# The Ties that Bind: Work Connections and Mutual Fund Investment Ideas

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**Abstract**

We document a significant increase in the sharing of investment ideas among mutual fund managers when they share a workplace connection. Mutual funds with managers who share a work connection at another fund have greater overlap in portfolio holdings, equity purchases, and equity sales. This result increases as the duration of the work connection increases and remains significant even after the work connection ends. We do not find this result among index mutual funds, where manager do not have discretion over portfolio holdings. Finally, we find that the investment ideas shared through workplace connections outperform portfolio holdings not generated through work connections.

## Introduction

Many studies in the corporate finance literature have documented the negative impact of social ties on diminishing the effectiveness of corporate governance and exacerbating agency cost. Specifically, social ties may compromise the independence of the board of directors, weakening its monitoring ability (Hwang and Kim, 2009; Fracassi and Tate, 2012; Nguyen, 2012; Balsam et al., 2017). Social ties can also bias the CEOs in their internal investment decisions: division managers connected to the CEO receive greater capital allocations than non-connected managers (Duchin and Sosyura, 2013). On the other hand, social ties can play a positive role in facilitating valuable information transfer and increase firm value (Duchin and Sosyura, 2013; Schmidt, 2015). Typically, social ties are defined as connections between two people through employment, affiliation with the same social organization, or attendance at the same education institutions.

Social connections are viewed more favorably in the asset management literature. Through their social connections, fund managers can gain an informational advantage and make better investment decisions. These connections can originate from mutual fund managers who are neighbors (Pool et al., 2015) or who live in the same city (Hong et al., 2005). They can come from shared educational networks between fund managers and corporate board members (Cohen et al., 2008) or geographic proximity between the funds and the portfolio companies (Coval and Moskowitz, 1999; Coval and Moskowitz, 2001). These studies show that mutual fund managers tend to put larger weights on connected holdings, and these holdings generate higher returns for the funds.

In this paper, we investigate an important social tie for mutual fund managers: current and past work connection with other fund managers. According to a recent study by Business Insider, the average person spends more than 90,000 hours in their lifetime at work, and the Wall Street

Journal shows that the average full-time employee in the United States spent 53.70% of their waking weekday hours at work.[1] As stated by Pool et al. (2015 pg. 2679), "…humans are social animals, so perhaps fund managers also trade stocks that they learn about from other managers." While Pool et al. (2015) focus on the connection of being neighbors, we explore the impact of connections developed through the workplace, given that fund managers spend a significant amount of time with their co-workers.

Using fund prospectuses from 2005 to 2016, we hand collect data on mutual fund managers of active domestic equity mutual funds in the top 35 largest fund families, which account for 79% of total assets under management in the mutual fund industry as of March 2005. We define a work connection as two managers managing the same fund together, and we examine the overlap in holdings between two other funds separately managed by these managers. We do not include in our analysis any fund-pair that shares a common manager. We also hand collect data on managers' addresses and managers' past degrees and educational institutions, which help us identify managers who are neighbors and who share an educational network. In total, our sample includes 1,416 unique managers from 2005 to 2016.

Aggregating manger-fund-pair level data to the fund-pair level, we document a significant and economically large increase in portfolio overlap between two funds where fund managers externally work together at another fund. Whereas the average fund overlap in our sample is 8.7%, when managers share a work connection, portfolio overlap increases to 14.4%, a 65% increase. In contrast, when fund managers are neighbors, the observed change in overlap is from 8.7% to 11.2%, and when they have a shared education the change is from 8.8% to 10.9%. While we do observe economic importance among social networks within neighborhoods and through shared

[1] https://www.businessinsider.com/disturbing-facts-about-your-job-2011-2 and https://graphics.wsj.com/time-use/.

education, the impact of the work network is more than twice as large. We document similar relations with trade-based measures of portfolio overlap; managers with work connections have significantly more equity sales and purchases in common when compared with shared neighborhood and educational connections.

Work connections present an ideal opportunity to share investment ideas between fund managers. However, when a fund is managed by a team, individual manager connections become less important as fund management decisions become more spread out. We explore the economic importance of how workplace connections impact portfolio overlap when managers that work together at one fund also manage a single-manager fund elsewhere. In the case of single-manager funds, the impact on portfolio overlap is an 146.0% increase, rising from 8.7% to 21.4%. We again find that work connections result in the largest source of shared investment ideas for fund managers.

Since managers may leave and join other mutual funds, we also explore the importance of prior work connections. We show that shared investment ideas do not disappear as the work connection ends. Though the impact is marginally lower, we find that prior work connections result in an increase in portfolio overlap from 8.7% to 13.4%, with similar results among equity purchases and sales. The longevity of the impact workplace connections have on sharing investment ideas further supports the importance of work connections in understanding how mutual fund managers develop investment ideas.

Next, we investigate whether the length of time managers have worked together have an impact on the sharing of investment ideas. We expect that the longer managers work together, the more likely they are to strengthen their work connection and share ideas with each other (Sabel, 1993; Sias and Cahill, 1998). We find that portfolio overlap, similar security sales, and similar security purchases all significantly increase as the time spent working together increases. This is consistent with the model for building trust through continued interactions with others as described by Sabel (1993), and highlights the importance of not only becoming connected with your work network, but maintaining that network to develop trust and expand the scope of shared ideas.

To ensure the validity of our results, as opposed to a mechanical relation, we consider how work connections impact portfolio holdings at index mutual funds. Because index mutual fund managers try to mimic the market portfolio instead of actively picking stocks, we expect that work connections do not have an impact on portfolio composition. As expected, this placebo test produces non-significant coefficients for portfolio overlap, buy overlap, and sale overlap. This ensures that our findings of managers sharing investment ideas at actively managed funds are not a mechanical artifact of our tests.

A better understanding of the source of investment ideas among mutual fund managers provides valuable insight into how managers create portfolios. However, if shared investment ideas do not differ in performance from other holdings, these new insights provide limited use in furthering our understanding of how mutual funds generate performance. There are two possible outcomes from shared investment ideas: Han and Yang (2013) model and discuss the negative implications of sharing investment ideas and their association with a free ride problem. If managers do not have to expend their own energy developing investment ideas, the net impact of sharing ideas through work connections is negative. In contrast, Cici et al. (2017) shows that sharing information within a fund family increases the value of a manager’s own information, resulting in improved performance.

Consistent with the benefits found by Cici et al. (2017), we show that investment ideas shared through workplace connections improve fund performance. Within a fund portfolio, we find that positions resulting from work connections generate significant outperformance over the subsequent quarter. We also find that newly initiated equity purchases resulting from work connections outperform, though new equity sales do not generate significantly different performance. Overall, our findings are consistent with the idea that significant benefits accrue from mutual fund managers' work connections.

Though our study takes place within the field of finance, the importance of social interactions and their role in spreading information extends to all areas of study. For example, the use of Snapchat as a channel for sharing experiences has been documented in information systems (Bayer et al., 2016); within social epidemiology, social networks are used to examine social contagion, or the spread of disease (El-Sayed et al., 20120); and in economics, research has shown that a purchase made by a neighbor directly impacts a consumer's subsequent purchases (Grinblatt et al., 2008).

Within finance, educational ties between analysts and firms as well as between mutual funds and firms (Cohen et al., 2008; 2010), location ties between mutual fund managers (Hong et al., 2005; Pool et al., 2015), financial ties between board members and the CEO (Hwang and Kim, 2009), and board of director ties between an acquirer and target firm (Cai and Sevilir, 2012) have been given substantial consideration. In all cases, these studies document strong information sharing across social networks developed through any one of these connections. Specific to work connections, Fracassi (2017) shows that companies with a greater number of current and past employment connections have more similar capital investments, while Engelberg et al. (2012) shows that when banks and firms are connected through prior employment, interest rates are significantly lower.

Building on the social networking literature in finance, specifically that relating to work connections, we show that current and prior work connections significantly increase the amount of portfolio overlap among mutual fund portfolios. Furthermore, we show that the work connection is significantly stronger than connections stemming from neighbors or classmates. By showing that work connections explain a significant portion of portfolio overlap, and that the relation does not disappear when managers no longer work together, we highlight the long-term importance of work connections in constructing an actively managed portfolio, while also building on the literature examining the sources of investment ideas.

The remainder of our paper is organized as follows. Section 1 provides an outline of our data, collection process, and sample creation. In section 2 we describe our measures of portfolio overlap and provide sample descriptive statistics. Section 3 explores the relation between work connections and portfolio overlap. We examine how performance differs across measures of work connections in section 4. Section 5 provides our conclusion.

## 1. Data and Sample Creation

Our investigation requires us to collect detailed data on a mutual fund manager's prior work history, address history, and education history to identify possible connections between a fund manager and other fund managers. To manage the scope of the data collection efforts, we focus on managers and funds in the top 35 families in the *Center for Research in Security Prices (CRSP) Survivor-Bias-Free U.S. Mutual Fund Database*, ranked by total assets of domestic equity funds under management, as of March 31, 2005. These 35 families account for 78.4% of assets under management in the mutual fund industry. Our sample is similar to the one used in Del

Guercio et al. (2018), though we include the largest 35 families instead of 30 and include data from 2005 to 2016.

We identify domestic equity funds by relying on Lipper objective codes (CA, EI, G, GI, I, MC, MR, and SG). We exclude variable annuities and target date funds since these funds include a large component of fixed income investments in their portfolios. We add funds as these 35 families start new funds or acquire existing funds from other families during the sample period, and retain funds until they merge or liquidate. We match CRSP mutual funds to their corresponding SEC filings by using the links to fund prospectuses provided by the SEC in quarterly indexes. The matches are implemented based on exact name or ticker matches.[2] For any remaining unmatched funds, we identify close name matches and manually verify accuracy.

We first collect the names of the managers of each fund in our sample from the Statement of Additional Information, which is a required supplementary document to the fund's prospectus filed with the SEC (form N-1A with form type 485BPOS or 485APOS). The SEC requires funds to disclose all managers "responsible for the day-to-day management of the fund." We use information from SEC filings to ensure that we accurately capture all managers with a work connection. Patel and Sarkisian (2017) find that the accuracy rate of CRSP-reported managerial structures of funds is only 77% compared to SEC filings. On the other hand, they report that the accuracy rate of Morningstar Direct is 96%. Since we are also interested in whether managers have worked with each other in the past (before our sample period starts in 2005), and managers may work together on a team outside the top 35 families, we supplement our SEC data on fund managers' team connections with data from Morningstar Direct.

[2] Available at https://www.sec.gov/Archives/edgar/full-index/. Since February 6, 2006, the SEC requires mutual funds to include tickers in their filings. We use a computer script to obtain tickers directly from the SEC Edgar website.

Figure 1 illustrates the mechanics of our *Work Connection* variable. In this example we have three mutual funds and four fund managers. Our managers of interest are the mangers of Fund A, John and Mary. John and Mary manage Fund A together and are therefore connected through this fund. John is also the manager of Fund B with Steve, and Mary is also the manager of Fund C with Ben. Our *Work Connection* variable is denoted by the solid arrow connecting Funds B and C. We classify this as a work connection because John and Mary connect the two funds through their joint management of the third fund, Fund A. We do not include fund-pairs A-B or A-C in our analysis because these fund pairs share a common manager and would have built-in overlap in holdings and performance. Our work connection of interest is outside of the jointly managed fund, or in this case, fund-pair B-C.

[*Insert Figure 1 near here*]

Next, we hand collect data on managers' education history from manager biographies reported in fund prospectuses, Morningstar, Bloomberg, and LinkedIn profiles. To ensure the accuracy of manager matches to Bloomberg and LinkedIn profiles, we verify that the names of managers' fund families match the names of employers reported on Bloomberg and LinkedIn. For each manager, we collect all undergraduate and graduate degrees he or she has received, universities that grant the degrees, majors, and graduation years if available. Cohen et al. (2008) find that mutual fund managers tend to invest in firms they are connected with via board members who share their educational networks. Following the definitions used in their paper, we identify four types of educational network connections within each mutual fund manager pair based on whether two fund managers attended the same school (CONNECTED1), attended the same school and received the same degree (CONNECTED2), attended the same school and graduated at the same time (CONNECTED3), and attended the same school, received the same degree, and graduated at the same time (CONNECTED4). Throughout our analysis, we use the definition of CONNECTED3 (attending the same school and graduating at the same time) in all of our tests.

Lastly, we hand collect data from Lexis Nexis public records to identify mutual fund managers who may be neighbors. Pool et al. (2015) find that managers who are neighbors tend to have higher overlap in fund holdings and trades than non-connected manager pairs. Since managers with a work connection may also choose to live near each other, we need to control for the neighbor connection to ensure that the result we obtain for the *Work Connection* variable is not confounded by the neighbor effect. Our methodology is similar to that used in Pool et al. (2015). First, we conduct a search of public records of each manager based on his or her full name and current age.[3] If this search yields only one single match, we capture the address history reported for that person. If the search yields multiple matches, we limit the matches to only people living within 50 miles of the fund family's headquarters location during the manager's period of employment. If this procedure yields one single match, we capture the address history reported for that person. We do not capture address history for managers matched to multiple different people in Lexis Nexis. We then construct a database of manager-pair-date distances between homes. We denote *Neighbor* as an indicator variable equal to one of a pair of managers is living in the same

[3] We hand collect birth year or current age from manager biographies in prospectuses, Morningstar, Bloomberg, or LinkedIn profiles. If the data is not available, we estimate current age by assuming that the manager is 22 years old when graduating from her undergraduate university. When conducting public record searches in Lexis Nexis, we use an age range of estimated current age +/- 2 to mitigate any inaccuracy inherent in our assumption. For example, if manager John Smith's estimated current age is 55, we search for any person named John Smith with age ranging from 53 to 57.

zip code at a particular point in time.[4] We denote *Prior Neighbors* as an indicator variable equal to one if a pair of managers used to live in the same zip code but no longer live near each other.

Our final sample includes 1,416 unique managers and 713 unique funds from 2005 to 2016. We document over 4.7 million manager-pair-quarter connections and over 1.7 million fund-pair-quarter connections in total.

## 2. Portfolio Overlap and Descriptive Statistics

In this section we describe our calculation of portfolio overlap, buy overlap, and sale overlap. We then present sample descriptive statistics.

### *2.1. Overlap Calculations*

A mutual fund manager is tasked with selecting the securities to be included in the fund portfolio and assigning weights to the securities. Obtaining trade insights from other fund managers can be very valuable. Pool et al. (2015) examine how mutual fund managers obtain investment ideas from their neighbors using a measure of portfolio overlap. Following this method, we calculate portfolio overlap as:

$$PortOverlap_{i,j,t} = \sum\nolimits_{k,h_t} \min\{w_{i,k,t}, w_{j,k,t}\}, \qquad (1)$$

where $w_{i,k,t}$ is fund $i$'s portfolio weight in stock $k$ during quarter $t$, $w_{j,k,t}$ is fund $j$'s portfolio weight in stock $k$ during quarter $t$, and $h_t$ is the set of all stocks held by funds $i$ and $j$ as reported at the end

[4] We take a simpler approach than Pool et al. (2015) in defining neighbors as managers living in the same zip code, whereas they calculate the actual driving distance between the homes of the fund managers.

of quarter *t*. This measure is aggregated to the mutual fund pair level ($PortOverlap_{i,j,t}$) and measures the percentage of overlap in holdings between two mutual funds in a given quarter.

In addition to general overlap in holdings, one signal of potential information sharing is if there is overlap in the trades that are taking place between two funds. We examine how purchases and sales overlap across funds as well. Our trade specific measures of overlap are also as in Pool et al. (2015):

$$BuyOverlap_{i,j,t} = \frac{\sum_{k,z_t} \min\{I^+_{i,k,t}, I^+_{j,k,t}\}}{\min\{\sum_{k,z_t} I^+_{i,k,t}, \sum_{k,z_t} I^+_{j,k,t}\}}, \qquad (2)$$

and

$$SaleOverlap_{i,j,t} = \frac{\sum_{k,z_t} \min\{I^-_{i,k,t}, I^-_{j,k,t}\}}{\min\{\sum_{k,z_t} I^-_{i,k,t}, \sum_{k,z_t} I^-_{j,k,t}\}}, \qquad (3)$$

where $I^+_{i,k,t}$ is one if fund *i* increased the number of shares in stock *k* between time *t – 1* and *t*, and zero otherwise. $I^-_{i,k,t}$ is one if fund *i* decreased the number of shares in stock *k* between time *t – 1* and *t*, and zero otherwise. $Z_t$ is the union of all stocks traded by funds *i* and *j*. The numerators represent common purchases in Eq. (2) and common sales in Eq. (3), measured across each fund pair. We standardize each value by the number of buys (sales) for the measure of *BuyOverlap* (*SaleOverlap*) of the individual funds. Measures of directional overlap range between zero and one. For a more detailed discussion of these measures see Pool et al. (2015).

### *2.2. Sample Descriptive Statistics*

We present sample descriptive statistics in Table 1. Panel A contains descriptive statistics at the fund-quarter level, Panel B at the manager-pair level, and Panel C at the fund-pair level. Within Panel A we observe an average fund size of $4.5 billion, with average monthly fund flows of 2.2%, average fund expense ratios of just over 1%, and quarterly gross alphas of just under 0.4%. Relative to other studies (Kacperczyk, et al., 2014; Cici et al., 2017), we have larger average fund sizes, though the remainder of our sample characteristics are similar despite our focus on the top 35 fund families. Of all manager pairs, we observe 0.3% with a work connection, 0.3% with a neighbor connection (a similar magnitude to that of Pool et al., (2015)), and 0.2% with a Connected 3 Education connection. These small numbers indicate that connections across managers are uncommon among the full sample possible manager pairs. Finally, we observe 0.6% of fund pairs in Panel C with a work connection, 1.2% with a neighbor connection, and 1.4% with an education connection. Connections at the fund-pair level are more common because many mutual fund have multiple fund managers, and whenever at least one pair of fund managers within a fund has a connection, we assign the entire fund-pair as connected.

[*Insert Table 1 near here*]

In Table 2 we explore values of portfolio overlap across various subsamples in Panel A, buy overlap in Panel B, and sale overlap in Panel C. Overall, we find that regardless of the type of social connection, all measures of portfolio overlap, buy overlap, and sale overlap measures are significantly greater at the funds with a connection. Specifically, we find that the greatest differences in all overlap measures are found at funds where managers currently work together at another fund, followed by funds where managers previously worked together. In the case of total overlap, funds with a current work connection have on average 14.4% portfolio overlap while those with no connection have just 8.7%, and looking at historical work connections yields an average overlap of 13.4%. Measures of total overlap, sale overlap, and buy overlap are even greater when two funds in the pair are managed by single managers only, with values as high as 23.0% for total overlap. In contrast to the overlap measures associated with work connections, we observe much smaller values for educational connections (10.8%) and neighborhood connections (11.4%). Our overlap descriptive statistics indicate how important work connections are when considering how mutual fund managers share investment ideas.

[*Insert Table 2 near here*]

We ensure that our portfolio overlap values are not driven by one particular period of time in Figure 2. Each year of our sample, we calculate the average portfolio overlap for mutual funds with and without a work connection and graph the yearly averages. We observe a consistently higher value of portfolio overlap during every year of our sample, with no large outliers. Our findings do not indicate the presence of any time specific patterns.

[*Insert Figure 2 near here*]

## 3. Work Connections and Portfolio Overlap

In this section we examine the relation between work connections and portfolio overlap across team managed and single managed funds. We then look at how the duration of a work connection impacts portfolio overlap. We finish with a placebo-test of index mutual funds.

### 3.1. Work Connections and Shared Investment Ideas

We explore the impact of social networks further through a multivariate regression:

$$Overlap_{i,j,t} = \beta_1 Work\ Connection_{i,j,t} + \beta_2 Prior\ Work\ Connection_{i,j,t} + \beta_3 Other\ Connections_{i,j,t} + Controls_{i,j,t} + \varepsilon_{i,j,t}, \qquad (4)$$

where *Overlap* takes on the value of *PortOverlap* in columns 1 through 3 of Table 3, the value of *SaleOverlap* in columns 4 through 6, and the value of *BuyOverlap* in columns 7 through 9. Our variable of interest, $Work\ Connection_{i.j.t}$ is an indicator variable that takes on the value of one if at least one manager of fund *i* also manages a fund with at least one manager of fund *j* during quarter *t*, and zero otherwise. $Prior\ Work\ Connection_{i.j.t}$ is an indicator variable that takes on the value of one if at least one manager of fund *i* managed a fund with at least one manager of fund *j* during the past, and zero otherwise.

We define $Neighbors_{i.j.t}$ as an indicator variable equal one if at least one manager from fund *i* is a neighbor of a manager from fund *j* during quarter *t*, and zero otherwise (Pool et al., 2015), $Prior\ Neighbors_{i.j,t}$ as an indicator that takes on the value of one if at least one manager from fund *i* was a neighbor or a manager from fund *j* in the past, and we define $Education_{i.j.t}$ as an indicator variable equal to one if at least one manager from fund *i* shares an educational connection with a manager from fund *j* during quarter *t*, and zero otherwise. For educational connection, we adopt the CONNECTED3 definition from Cohen et al. (2008), with two managers sharing a connection if they attended the same school and graduated at the same time. Other control variables include an indicator variable that takes on the value of one if the two mutual funds in a pair are located in the same city and zero otherwise, the log of the absolute value of the difference in total net assets between each mutual fund in the pair, and an indicator variable equal to one if each mutual fund in a pair are in the same investment objective. As in Pool et al. (2015), we cluster standard errors two-ways by each fund in the pair.

We first determine that managers sharing a work connection have greater portfolio overlap than those without this shared connection. If our multivariate results mirror our univariate ones, we expect to find a significant and economically meaningful coefficient on *Work Connection*. Our models in columns 2, 5, and 8 confirm that work connections are associated with greater portfolio overlap, buy overlap, and sale overlap, with 3.2%, 3.3%, and 2.6% more overlap, respectively. Relative to other current connections, the importance of the connections developed through work represent between 65.0% and 113.4% greater importance to measures of portfolio overlap.

[*Insert Table 3 near here*]

Given the amount of time spent at work, the results presented thus far support the importance of the work connection. Next, we investigate if this work connection still remains significant even after managers are no longer co-workers. In Columns 3, 6, and 9 we include measures of past work connections and past neighbors. Across all three measures of overlap, we observe a strong and positive coefficient on *Prior Work Connection*, though of a slightly smaller magnitude than what we simultaneously observe for current *Work Connection*. For measures of portfolio overlap, buy overlap, and sale overlap, prior work connections are 85.9%, 67.0%, and 72.1% as important as current work connections. In contrast, managers who were neighbors in the past only display greater sale overlap. This indicates that the connections developed while working together last beyond the time managers actually spend as coworkers, further highlighting the importance of understanding how work connections impact portfolio allocation decisions.

### *3.2. Single Managers, Work Connections, and Shared Investment Ideas*

Results presented in Table 3 show the importance of work connections in sharing investment advice across all mutual funds. However, many funds are team managed, reducing the direct decision-making authority given to any one manager. In this analysis, we focus on mutual funds managed by single managers. We consider single managed funds as those fulfilling the following requirements: Mutual fund A is managed by two (or more) managers. Each of the two managers also manages another single-manager mutual fund (fund B and C). This relationship allows for a work connection through A while also giving each manager sole responsibility for funds B and C, respectively.

We test the impact at single-manager mutual funds by replicating the tests of Eq. (4) on a subsample of single-manager funds in Table 4. Results confirm our findings from Table 3 and illustrate how work connections matter more among single-manager mutual funds. Whereas work connections among all funds increase measures of overlap between 2.6% and 3.3%, among single managed funds that increases to between 4.6% and 7.1%. Furthermore, prior work connections are of greater importance as well, with increases in overlap, buy overlap, and sale overlap increasing by 6.9%, 6.4%, and 5.1%, respectively. Results from our sample of single-manager funds support the idea that fund managers share investment ideas with their colleagues, both present and past.

[*Insert Table 4 near here*]

### *3.3. Duration of work connection*

Trust is built over time, through repeated interactions with individuals (Sabel, 1993). As a result, we expect the impact of a work connection to increase the longer period two individuals spend working together. We explore this in Table 5 by including a measure for the duration of current work connections as well as for the duration of prior work connections. We include as control variables those included in Tables 3 and 4. We explore portfolio overlap in columns 1 and 2, buy overlap in columns 3 and 4, and sale overlap in columns 5 and 6. Odd columns exclude connections outside of work, and even columns include current and prior neighbors as well as educational connections.

As suggested by the trust work of Sabel (1993), idea sharing becomes more pronounced as connections lengthen. Among current work connections, those with an average duration have 1.3% more overlap, 1.8% more buy overlap, and 1.5% more sale overlap. For each standard deviation increase in the duration of a current work connection, overlap measures increase by 0.17%, 0.14%, and 0.09%, respectively. Whereas prior work connections matter, the duration of those connections is less important, as we observe positive, but insignificant coefficients on all measures of past work connection duration. The implications of Table 5 are consistent with the notion of trust discussed by Sabel (1993), and indicate that the strength of a work connection grows over.

[*Insert Table 5 near here*]

### *3.4. Index Mutual Funds*

Among our sample of actively managed mutual funds we observe that work connections result in significantly greater overlap in portfolio holdings, securities purchases, and securities sales between two funds. To ensure our result is not mechanical in nature, we utilize index mutual funds as a placebo test. While index mutual fund managers can still cultivate work connections, they have little to no authority regarding which equities they choose to hold. Because their holdings are mandated by the underlying index, work connections should not impact index mutual funds in the same way they impact active funds. We replicate the tests from Table 3 on a sample of index mutual funds, including measures of *Work Connection, Education, MF Same City, MF TNA Diff*, and *Same Objective* as calculated in Eq. (4). We do not include the *Neighbors* variable because of data availability restrictions.

Results presented in Table 6 confirm our hypothesis that index fund managers do not increase portfolio overlap through work connections. Coefficients across portfolio overlap, buy overlap, and sale overlap are not significantly different from zero. This non-result shows that work-based connections are important at *only* actively managed mutual funds as a source of shared investment ideas.

[*Insert Table 6 near here*]

## 4. Performance of Connected Trades

We document significant increases in overlap of portfolio holdings, portfolio purchases, and portfolio sales associated with work connections. Whether the shared investments help or hurt fund performance are an empirical question. A negative outcome of shared investment ideas through work connections involves the free rider problem. Han and Yang (2013) model this free rider problem when information is costly to obtain. In the Han and Yang environment, shared investment ideas through work connections represent a negative. In contrast, Cici et al. (2017)

show that within fund families, quickly sharing investment information leads to an increase in fund performance, a net positive for shared ideas through work connections. In this section we explore the relation between work connections, overlapping buying or selling, and subsequent stock performance.

Our primary focus is on a measure of excess buying relative to what all other mutual funds in our sample do. If all funds in our sample purchase Apple during a quarter, a fund with a work connection buying Apple should not be of interest. Rather, if all funds in our sample purchase Apple at 5% of their portfolio TNA and a fund with a work connection purchases Apple at 8% of their portfolio TNA, their excess buy amounts to 3%. By using excess buying, we remove market-wide buying trends and focus on fund specific decisions. We replicate this process with selling, taking the absolute value so that excess selling is a positive number for ease of interpretation. We focus our performance tests on individual stocks, and measure performance as monthly DGTW excess returns (Daniel et al., 1997) averaged over the quarter as in Pool et al. (2015).

We examine the relation between work connections, excess buying (selling), and holding performance as:

$$DGTW\ Returns_{i,s,t+1} = \beta_1 Work\ Connection\ Buy_{z,s,t} + \beta_2 Excess\ Buy_{i,s,t}$$
$$+\beta_3 Work\ Connection\ Buy_{z,s,t} \times Excess\ Buy_{i,s,t} + Fixed\ Effects + \varepsilon \quad (5)$$

The unit of analysis is fund-stock-quarter observations. $DGTW\ Returns_{i,s,t+1}$ is the average monthly DGTW excess return of stock $s$ in fund $i$ averaged over quarter $t+1$. $Work\ Connection\ Buy_{z,s,t}$ is an indicator variable equal to one if the stock $s$ is purchased by at least one other fund (any fund $z$ that's not fund $i$) with a work connection during quarter $t$. $Excess\ Buy_{i,s,t}$ is measured as the percent of portfolio $i$ TNA allocated to the purchase of stock $s$ during quarter $t$ minus the average portfolio weight attributed to the purchase of stock $s$ during quarter *t* across all funds in our sample. The interaction term of *Work Connection Buy* and *Excess Buy* captures the performance of holdings purchased more than average by the fund *and* also purchased by at least one other fund with a work connection.

We present the performance of connected buys in Columns 1 and 2 of Panel A and connected sales in Columns 3 and 4 of Panel A in Table 7. We include stock and year-quarter fixed effects in all columns and add clustered standard errors by year-quarter in columns 2 and 4. The interaction term, our variable of interest, is positive and significant, indicating that when a fund makes an excess purchase of a stock that is also purchased by another fund with a shared work connection, the stock outperforms during the subsequent quarter. The magnitude of the outperformance is economically large, amounting to annualized DGTW excess returns of 0.90% (0.075% per month) for a 1% increase in excess buying. In contrast to the subsequent outperformance associated with work connections and excess buying, we observe no relation between selling and future performance. In Panel B we replace current work connections with past work connections and observe similar results for excess buying as in Panel A. Among excess selling, we now document a benefit. When a fund sells excess amounts of a security that is simultaneously sold by another fund with a prior work connection, the sold security underperforms by an annualized 0.80% (0.067% per month). Our results document a clear advantage to investment ideas shared through work connections, with common purchases subsequently outperforming, and in certain cases common sales subsequently underperforming. These benefits are consistent with the argument in Cici et al. (2017) that shows sharing information among fund managers provides a net benefit, rather than the free rider problem in Han and Yang (2013).

[*Insert Table 7 near here*]

Table 4 shows that the impact of a work connection is significantly larger among single-manager mutual funds. We extend the single manager analysis to our performance results in Table 8. Results presented in Table 8 mirror those of Tables 4 and 7; the impact of work connections is larger among single-manager funds and the shared investment ideas generate significant outperformance. Within single-manager funds, we find that when connected via a work connection, a 1% increase in excess purchases leads to 2.6% annualized outperformance (0.214% per month). The significant impact on performance holds for prior work connections, as shown in Panel B of Table 8. Single manager results confirm the benefits associated with information sharing throughout a work connection while also highlighting the increased importance when a single fund manager is in control of a mutual fund.

[*Insert Table 8 near here*]

## 5. Conclusion

A better understanding of the source of mutual fund managers investment ideas is of great value to investors, academics, and practitioners. Americans spend over 50% of their waking weekday hours at work, with some Wall Street employees spending nearly 75%. Given the large proportion of one's day spent with work colleagues, it is important to understand workplace interactions in more detail. In this paper, we explore the impact of work connections on the actions and investment decisions of portfolio managers.

We show that managers of separate mutual funds that are bound together by a workplace connection have significantly greater portfolio commonalities than those managers that do not possess this connection. We document significantly greater portfolio overlap and more common security purchase and sale activity. This impact is present among all mutual funds with a shared work connection, but becomes significantly greater among single managed funds. This is consistent with managers with greater autonomy utilizing their shared work connections to a greater extent. The importance of work connections extends beyond current employment, as we show that prior connections significantly increase measures of portfolio overlap as well. Managers who worked together in the past continue to have greater commonalities in their portfolio holdings and actions than those without a similar connection. This impact increases in magnitude the longer two managers work together, as longer work connections permit the growth of trust (Sabel, 1993).

Finally, we show that investment actions derived from work connections provide actionable investment ideas. The performance of securities purchased by two funds sharing a work connection generate significant excess performance over the subsequent quarter. We show that past connections generate profitable purchases and sales, further adding support to the value contained within investment ideas generated through work connections.

Overall, the results of our analysis shed light on the importance of work connections within the asset management field. When managers share work connections, their portfolios have significantly more in common and their trading behaviors are more similar. While concerns over a free rider problem exist, our evidence alleviates them, providing evidence that workplace networks provide valuable information that lead to significant outperformance. Our findings indicate that consideration of workplace connections are important when evaluating the source of mutual fund managers’ investment ideas.

**Appendix A. Variable definitions**

| Variable name | Definition |
|---|---|
| Fund-pair-quarter connection variables: | |
| *Work Connection* | Equal to one if at least one of each fund's managers currently co-manage another fund together |
| *Prior Work Connection* | Equal to one if at least one of each fund's managers previously co-manage another fund in the past |
| *Work Connection Duration* | Number of years two managers have worked together up until the current quarter |
| *Prior Work Connection Duration* | Number of years two managers worked together previously (from beginning to end) |
| *Neighbors* | Equal to one if at least one of each fund's managers currently live in the same zip code |
| *Prior Neighbors* | Equal to one if at least one of each fund's managers previously lived in the same zip code in the past |
| *Education* | Equal to one of at least one of each fund's managers attended the same school and graduated at the same time (similar to *Connected3* variable in Cohen et al. (2008)) |
| Fund-pair-quarter control variables | |
| *Same Fund Family* | Equal to one if two funds are in the same family |
| *Fund in Same City* | Equal to one if two funds are located in the same city |
| *Ln(Absolute Value TNA Difference)* | Natural log of the absolute value of the difference in total net assets between two funds |
| *Same Objective* | Equal to one if two funds have the same investment objective (as classified by Lipper) |
| Fund-stock-quarter variables | |
| *Work Connection Buy* | Equal to one if the stock is purchased by at least another fund with a work connection |
| *Excess Buy* | A fund's portfolio weight in buying a stock in one quarter subtracted by the average portfolio weight in buying that stock by all funds in the sample in that quarter |
| *Work Connection Sale* | Equal to one if the stock is sold by at least another fund with a work connection |
| *Excess Sale* | A fund's portfolio weight in selling a stock in one quarter subtracted by the average portfolio weight in selling that stock by all funds in the sample in that quarter (absolute value is taking for east of interpretation) |
| *Prior Work Connection Buy* | Equal to one if the stock is purchased by at least another fund with a prior work connection |
| *Prior Work Connection Sale* | Equal to one if the stock is sold by at least another fund with a prior work connection |

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**Figure 1**
**Work Connection**

This figure illustrates how we classify work connections. The dashed arrows indicate additional funds managed by John and Mary from Fund A. The solid arrow labeled Work Connection indicates the fund-pair defined as having a work connection in our analysis. John manages Fund B and Mary manages Fund C. John and Mary are connected through a work connection derived from their joint management of Fund A.

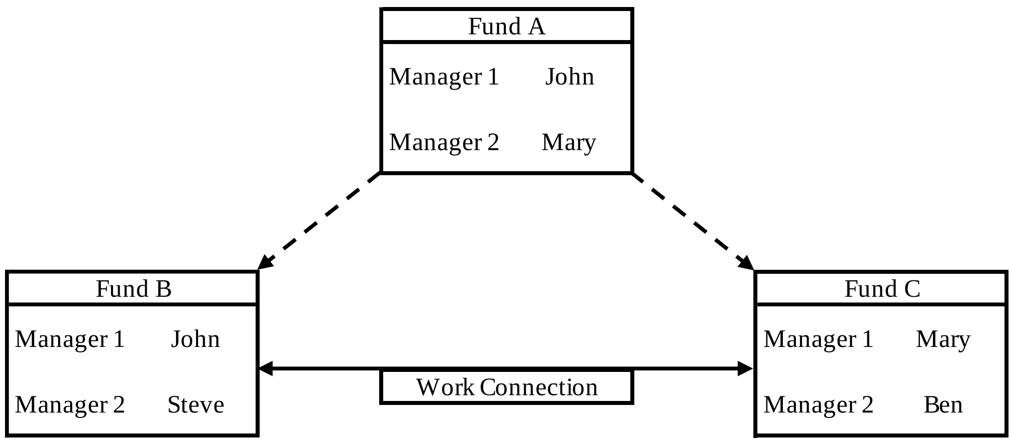

**Figure 2**
**Portfolio Overlap**

This figure plots the annual average portfolio overlap (as a decimal) during each year of our sample period. We present the average values for funds with a shared work connection and for those without a shared work connection.

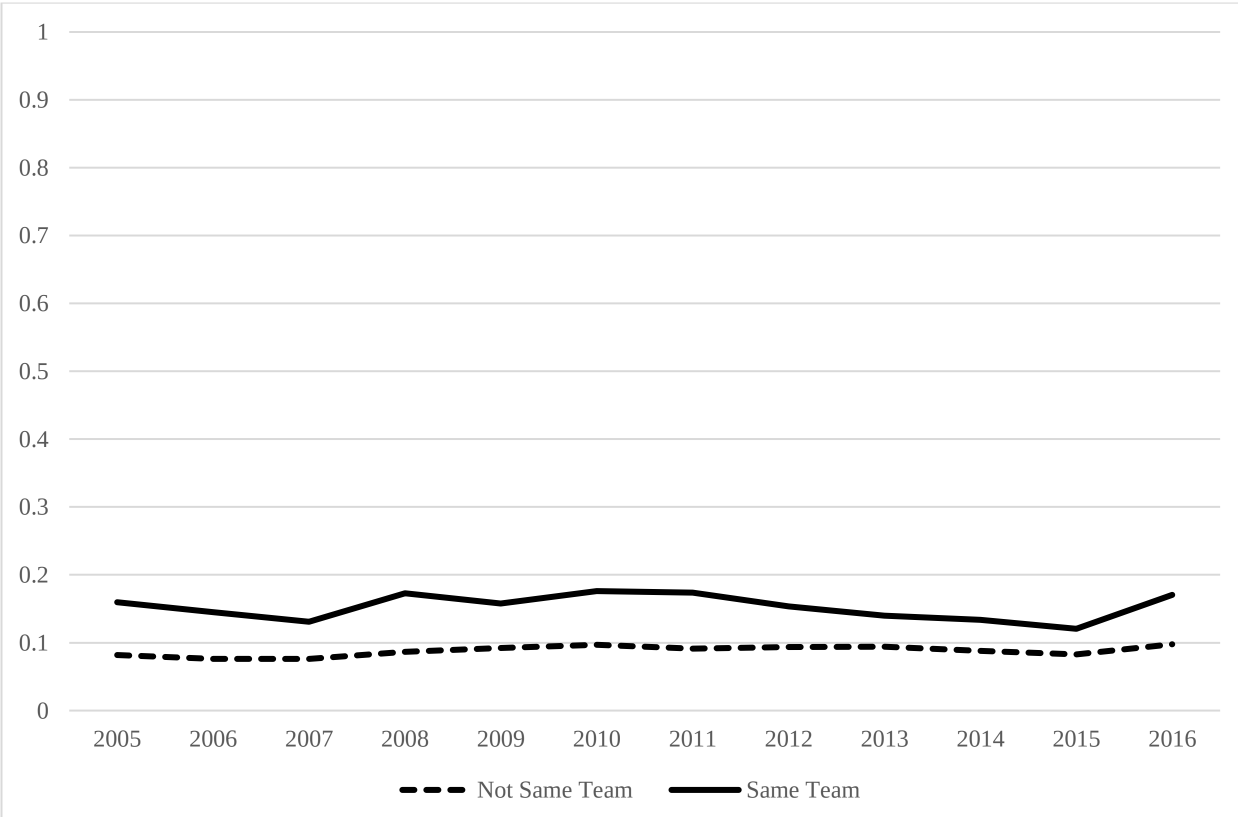

**Table 1 - Sample Descriptive Statistics**

This table presents average descriptive statistic values for mutual funds in our sample at the quarter level in Panel A. We report average characteristics at the manager pair level in Panel B and at the fund pair level in Panel C. Variable definitions are provided in Appendix A.

| ***Panel A: Fund Quarter*** | | | | | |
|---|---|---|---|---|---|
| **Variable** | **Obs** | **Mean** | **Standard Deviation** | **Q1** | **Q3** |
| *Portfolio TNA* | 19,480 | 4501.594 | 12613.240 | 291.350 | 3469.467 |
| *Flow* (percent) | 19,471 | 2.176 | 70.491 | -1.451 | 1.037 |
| *Fund Age* (years) | 19,480 | 18.363 | 13.033 | 8.912 | 23.487 |
| *Expense Ratio* (percent) | 19,480 | 1.053 | 0.370 | 0.813 | 1.298 |
| *Turnover* (percent) | 19,479 | 73.272 | 60.598 | 30.000 | 97.000 |
| *Gross Alpha* (quarterly percent) | 18,714 | 0.357 | 2.654 | -1.022 | 1.715 |
| *Cash* (percent) | 19,480 | 2.519 | 5.273 | 0.080 | 3.170 |
| ***Panel B: Manager Pair*** | | | | | |
| **Variable** | **Obs** | **Mean** | **Standard Deviation** | **Q1** | **Q3** |
| *Work Connection* (percent) | 4,752,783 | 0.306 | 5.525 | 0.000 | 0.000 |
| *Prior Work Connection* (percent) | 4,752,783 | 0.329 | 5.729 | 0.000 | 0.000 |
| *Work Connection Duration* (years) | 14,554 | 3.612 | 3.823 | 0.997 | 4.914 |
| *Prior Work Connection Duration* (years) | 15,649 | 2.514 | 2.896 | 0.753 | 3.001 |
| *Neighbors* (percent) | 2,865,738 | 0.298 | 5.448 | 0.000 | 0.000 |
| *Prior Neighbors* (percent) | 2,865,738 | 1.534 | 12.289 | 0.000 | 0.000 |
| *Connected1* (percent) | 4,664,659 | 5.333 | 22.470 | 0.000 | 0.000 |
| *Connected2* (percent) | 4,664,659 | 2.577 | 15.846 | 0.000 | 0.000 |
| *Connected3* (percent) | 4,664,659 | 0.218 | 4.666 | 0.000 | 0.000 |
| *Connected4* (percent) | 4,664,659 | 0.100 | 3.159 | 0.000 | 0.000 |
| *Similar Age* (percent) | 4,664,659 | 34.682 | 47.596 | 0.000 | 100.000 |
| ***Panel C: Fund Pair*** | | | | | |
| **Variable** | **Obs** | **Mean** | **Standard Deviation** | **Q1** | **Q3** |
| *Work Connection* (percent) | 1,729,971 | 0.607 | 7.770 | 0.000 | 0.000 |
| *Prior Work Connection* (percent) | 1,729,971 | 0.997 | 9.937 | 0.000 | 0.000 |
| *Work Connection Duration* (years) | 10,509 | 1.292 | 1.291 | 0.334 | 1.832 |
| *Prior Work Connection Duration* (years) | 17,255 | 0.604 | 0.858 | 0.059 | 0.762 |
| *Neighbors* (percent) | 1,729,971 | 1.209 | 10.928 | 0.000 | 0.000 |
| *Prior Neighbors* (percent) | 1,729,971 | 5.832 | 23.434 | 0.000 | 0.000 |
| *Education* (percent) (using Connected3) | 1,729,971 | 1.425 | 11.852 | 0.000 | 0.000 |
| *Same Fund Family* (percent) | 1,729,971 | 5.401 | 22.605 | 0.000 | 0.000 |
| *Fund in Same City* (percent) | 1,729,971 | 15.635 | 36.319 | 0.000 | 0.000 |
| *Ln(Absolute Value TNA Difference)* | 1,729,971 | 7.495 | 1.856 | 6.364 | 8.679 |
| *Same Objective* (percent) | 1,729,971 | 22.070 | 41.472 | 0.000 | 0.000 |

**Table 2 - Overlap Descriptive Statistics and T-Tests**

This table presents the average portfolio overlap in panel A, sale overlap in panel B, and buy overlap in panel C. We report average values and differences between funds with a certain type of connection and those without that connection. These connections are variations of social networks, including work connections, educational connections, and neighbor connections. Definitions are provided in Appendix A. We also perform t-tests of difference in means between the two groups in column (3). T-statistics are not tabulated. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

| | Yes | No | Difference |
|---|---|---|---|
| *Panel A: Portfolio Overlap* | | | |
| Work connection | 14.4% | 8.7% | 5.7%*** |
| Prior work connection | 13.4% | 8.7% | 4.7%*** |
| Neighbors | 11.2% | 8.7% | 2.5%*** |
| Prior neighbors | 9.7% | 8.7% | 1.0%*** |
| Attended the same school | 8.6% | 8.8% | -0.2%*** |
| Attended the same school & received the same degree | 8.8% | 8.7% | 0.1%*** |
| Attended the same school at the same time | 10.9% | 8.7% | 2.2%*** |
| Attended the same school at the same time and received the same degree | 10.6% | 8.7% | 1.9%*** |
| Single manager & work connection | 21.4% | 8.7% | 12.7%*** |
| Single manager & prior work connection | 23.0% | 8.7% | 14.3%*** |
| *Panel B: Buy Overlap* | | | |
| Work connection | 13.4% | 7.5% | 5.9%*** |
| Prior work connection | 11.9% | 7.5% | 4.4%*** |
| Neighbors | 10.0% | 7.5% | 2.5%*** |
| Prior neighbors | 8.4% | 7.4% | 1.0%*** |
| Attended the same school | 7.4% | 7.5% | -0.1%*** |
| Attended the same school & received the same degree | 7.6% | 7.5% | 0.1%*** |
| Attended the same school at the same time | 9.7% | 7.5% | 2.2%*** |
| Attended the same school at the same time and received the same degree | 9.6% | 7.5% | 2.1%*** |
| Single manager & work connection | 20.1% | 7.5% | 12.6%*** |
| Single manager & prior work connection | 21.3% | 7.5% | 13.8%*** |
| *Panel C: Sale Overlap* | | | |
| Work connection | 10.8% | 6.2% | 4.6%*** |
| Prior work connection | 9.7% | 6.2% | 3.5%*** |
| Neighbors | 8.5% | 6.2% | 2.3%*** |
| Prior neighbors | 7.4% | 6.1% | 1.3%*** |
| Attended the same school | 6.2% | 6.1% | 0.1%*** |
| Attended the same school & received the same degree | 6.4% | 6.1% | 0.3%*** |
| Attended the same school at the same time | 8.2% | 6.2% | 2.0%*** |
| Attended the same school at the same time and received the same degree | 8.0% | 6.2% | 1.8%*** |
| Single manager & work connection | 15.1% | 6.2% | 8.9%*** |
| Single manager & prior work connection | 17.2% | 6.2% | 11.0%*** |

**Table 3 - Portfolio Overlap Measures and Work Connections**

The sample includes all active domestic equity mutual funds in the CRSP Mutual Fund Database that belong to the 35 largest fund families in CRSP, ranked by total domestic equity mutual fund assets as of March 2005, from 2005 to 2016. Data on fund returns and characteristics are obtained from the CRSP Mutual Fund Database. Data on fund managers and work connections are collected from fund prospectuses and supplemented from Morningstar Direct. Data on managers' addresses and educational history are collected from Lexis Nexis public records and available online sources. Manage-fund-pair-quarter observations are aggregated to fund-pair-quarter observations. Variable definitions are provided in Appendix A. Standard errors are clustered two-way by each fund in the pair. *T*-statistics are in parentheses below the coefficients. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

| | **Portfolio Overlap** | | | **Buy Overlap** | | | **Sale Overlap** | | |
|---|---|---|---|---|---|---|---|---|---|
| | **[1]** | **[2]** | **[3]** | **[4]** | **[5]** | **[6]** | **[7]** | **[8]** | **[9]** |
| *Work Connection* | 3.258*** | 3.230*** | 2.733*** | 3.318*** | 3.290*** | 2.881*** | 2.657*** | 2.628*** | 2.249*** |
| | (4.45) | (4.46) | (4.15) | (5.14) | (5.14) | (4.81) | (4.83) | (4.83) | (4.52) |
| *Prior Work Connection* | | | 2.349*** | | | 1.929*** | | | 1.622*** |
| | | | (3.60) | | | (3.58) | | | (3.42) |
| *Neighbors* | | 1.634*** | 1.500** | | 1.542*** | 1.436*** | | 1.593*** | 1.412*** |
| | | (2.75) | (2.57) | | (3.37) | (3.18) | | (3.48) | (3.09) |
| *Prior Neighbors* | | | 0.407 | | | 0.316 | | | 0.758*** |
| | | | (1.05) | | | (1.16) | | | (2.61) |
| *Education* | | 1.589*** | 1.512*** | | 1.762*** | 1.703*** | | 1.638*** | 1.506*** |
| | | (2.89) | (2.82) | | (4.06) | (4.04) | | (4.09) | (3.90) |
| *Same Fund Family* | 2.929*** | 2.869*** | 2.665*** | 3.757*** | 3.700*** | 3.532*** | 2.227*** | 2.168*** | 2.008*** |
| | (5.17) | (5.10) | (4.63) | (7.81) | (7.76) | (7.22) | (5.15) | (5.06) | (4.60) |
| *Fund in Same City* | 0.989* | 0.963* | 0.944* | 0.562 | 0.535 | 0.521 | 1.048*** | 1.022*** | 0.986*** |
| | (1.93) | (1.88) | (1.86) | (1.55) | (1.48) | (1.44) | (2.91) | (2.84) | (2.76) |
| *Ln(\|TNA Difference\|)* | 0.502*** | 0.500*** | 0.499*** | 0.316*** | 0.314*** | 0.313*** | 0.331*** | 0.330*** | 0.328*** |
| | (6.02) | (6.01) | (6.02) | (4.10) | (4.09) | (4.09) | (4.63) | (4.61) | (4.63) |
| *Same Objective* | 8.087*** | 8.084*** | 8.085*** | 5.915*** | 5.911*** | 5.912*** | 5.437*** | 5.434*** | 5.436*** |
| | (21.56) | (21.58) | (21.58) | (19.81) | (19.84) | (19.84) | (19.90) | (19.93) | (19.95) |
| Two-way Fund Clusters | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| Observations | 1,729,971 | 1,729,971 | 1,729,971 | 1,710,881 | 1,710,881 | 1,710,881 | 1,710,881 | 1,710,881 | 1,7108,81 |
| R2 | 0.123 | 0.123 | 0.124 | 0.068 | 0.068 | 0.069 | 0.051 | 0.052 | 0.053 |

**Table 4 - Single-Manager Funds and Measures of Overlap**

The sample includes all active domestic equity mutual funds *managed by single managers* in the CRSP Mutual Fund Database that belong to the 35 largest fund families in CRSP, ranked by total domestic equity mutual fund assets as of March 2005, from 2005 to 2016. Data on fund returns and characteristics are obtained from the CRSP Mutual Fund Database. Data on fund managers and work connections are collected from fund prospectuses and supplemented from Morningstar Direct. Data on managers' addresses and educational history are collected from Lexis Nexis public records and available online sources. Manage-fund-pair-quarter observations are aggregated to fund-pair-quarter observations. Variable definitions are provided in Appendix A. Standard errors are clustered two-way by each fund in the pair. *T*-statistics are in parentheses below the coefficients. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

| | **Portfolio Overlap** | | | **Buy Overlap** | | | **Sale Overlap** | | |
|---|---|---|---|---|---|---|---|---|---|
| | **[1]** | **[2]** | **[3]** | **[4]** | **[5]** | **[6]** | **[7]** | **[8]** | **[9]** |
| *Work Connection* | 6.992*** | 7.095*** | 7.164*** | 6.983*** | 7.069*** | 7.093*** | 4.527*** | 4.607*** | 4.660*** |
| | (4.07) | (4.13) | (4.12) | (4.49) | (4.52) | (4.51) | (2.91) | (2.95) | (2.97) |
| *Prior Work Connection* | | | 6.894*** | | | 6.431*** | | | 5.090*** |
| | | | (2.96) | | | (2.94) | | | (2.76) |
| *Neighbors* | | 2.302 | 2.838* | | 2.434* | 2.703* | | 2.031** | 2.448** |
| | | (1.47) | (1.82) | | (1.69) | (1.87) | | (2.01) | (2.40) |
| *Prior Neighbors* | | | 3.043*** | | | 1.341* | | | 2.382*** |
| | | | (2.83) | | | (1.90) | | | (3.08) |
| *Education* | | 2.448 | 2.487 | | 0.655 | 0.717 | | 1.204 | 1.230 |
| | | (1.25) | (1.26) | | (0.64) | (0.69) | | (1.35) | (1.36) |
| *Same Fund Family* | 3.748*** | 3.619*** | 3.021** | 5.593*** | 5.454*** | 5.085*** | 3.190*** | 3.075*** | 2.616*** |
| | (3.05) | (2.98) | (2.48) | (6.74) | (6.69) | (6.21) | (3.89) | (3.78) | (3.22) |
| *Fund in Same City* | 3.511*** | 3.414*** | 3.283*** | 1.847** | 1.769** | 1.710** | 2.783*** | 2.710*** | 2.607*** |
| | (2.92) | (2.85) | (2.75) | (2.52) | (2.39) | (2.31) | (3.71) | (3.61) | (3.46) |
| *Ln(\|TNA Difference\|)* | 0.357** | 0.357** | 0.329* | 0.257 | 0.257 | 0.242 | 0.405** | 0.405** | 0.383** |
| | (1.98) | (1.98) | (1.87) | (1.28) | (1.28) | (1.22) | (2.52) | (2.52) | (2.47) |
| *Same Objective* | 7.536*** | 7.551*** | 7.574*** | 5.484*** | 5.501*** | 5.519*** | 5.077*** | 5.090*** | 5.108*** |
| | (9.95) | (9.97) | (10.10) | (9.07) | (9.10) | (9.17) | (10.19) | (10.25) | (10.37) |
| Two-way Fund Clusters | Y | Y | Y | Y | Y | Y | 4.527*** | 4.607*** | 4.660*** |
| Observations | 157,231 | 157,231 | 157,231 | 155,989 | 155,989 | 155,989 | 155,989 | 155,989 | 155,989 |
| R2 | 0.159 | 0.160 | 0.166 | 0.119 | 0.120 | 0.123 | 0.090 | 0.091 | 0.094 |

## Table 5 - Duration of Work Connections

The sample includes all active domestic equity mutual funds in the CRSP Mutual Fund Database that belong to the 35 largest fund families in CRSP, ranked by total domestic equity mutual fund assets as of March 2005, from 2005 to 2016. Data on fund returns and characteristics are obtained from the CRSP Mutual Fund Database. Data on fund managers and work connections are collected from fund prospectuses and supplemented from Morningstar Direct. Data on managers' addresses and educational history are collected from Lexis Nexis public records and available online sources. Manage-fund-pair-quarter observations are aggregated to fund-pair-quarter observations. Variable definitions are provided in Appendix A. Standard errors are clustered two-way by each fund in the pair. *T*-statistics are in parentheses below the coefficients. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

| | **Portfolio Overlap** | | **Buy Overlap** | | **Sale Overlap** | |
|---|---|---|---|---|---|---|
| | **[1]** | **[2]** | **[3]** | **[4]** | **[5]** | **[6]** |
| *Work Connection* | 1.312* | 1.304* | 1.849** | 1.842** | 1.561** | 1.542** |
| | (1.83) | (1.82) | (2.42) | (2.41) | (2.24) | (2.20) |
| *Work Connection Duration* | 1.244*** | 1.222*** | 0.966** | 0.948** | 0.632* | 0.602* |
| | (3.24) | (3.16) | (2.30) | (2.25) | (1.90) | (1.80) |
| *Prior Work Connection* | 1.911** | 1.814** | 1.341* | 1.250* | 1.483** | 1.359** |
| | (2.33) | (2.23) | (1.91) | (1.78) | (2.57) | (2.37) |
| *Prior Work Connection Duration* | 0.740 | 0.759 | 0.993 | 1.013 | 0.349 | 0.371 |
| | (0.98) | (1.01) | (1.27) | (1.29) | (0.64) | (0.68) |
| *Neighbors* | | 1.490** | | 1.427*** | | 1.407*** |
| | | (2.55) | | (3.15) | | (3.08) |
| *Prior Neighbors* | | 0.403 | | 0.313 | | 0.756*** |
| | | (1.04) | | (1.15) | | (2.60) |
| *Education* | | 1.519*** | | 1.711*** | | 1.510*** |
| | | (2.84) | | (4.06) | | (3.91) |
| *Same Fund Family* | 2.711*** | 2.644*** | 3.570*** | 3.508*** | 2.076*** | 1.998*** |
| | (4.65) | (4.59) | (7.21) | (7.16) | (4.66) | (4.56) |
| *Fund in Same City* | 0.987* | 0.943* | 0.560 | 0.520 | 1.047*** | 0.986*** |
| | (1.93) | (1.85) | (1.55) | (1.44) | (2.90) | (2.76) |
| *Ln(\|TNA Difference\|)* | 0.501*** | 0.499*** | 0.315*** | 0.313*** | 0.331*** | 0.328*** |
| | (6.03) | (6.01) | (4.09) | (4.08) | (4.62) | (4.62) |
| *Same Objective* | 8.086*** | 8.083*** | 5.914*** | 5.911*** | 5.437*** | 5.435*** |
| | (21.56) | (21.59) | (19.81) | (19.84) | (19.89) | (19.94) |
| Two-way Fund Clusters | Y | Y | Y | Y | Y | Y |
| Observations | 1,729,971 | 1,729,971 | 1,710,881 | 1,710,881 | 1,710,881 | 1,710,881 |
| R2 | 0.123 | 0.124 | 0.068 | 0.069 | 0.052 | 0.053 |

**Table 6 - Index Mutual Funds**

The sample includes all index mutual funds in the CRSP Mutual Fund Database that belong to the 35 largest fund families in CRSP, ranked by total domestic equity mutual fund assets as of March 2005, from 2005 to 2016. Data on fund returns and characteristics are obtained from the CRSP Mutual Fund Database. Data on fund managers and work connections are collected from fund prospectuses and supplemented from Morningstar Direct. Data on managers' addresses and educational history are collected from Lexis Nexis public records and available online sources. Manage-fund-pair-quarter observations are aggregated to fund-pair-quarter observations. Variable definitions are provided in Appendix A. Standard errors are clustered two-way by each fund in the pair. *T*-statistics are in parentheses below the coefficients. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

| | **Portfolio Overlap** | **Buy Overlap** | **Sale Overlap** |
|---|---|---|---|
| | [1] | [2] | [3] |
| *Work Connection* | 1.975 | -1.440 | 0.845 |
| | (0.60) | (-0.58) | (0.33) |
| *Prior Work Connection* | 2.395 | -1.303 | 2.910 |
| | (0.64) | (-0.43) | (0.94) |
| *Education* | 9.399 | 4.448* | 19.646 |
| | (0.83) | (1.67) | (1.20) |
| *Same Fund Family* | -3.490 | 10.823* | 2.391 |
| | (-0.52) | (1.79) | (0.48) |
| *Fund in Same City* | -2.266 | -4.624* | 0.342 |
| | (-0.59) | (-1.93) | (0.13) |
| *Ln(\|TNA Difference\|)* | 3.908*** | 6.473*** | 2.320*** |
| | (4.94) | (6.48) | (3.38) |
| *Same Objective* | 27.641*** | 24.189*** | 20.132*** |
| | (5.71) | (6.94) | (4.11) |
| Two-way Fund Clusters | Y | Y | Y |
| Observations | 25,890 | 25,710 | 25,710 |
| R2 | 0.164 | 0.250 | 0.107 |

## Table 7 - Performance of Connected Trades

The sample includes all stock purchases and sales of active domestic equity mutual funds in the CRSP Mutual Fund Database that belong to the 35 largest fund families in CRSP, ranked by total domestic equity mutual fund assets as of March 2005, from 2005 to 2016. The unit of analysis is fund-stock-quarter observations. Stock DGTW returns are calculated by following the methodology in Daniel et al. (1997). Variable definitions are provided in Appendix A. Standard errors are clustered at the year-quarter level. *T*-statistics are in parentheses below the coefficients. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

| ***Panel A: Current Work Connections*** | | | | |
|---|---|---|---|---|
| | **Stock DGTW** | | **Stock DGTW** | |
| | **[1]** | **[2]** | **[3]** | **[4]** |
| *Work Connection Buy* | -0.001*** | -0.001*** | | |
| | (-4.05) | (-2.81) | | |
| *Excess Buy* | -0.010 | -0.010 | | |
| | (-0.77) | (-1.54) | | |
| *Work Connection Buy * Excess Buy* | 0.075** | 0.075** | | |
| | (2.30) | (2.07) | | |
| *Work Connection Sale* | | | -0.001*** | -0.001*** |
| | | | (-5.25) | (-3.50) |
| *Excess Sale* | | | 0.027* | 0.027 |
| | | | (1.75) | (1.38) |
| *Work Connection Sale * Excess Sale* | | | 0.009 | 0.009 |
| | | | (0.20) | (0.25) |
| Stock FEs and Year-quarter FEs | Y | Y | Y | Y |
| Year-quarter Clusters | N | Y | N | Y |
| Observations | 784,276 | 784,276 | 500,364 | 500,364 |
| R2 | 0.072 | 0.072 | 0.069 | 0.069 |

| ***Panel B: Prior Work Connections*** | | | | |
|---|---|---|---|---|
| | **Stock DGTW** | | **Stock DGTW** | |
| | **[1]** | **[2]** | **[3]** | **[4]** |
| *Prior Work Connection Buy* | -0.001*** | -0.001*** | | |
| | (-4.61) | (-3.42) | | |
| *Excess Buy* | -0.011 | -0.011* | | |
| | (-0.80) | (-1.78) | | |
| *Prior Work Connection Buy * Excess Buy* | 0.068** | 0.068** | | |
| | (2.22) | (2.64) | | |
| *Prior Work Connection Sale* | | | -0.001*** | -0.001** |
| | | | (-3.88) | (-2.51) |
| *Excess Sale* | | | 0.040** | 0.040* |
| | | | (2.48) | (1.86) |
| *Prior Work Connection Sale * Excess Sale* | | | -0.067* | -0.067* |
| | | | (-1.74) | (-1.71) |
| Stock FEs and Year-quarter FEs | Y | Y | Y | Y |
| Year-quarter Clusters | N | Y | N | Y |
| Observations | 784,276 | 784,276 | 500,364 | 500,364 |
| R2 | 0.072 | 0.072 | 0.069 | 0.069 |

## Table 8 - Performance of Connected Trades – Single-manager Funds Only

The sample includes all stock purchases and sales of active domestic equity mutual funds, *managed by single managers*, in the CRSP Mutual Fund Database that belong to the 35 largest fund families in CRSP, ranked by total domestic equity mutual fund assets as of March 2005, from 2005 to 2016.The unit of analysis is fund-stock-quarter observations. Stock DGTW returns are calculated by following the methodology in Daniel et al. (1997). Variable definitions are provided in Appendix A. Standard errors are clustered at the year-quarter level. *T*-statistics are in parentheses below the coefficients. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

| ***Panel A: Single Manager Current Work Connections*** | | | | |
|---|---|---|---|---|
| | **Stock DGTW** | | **Stock DGTW** | |
| | **[1]** | **[2]** | **[3]** | **[4]** |
| *Work Connection Buy* | -0.001 | -0.001 | | |
| | (-1.20) | (-0.47) | | |
| *Excess Buy* | -0.008 | -0.008 | | |
| | (-0.39) | (-0.45) | | |
| *Work Connection Buy * Excess Buy* | 0.214** | 0.214* | | |
| | (2.41) | (1.87) | | |
| *Work Connection Sale* | | | -0.001* | -0.001 |
| | | | (-1.88) | (-1.26) |
| *Excess Sale* | | | 0.013 | 0.013 |
| | | | (0.52) | (0.42) |
| *Work Connection Sale * Excess Sale* | | | 0.126 | 0.126 |
| | | | (1.02) | (1.38) |
| Stock FEs and Year-quarter FEs | Y | Y | Y | Y |
| Year-quarter Clusters | N | Y | N | Y |
| Observations | 272,115 | 272,115 | 166,948 | 166,948 |
| R2 | 0.104 | 0.104 | 0.098 | 0.098 |

| ***Panel B: Single Manager Prior Work Connections*** | | | | |
|---|---|---|---|---|
| | **Stock DGTW** | | **Stock DGTW** | |
| | **[1]** | **[2]** | **[3]** | **[4]** |
| *Prior Work Connection Buy* | -0.001** | -0.001 | | |
| | (-2.33) | (-1.45) | | |
| *Excess Buy* | -0.016 | -0.016 | | |
| | (-0.78) | (-0.85) | | |
| *Prior Work Connection Buy * Excess Buy* | 0.205*** | 0.205*** | | |
| | (3.00) | (3.30) | | |
| *Prior Work Connection Sale* | | | -0.000 | -0.000 |
| | | | (-0.34) | (-0.20) |
| *Excess Sale* | | | 0.039 | 0.039 |
| | | | (1.50) | (1.10) |
| *Prior Work Connection Sale * Excess Sale* | | | -0.202** | -0.202** |
| | | | (-2.49) | (-2.10) |
| Stock FEs and Year-quarter FEs | Y | Y | Y | Y |
| Year-quarter Clusters | N | Y | N | Y |
| Observations | 272,115 | 272,115 | 166,948 | 166,948 |
| R2 | 0.104 | 0.104 | 0.098 | 0.098 |