}^{N} 1/(1+Distance_{j,i})$$

Here, $i=1,\ldots,N$ are all funds in the sample that do not belong to the same fund family as fund *j*. Every quarter, the funds are ranked into quartiles $Q1^{FF}$ through $Q4^{FF}$ based on $(Links)_j^{FF}$, with $Q4^{FF}$ being the *Strong Fund-Fund Links* portfolio and $Q1^{FF}$ being the *Weak Fund-Fund Links* portfolio. For each fund, returns are computed in each quarter for a *FC* links portfolio as

$$\mathrm{R}^{\mathrm{raw}} = (1/3) * \sum_{i=1}^{S} \sum_{t=1}^{3} w_{i,t} R_{i,t}$$

where $w_{i,t}$ is the portfolio weight of stock *i* in month *t*, and *S* is the number of stocks in the portfolio. Characteristic-adjusted *FC* links portfolio returns are computed in each quarter as:

$$\mathrm{R}^{\mathrm{adj}} = (1/3) * \sum_{i=1}^{S} \sum_{t=1}^{3} w_{i,t} (R_{i,t} - R_i^{bench})$$

where R_i^{bench} is the value-weighted monthly return of stock *i*'s DGTW quintile benchmark portfolio (following Daniel et al. (1997)). Every quarter the funds are sorted into terciles by total net assets (TNA) in the month prior to the beginning of the quarter. The lowest and highest terciles are the small and large funds respectively. Panel A (Panel B) reports returns for small (large) funds. Returns (expressed in annual percentage rates) are value-weighted by fund total net assets (TNA) within each *FF* quartile and averaged across quarters. ***, **, * represent significance at 1%, 5% and 10% level respectively.

Panel A: Small Funds						
	Weak Fund-Fund (FF) Links $Q1^{FF}$	$Q2^{FF}$	$Q3^{FF}$	*Strong Fund-Fund (FF) Links* $Q4^{FF}$	Marginal Impact: *FF Links* $(Q4^{FF} – Q1^{FF})$	[t-statistic]
Strong Fund-Company (FC) Links						
$Q4^{FC}$	1.76	2.03	1.83	-0.23	-1.99**	[-2.21]
$Q3^{FC}$	1.23	1.20	0.75	0.14	-1.09	[-1.38]
$Q2^{FC}$	0.94	-0.07	-0.30	-0.18	-1.12	[-1.42]
$Q1^{FC}$	0.34	1.57	1.28	1.93	1.59*	[1.99]
Weak Fund-Company (FC) Links						
Marginal Impact:						
FC Links $(Q4^{FC} – Q1^{FC})$	1.42	0.46	0.55	-2.16**		
[t-statistic]	[1.23]	[0.37]	[0.68]	[-2.31]		

Panel B: Large Funds						
	Weak Fund-Fund (FF) Links $Q1^{FF}$	$Q2^{FF}$	$Q3^{FF}$	*Strong Fund-Fund (FF) Links* $Q4^{FF}$	Marginal Impact: *FF Links* $(Q4^{FF} – Q1^{FF})$	[t-statistic]
Strong Fund-Company (FC) Links						
$Q4^{FC}$	1.34	1.65	-1.02	-1.13	-2.47***	[-2.93]
$Q3^{FC}$	0.71	0.66	-0.50	-0.82	-1.53*	[-1.72]
$Q2^{FC}$	-0.40	-0.09	0.32	-0.07	0.33	[0.62]
$Q1^{FC}$	-0.57	-0.13	1.24	1.28	1.85**	[2.15]
Weak Fund-Company (FC) Links						
Marginal Impact:						
FC Links $(Q4^{FC} – Q1^{FC})$	1.91**	1.78**	-2.26***	-2.41***		
[t-statistic]	[2.23]	[2.01]	[-2.72]	[-2.77]		

Table VII
Multivariate Regressions

Every quarter, the likelihood of a fund-company (*FC*) information channel existing between fund manager *j* and each company issuing stock *n* that is held in *j*'s portfolio is calculated as $L^{FC}(Links)_{j,n}$ = 1/(1+ $Distance_{j,n}$). Here, $Distance_{j,n}$ is the natural logarithm of the geographical distance (in km) between the city where fund *j* is located and the city in which company *n* is headquartered. Each fund's holdings are ranked into quartiles $Q1^{FC}$ through $Q4^{FC}$ based on $L^{FC}(Links)_{j,n}$, with $Q4^{FC}$ being the *Strong Fund-Company Links* portfolio and $Q1^{FC}$ being the *Weak Fund-Company Links* portfolio. The likelihood of an information channel existing between fund manager *j* and fund manager *i* is $L^{FF}(Links)_{j,i} = 1/(1+Distance_{j,i})$ where $Distance_{j,i}$ is the natural logarithm of the geographical distance between the city where fund *j* is located and the city in which fund *i* is located. The strength of fund-fund (*FF*) informal information links a fund manager *j* has with other fund managers is computed as

$$(Links)_j^{FF} \;=\; \sum_{i=1}^{N} L^{FF}(Links)_{j,i} = \sum_{i=1}^{N} 1/(1+Distance_{j,i})$$

Here, $i=1,\ldots,N$ are all funds in the sample that do not belong to the same fund family as fund *j*. Every quarter, the funds are ranked into quartiles $Q1^{FF}$ through $Q4^{FF}$ based on $(Links)_j^{FF}$, with $Q4^{FF}$ being the *Strong Fund-Fund Links* portfolio and $Q1^{FF}$ being the *Weak Fund-Fund Links* portfolio. For each fund, returns are computed in each quarter for a *FC* links portfolio as

$$\mathrm{R}^{\mathrm{raw}} = (1/3) * \sum_{i=1}^{S} \sum_{t=1}^{3} w_{i,t} R_{i,t}$$

where $w_{i,t}$ is the portfolio weight of stock *i* in month *t*, and *S* is the number of stocks in the portfolio. Characteristic-adjusted *FC* links portfolio returns are computed in each quarter as:

$$\mathrm{R}^{\mathrm{adj}} = (1/3) * \sum_{i=1}^{S} \sum_{t=1}^{3} w_{i,t} (R_{i,t} - R_i^{bench})$$

where R_i^{bench} is the value-weighted monthly return of stock *i*'s DGTW quintile benchmark portfolio (following Daniel et al. (1997)). The dependent variable in the regressions is the annualized value-weighted $\mathrm{R}^{\mathrm{adj}}$ for an *FC* quartile in a fund's portfolio in a given quarter. *Strong (Weak) FF Dummy* assumes a value of one if the fund is in the third or fourth (first and second) quartiles of funds formed by the sorted and ranked *FF* measure, and zero otherwise. *Strong (Weak) FC Dummy* assumes a value of one if the portfolio in the dependent variable is the third or fourth (first and second) quartiles of holdings formed by the sorted and ranked *FC* measure. *Strong FF x Strong FC* is the interaction term for *Strong FF Dummy* and *Strong FC Dummy*. *Weak FF x Strong FC* is the interaction term for *Weak FF Dummy* and *Strong FC Dummy*. *Big City Dummy* assumes a value of one if the fund is located in one of the top 20 cities by general population, and zero otherwise. *Local Bias Dummy* assumes a value of one if the fund is in the highest quartile based on Coval and Moskowitz's (2001) local bias measure, and zero otherwise. *Log (TNA)*, *Log (Family Size)*, *Log (Tenure)*, and *Log (Fund Age)* are the natural logarithms of fund total net assets in the month prior to the quarter, number of funds in the family, length of manager tenure and fund age since first offer, respectively. *Expenses* and *Turnover* are the fund's expense and turnover ratios, respectively. *Fund-*, *Time-*, *Objective-* and *State fixed-effect* regressions include fund dummies, quarter dummies, ICDI objective dummies and state of location dummies, respectively. The coefficients and p-values based on robust standard errors are reported. ***, **, * represent significance at 1%, 5% and 10% level respectively.

	(1)		(2)		(3)		(4)		(5)	
	Coeff.	*p*-value	Coeff.	*p*-value	Coeff.	*p*-value	Coeff.	*p*-value	Coeff.	*p*-value
Strong FF Dummy	0.013**	0.02	0.015***	0.01	0.018***	0.00	0.018***	0.01	0.021***	0.00
Strong FF x *Strong FC*	-0.021***	0.00	-0.018**	0.03	-0.016***	0.01	-0.027***	0.00	-0.025***	0.01
Weak FF x *Strong FC*	0.019***	0.00	0.020***	0.00	0.021***	0.00	0.013**	0.03	0.014***	0.00
Big City Dummy					0.003	0.54			0.001	0.82
Big City x *Strong FF* x *Strong FC*					0.009	0.48			-0.012	0.21
Big City x *Weak FF* x *Strong FC*					0.004	0.66			0.013	0.27
Local Bias Dummy							0.003	0.53	0.001	0.91
Local Bias x *Strong FF* x *Strong FC*							-0.002	0.79	-0.002	0.80
Local Bias x *Weak FF* x *Strong FC*							0.004	0.61	0.004	0.57
Log (*TNA*)			-0.008**	0.04	-0.008*	0.09			-0.008*	0.08
Log (*Family Size*)			0.003	0.34	0.002	0.23			0.002	0.38
Log (*Tenure*)			-0.010	0.49	-0.009	0.60			-0.009	0.63
Log (*Fund Age*)			-0.001	0.82	0.000	0.93			-0.001	0.88
Expenses			-0.109	0.28	-0.112	0.22			-0.111	0.27
Turnover			0.023	0.50	0.019	0.71			0.020	0.62
Fund Fixed-effects	YES		NO		NO		YES		NO	
Time Fixed-effects	YES		YES		YES		YES		YES	
Objective Fixed-effects	NO		YES		YES		NO		YES	
State Fixed-effects	NO		YES		YES		NO		YES	
N	169,896		169,663		169,663		169,663		169,663	
Adjusted R-sq.	0.078		0.046		0.049		0.083		0.062	

Table VIII
Copycat Portfolio Strategies

Every quarter, the likelihood of a fund-company (*FC*) information channel existing between fund manager *j* and each company issuing stock *n* that is held in *j*'s portfolio is calculated as $L^{FC}(Links)_{j,n}$ = 1/(1+ $Distance_{j,n}$). Here, $Distance_{j,n}$ is the natural logarithm of the geographical distance (in km) between the city where fund *j* is located and the city in which company *n* is headquartered. Each fund's holdings are ranked into quartiles $Q1^{FC}$ through $Q4^{FC}$ based on $L^{FC}(Links)_{j,n}$, with $Q4^{FC}$ being the *Strong Fund-Company Link*s portfolio and $Q1^{FC}$ being the *Weak Fund-Company Links* portfolio. The likelihood of an information channel existing between fund manager *j* and fund manager *i* is $L^{FF}(Links)_{j,i} = 1/(1+Distance_{j,i})$ where, $Distance_{j,i}$ is the natural logarithm of the geographical distance between the city where fund *j* is located and the city in which fund *i* is located. The strength of fund-fund (*FF*) informal information links a fund manager *j* has with other fund managers is computed as

$$(Links)_j^{FF} \;=\; \sum_{i=1}^{N} L^{FF}(Links)_{j,i} = \sum_{i=1}^{N} 1/(1+Distance_{j,i})$$

Here, $i=1,\ldots,N$ are all funds in the sample that do not belong to the same fund family as fund *j*. Every quarter, the funds are ranked into quartiles $Q1^{FF}$ through $Q4^{FF}$ based on $(Links)_j^{FF}$, with $Q4^{FF}$ being the *Strong Fund-Fund Links* portfolio and $Q1^{FF}$ being the *Weak Fund-Fund Links* portfolio. A hypothetical equally-weighted portfolio called the Best Information Portfolio (*BIP*) comprising of stocks which are classified as (1) *Strong Fund-Company Links* stocks for *Weak Fund-Fund Links* funds and (2) *Weak Fund-Company Links* stocks for *Strong Fund-Fund Links* funds is created. *BIP* is formed at the beginning of month *t*, based on the publicly released information on mutual fund holdings for a quarter comprising months *t*-3, *t*-2, *t*-1. *BIP (Qtr t)* is the *BIP* constructed in quarter *t* in the sample period, where *t*=1,..,10. Panel A (Panel B) presents the average monthly raw returns (characteristic-adjusted returns) of an equally-weighted portfolio of *BIP* stocks for 3-, 6-, 9-, 12-month holding periods. Characteristic-adjusted returns are computed following Daniel et al. (1997). *p*-values based on robust standard errors are reported in parentheses. ***, **, * represent significance at 1%, 5% and 10% level respectively.

	Panel A: Average Monthly Raw Returns			
Hypothetical Portfolio	3-mth return (%)	6-mth return (%)	9-mth return (%)	12-mth return (%)
BIP (*Overall*)	1.63***	1.81***	1.35**	0.85
	(0.01)	(0.00)	(0.03)	(0.17)
BIP (*Small Fund Families*)	1.49**	1.52***	0.88*	0.79
	(0.05)	(0.01)	(0.10)	(0.25)
BIP (*Large Fund Families*)	1.82***	2.13***	1.59**	0.97
	(0.00)	(0.00)	(0.02)	(0.19)
BIP (*Small Funds*)	1.32**	1.45**	0.69	0.62
	(0.04)	(0.03)	(0.32)	(0.43)
BIP (*Large Funds*)	2.02***	2.28***	1.73***	1.03*
	(0.00)	(0.00)	(0.00)	(0.09)

	Panel B: Average Monthly Characteristic-adjusted Returns			
Hypothetical Portfolio	3-mth return (%)	6-mth return (%)	9-mth return (%)	12-mth return (%)
BIP (*Overall*)	0.82***	1.02***	0.53	-0.05
	(0.00)	(0.00)	(0.13)	(0.95)
BIP (*Small Fund Families*)	0.72**	0.77***	0.24	-0.48
	(0.03)	(0.00)	(0.49)	(0.35)
BIP (*Large Fund Families*)	1.13***	1.25***	0.69*	0.28
	(0.00)	(0.00)	(0.10)	(0.62)
BIP (*Small Funds*)	0.80**	0.91**	0.42	-0.59
	(0.02)	(0.02)	(0.39)	(0.32)
BIP (*Large Funds*)	0.95***	1.27***	0.70*	0.45
	(0.00)	(0.00)	(0.09)	(0.40)