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Hidden Alpha*

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ABSTRACT

Using the setting of financial agents, we explore the importance of hidden connections relative to all other network connections. We find that hidden connections are those associated with the largest and most significant abnormal returns accruing to fund managers—on average 135 basis points per month (over 16% alpha per year, t-stat = 3.54) across the universe of mutual funds and public firms. This is relative to insignificant abnormal returns accruing on average to all other trades, including those to trades of "visible" connections. The hidden connection premium does not appear to be driven by endogenous selection or familiarity, as fund managers seem to be correctly timing when to hold (and when to avoid) stocks of firm officers to whom they are tied. Further, the more hidden the connection is, the more valuable the information that appears to be associated with the trading across it. This hidden connection premium exists across industries, styles, time periods, and firm types; remaining strong and significant through the present day. More broadly, our findings highlight the importance of missing nodes and hidden edges when attempting to understand the true nature of shock propagation in complex network systems.

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Social networks form the structural foundation underpinning all groups of individuals, from small assemblies up through complex societies. Various types of networks among countries and firms and down to the level of individuals have been used to develop a better understanding of the patterns and themes in the data. However, that work has relied on the ability to observe the true network structure from both an estimation and an inference standpoint. If the true nature of all nodes in the network can be fully observed along with each connection among those nodes, then inference can be reliably carried out. Unfortunately, for many real world networks, this is not the case. The presence of nodes and edges that are "hidden"—either intentionally or unintentionally—can have profound impacts on estimations of how information, shocks, or other phenomena are transmitted within the network itself.

In this paper, we provide novel evidence on the powerful impact of such hidden connections among influential agents in financial markets. In particular, we explore hidden connections between mutual fund managers and firm executives of the publicly traded companies whose stocks the funds invest in. To address our research question, we make use of social connection data from the world's largest social networking platform—Facebook (facebook.com)—which at the time of writing numbered more than two billion monthly active users. Specifically, we assemble a data set of 71,000 manually identified Facebook profiles of fund managers and firm officers active in the period 1984–2020. Using data on their connections and interactions on Facebook, we classify friendship ties that are public versus those that are hidden by one (or even both) sides of a connected pair.

Facebook connections provide a number of advantages relative to past work on social networks in financial markets. In particular, the data allow us not only to establish the timing and currentness of a given connection, but also to measure its intensity (e.g., "likes" of current content) or the connectivity to other related nodes (e.g., significant others, parents, or children connected to the same node). More centrally, we are able to uncover hidden connections and find rich and substantive information above and beyond what can be observed from the non-hidden connections in the network. In fact, the hidden connections are on average the most valuable in the network by our measures. Thus, ignoring them leads to an incomplete and potentially even deceptive view of the network structure and impulses passing across the network.

To better understand our approach, consider the following examples from our sample.[1] The first example involves Ms. Ananke, the CEO and a subsequent board member of a large healthcare-related firm. Among her many activities, Ananke had maintained an active and lively social network on Facebook. Her friends on the platform included Mr. Bergelmir, a fund

[1]Note that the examples we use come directly from our sample, however, we mask the individuals' names.

manager of a large active mutual fund. Interestingly, there were no documented meetings, mentions, or interactions between Ananke and Bergelmir precipitating their connection, nor any other observable or detectable common network ties (i.e., no common school networks, work networks, location networks, common friends, etc.).

[Insert Figure 1 near here.]

As shown in Figure 1, in addition to being a Facebook friend of Ananke, Bergelmir was also an active trader of her stock over a number of years—and a very successful one indeed: seeming to enter before many stock rises, only to exit prior to precipitous stock declines and subsequently re-establish positions before another stock price climb. Over their trading history, Bergelmir earned an average abnormal return in Ananke's firm of 233 basis points per month (t-stat = 2.12), or 28% abnormal return per year. This was 18 percentage points higher than Bergelmir's abnormal return on all other stocks in his portfolio over the same time period. Moreover, Bergelmir was also connected to a number of other firm officers whose stocks he actively traded over this time period. His average abnormal return on the entire set of these Facebook connections was 185 basis points in monthly alpha (t-stat = 2.68), or over 22% per year. This again was more than 14 percentage points higher than the performance of Bergelmir's trades in all other stocks that he also bought and held from firms whose management personnel were not among his Facebook friends.

A second example from our sample helps illustrate how we classify connections depending on whether or not they are publicly observable. This example involves a friendship tie between Ms. Calypso—an active fund manager of multiple large funds throughout our sample period—and Mr. Deimos, a longtime firm officer who most recently was serving on the board of a large international retail firm. Unlike the friendship tie between Ananke and Bergelmir (which was publicly observable through Bergelmir's Facebook friends list), we classify the connection between Calypso and Deimos as "invisible." We do so because—although they grew up in the same hometown and were classmates in high school—their friendship tie cannot be seen on Calypso's Facebook profile because she opted to "hide" her profile's friends list. However, Deimos did not make that same decision, and his connections can be seen by anyone with knowledge of his Facebook identity. Thus, in spite of the hidden features of Calypso's node, we can identify her connection to Deimos, along with the common high school class attendance, pictures taken together over the years, and so forth. In Section I we will show that we are also in fact able to infer "doubly invisible" friendship ties that are hidden by both sides of a connection.

With regard to performance, we find that Calypso did remarkably well in her trading in Deimos's stock. She earned monthly alphas of over 300 basis points (t-stat = 1.91) on these trades versus slightly negative and insignificant alphas in point estimate of -6 basis points per month (t-stat = -0.32) on all of her other positions over the same time period. In fact beyond this, while Calypso did have holdings in the particular firm beforehand, she substantially increased her holdings following Deimos's appointment (between 4- and 16-fold across the active mutual funds she managed). Moreover, like Bergelmir, Calypso also broadly outperformed on the other firms to whom she was invisibly tied through Facebook connections. Calypso's trading in all of her hidden connections earned her over 13% abnormal return per year (t-stat = 2.20)—a figure more than 10% percentage points higher than the average performance of her remaining trades over the same time period.

In our study, we find the above patterns to be valid on average across the entire universe of Facebook-identified fund managers and firm officers throughout the sample period. In particular, using data from the period 1984–2020, we find that the most hidden connections result in abnormal risk-adjusted returns of 135 basis points per month on average (t-stat = 3.54). In the same time, fund managers hiding their network connections are not simply better performers, as their risk-adjusted returns on nonconnected holdings are associated with small abnormal returns that are statistically indistinguishable from zero (16 basis points per month, t-stat = 0.88). Further, the outperformance on hidden connections appears to be uncorrelated with known return determinants, as the monthly risk-adjusted 136 basis points return (t-stat = 3.57) of a value-weighted long-short strategy is nearly identical to the strategy's raw return of 148 basis points (t-stat = 3.88). Consistent with our finding of hidden ties being unique, important, and information-rich nodal edges within the network structure, we find abnormal returns on network connections to monotonically increase with their level of hiddenness. Specifically, as noted above, returns on perfectly "visible" fund manager–firm officer connections are statistically zero. In contrast, "invisible" connections are associated with risk-adjusted returns of 6.7% per year (t-stat = 1.81), while "doubly invisible" connections generate risk-adjusted returns of over 16% per year (t-stat = 3.54).

The article also explores the individuals' investment behavior vis-a-vis their connections. In particular, we ask whether fund managers overweight connected firms, and find that the most hidden connections are again those associated with the most abnormal weights. More precisely, while we see a roughly 65% overweight in stocks pertaining to publicly visible connections, the overweight rises to almost 200% for doubly invisible connections, and remains statistically large and significant when controlling for time and firm fixed effects—for example, when comparing the weights of two fund managers over the same time period, one of which is hidden-connected to the firm's active firm officers, while the other is not.

To explore the mechanism in more depth, we examine the extent to which our results could be driven by either a familiarity or a selection mechanism. For instance, fund managers may prefer to invest in their friends' ventures not because of any information possibly being passed along the edges (hidden or not), but because of familiarity toward such stocks. However, a familiarity bias can neither explain the outperformance of connected stocks relative to nonconnected stocks, nor why it increases along with the connections' hiddenness.

In contrast, a more convincing version of the argument includes selection. Selection might be able to drive both the dispersion in average performance between returns earned on connected relative to nonconnected stocks and the dispersion in average performance earned on stocks associated with more-hidden relative to less-hidden connections. First, high type individuals may select to or be more likely to jointly match (i.e., the more successful the fund manager, the more likely the firm officer to match with the fund manager, if the firm officer too is successful). Second, unobserved characteristics (e.g., skill or ability) may simultaneously affect both the likelihood of a connection to be hidden and the likelihood of a connection to be associated with performance. In both these scenarios—that is, if our story is either one of a correlation between mutual success and the likelihood of forming friendships, or if it is one of an unobserved characteristic which causes hidden connections to select on better quality fund-stock pairs—we would expect to find identical returns on both the (hiddenly) connected stocks that the fund managers invest in and the (hiddenly) connected stocks that the fund managers choose to avoid, because these two groups sort on the same (hidden-connection) characteristics. Having said that, we find holdings of hiddenly-connected stocks to outperform significantly in times when they are held by the fund managers relative to times when they are not held—by 119 basis points in abnormal returns per month (t-stat = 2.59), or 14% per year. This finding is more consistent with hidden connections being valuable sources for fund managers, and it is less consistent with a familiarity heuristic or selection explanation.

If the hidden connections are truly driving the empirical patterns, then we would also expect a variation in the strengths of the underlying connections to alter the abnormal returns that they generate. To explore this mechanism, we proxy for tie strength of connections using a unique aspect of the Facebook data itself. In particular, Facebook users can actively engage with others' content via likes, comments, and tags. This allows us to sort connections by the extent to which the individuals in a pair actively engage with each other. Using these engagements as a proxy for friendship tie strength, we find stronger ties to be associated with larger returns across all our measures of visibility.

Finally, we run a number of additional tests and subsample analyses to understand the mechanisms and explore the robustness of our results. While we find the returns to be highly concentrated around corporate news announcements, we also find that the results do not seem to be concentrated in any given industry, investment style, or subperiod; they are instead large and significant across all of them. In addition, the results are not concentrated solely in small stocks—all results reported in this paper are value-weighted returns and structurally based on the universe of firms traded by active mutual funds, which biases toward more liquid firms. We also analyze the persistence of the returns earned on hiddenly-connected stocks in a multivariate regression framework that allows us to control for more return determinants—with coefficients remaining large and significant. More broadly, we find that the abnormal returns accruing to the hiddenly-connected stocks continue to accrue for an extended period following the trading. Further, and importantly, we observe no sign of any return reversal in the future, suggesting that the information associated with these trades is important for the fundamental firm value and is eventually incorporated into it. Lastly, we show that the effects and hidden-network dynamics that we find remain strong and significant to the present day.

Our paper connects to the growing literature concerned with the role of social ties in the transfer of information in financial markets. Papers in this spirit include Cohen, Frazzini, and Malloy (2008), who find that mutual fund managers place larger bets and make more profitable trades on firms run by management personnel with whom they share educational commonalities. Engelberg, Gao, and Parsons (2012) provide evidence that firms that have social ties with their banks obtain loans with lower interest rates and fewer covenants. Hochberg, Ljungqvist, and Lu (2007) show that better-networked venture capital investors exhibit higher fund performance. Findings from Cai and Sevilir (2012) suggest that target–acquirer board connections lead to better merger performance. Finally, Engelberg, Gao, and Parsons (2013) find that CEOs with social connections to outsiders bring more valuable information into the firm and receive higher compensation.

Empirically identifying networks among agents in financial markets is challenging because direct observations of connections among individuals are rare. Instead, existing evidence relies on indirect proxies of social connections, such as geographic proximity or common school ties. As noted by other authors (e.g., Pool, Stoffman, and Yonker (2015)), proxies for social connection are noisy at best, have a high chance to wrongly classify individuals as connected to one another, and likely fail to capture the true magnitude of the effects of social connectedness in general. Unlike all prior studies, our article is the first to directly observe whether agents in financial markets (in our setting, fund managers and firm officers) know and interact with each other, and the first to explore the hiddenness of these connections.

The remainder of this paper proceeds as follows. Section I presents our data collection procedures, sample construction, and summary statistics. Section II provides our main results on the return predictability pattern associated with the hidden network relationships in our data. Section III conducts robustness tests and examines the horizon of the return effect. Section IV concludes.

I. Data and Sample Construction

We combine data from various sources in this paper.[2] To determine the existence of friendship relations between the individuals in our sample, we use publicly accessible data that we collect from Facebook by Meta Platforms (Facebook). We obtain information on mutual fund managers, mutual fund holdings, and mutual fund returns from Morningstar Direct (MS Direct). For each stock held in the mutual fund portfolios, we collect data on the firm's management personnel from BoardEx of Management Diagnostics (BoardEx). Stock returns come from the Center for Research in Security Prices (CRSP). Compustat is the source of stock characteristics. Firm-level news data are from RavenPack.

A. *Facebook Profiles*

In this study, we explore the personal relationships between individuals based on their social ties to one another. To uncover these ties, we use Facebook friendships as our laboratory network metric. A central measure of interest in the paper is an indicator variable for whether a fund manager and a firm officer are connected via a friendship relation on Facebook. To establish whether such a relation exists between any two sample individuals, we must identify their Facebook profiles. Facebook profiles are personal user pages created upon joining the platform. They typically comprise a user's name, profile picture, friends list, timeline, photos tab, and the "about" section. The latter includes biographical, demographic, and other types of descriptive information on the user, such as work experience, educational background, places lived, family members, and relationship status.

Facebook profiles serve as organizational tools allowing users to form relationships with other users that typically parallel the users' real-life relationships, such as friends, family, classmates, co-workers, romantic partners, and so forth. To establish a connection between their profiles, users must mutually confirm their friendship on the platform. The users will then appear in the other's friends list, may have increased access privileges to content, and may receive updates on information generated by or associated with the other person.

[2] Appendix A defines the main variables and data sources used in this paper.

Identifying an individual's Facebook profile can pose a challenge for multiple reasons. First, given Facebook's wide reach, many potentially discriminating characteristics to identify individuals on the platform (e.g., name, workplace, education, location) are widely shared among Facebook's user base. Second, Facebook users can restrict the visibility of certain profile attributes by adjusting their privacy settings, which may hamper the identification of their profiles and require the collection of additional data to support the matching procedure. Third, given the substantial data access restrictions that Facebook has imposed on their platform in recent years,[3] hardly any Facebook user data can be accessed by means of an API. Instead, the data must be manually collected via Facebook's web interface.

B. Matching of Facebook Profiles

As we attempt to match the Facebook profiles of a large group of individuals, we define a three-step identification procedure to standardize the identification of user profiles. In the first step, for each individual target identity (target) in our sample, we retrieve a plurality of candidate users (candidates) whose profiles hold attributes similar to the target's known attributes. In the second step, we determine each candidate's probability of matching its corresponding target by calculating a confidence score based on different similarity and proximity measures. In the third step, we rank each target's candidates based on their confidence scores and try to manually match the target's true profile from its given set of candidates. We illustrate these details of the procedure using the following description.

In the first step of the identification procedure, for each target in our sample, we populate a list of candidates that we retrieve from different sources. We start by querying each target using Facebook's internal search engine, which takes a name and a set of search parameters as input and returns a list of candidates with matching attributes. Filters available to refine the search include location, work, and education. To overcome several limitations arising from the search engine's web interface, we prepare customized query strings in which we embed the search parameters' internal identifiers.[4] Appending these query strings to Facebook's base URL allows us to execute a large number of search queries. We provide details on the collection of the search parameters' identifiers and the syntax of the query strings in

[3] In response to several controversies (e.g., the Cambridge Analytica incident), Facebook severely restricted their API ("Facebook Graph API") in April 2018 by deprecating most of its major endpoints. Further restrictions were imposed in June 2019 when Facebook disabled their semantic "Graph Search" engine. This strongly limits the capacity of researchers to access user-generated Facebook data.

[4] Filters available through the search engine's menu interface cannot be readily set by entering keywords or identifiers. Instead, entering a value will populate a drop-down menu with suggestions. As this approach is not feasible for executing a large number of search queries, we use query strings instead.

Appendix B. However, since the search engine will only search the subset of users that have added (and publicly shared) the queried attribute, we compensate for the potential scarcity of publicly disclosed information by relying on a range of other sources to retrieve candidates, most notably the friends lists of successfully matched target entities.

In the second step, for each candidate associated with a target, we calculate a confidence score indicating the likelihood of the identity behind the candidate being equivalent to the target. The score is calculated based on a range of measures representing similarities between the candidate and the target. With each measure, we focus on capturing a different aspect of potential similarity. Using semantic measures, we analyze a candidate's various profile attributes (e.g., screen name, username, education, workplace, location) and compare their values to those held by the target. Before the comparison of attributes, we selectively augment the target's attribute values with their semantically equivalent representations, if applicable. For example, the name value "Robert" may be augmented by "Rob" and "Bob," the alma mater value "University of Mississippi" may be augmented by "Ole Miss," and the employer value "Alphabet" may be augmented by "Google." For some measures, in addition to looking for perfect matches between entire strings of attribute values, we consider flexible matching schemes to capture partial overlaps between the attribute values' meaningful units. For other measures, we use attributes that are not observed but inferred from information associated with the user. For instance, for candidates with a user ID value in the space between zero and $3.5e8$, we infer the educational institution attended by the user from the numeric value of the user ID, irrespective of whether or not the education attribute can be observed from the user's profile. For example, when evaluating the similarity of candidate fb.com/manu.sekhri.9 to the given target "Manu K. Sekhri," a 1996 graduate of University of Waterloo, even though the candidate's education attribute is not disclosed on his profile, we are able to infer it from the value of his user ID ("122,614,211"), which matches the customized user ID space that used to be assigned to all registrants affiliated with the University of Waterloo (122,600,000–122,699,999).[5] In addition to inferring attributes from the user's information we may also infer attributes from information pertaining to the user's connections, such as the most frequently appearing attribute value among those connections. Specifically, for some measures, we retrieve the plurality of users connected to the candidate (i.e., friends) and determine the number of friends who share a certain attribute. For example,

[5]A unique numeric user ID is automatically assigned to every new Facebook user upon registration. To infer the educational institution that the user was affiliated with before or at the time of registration, we exploit our finding that user IDs with values between zero and $3.5e8$ were not assigned in sequential order, but segmented by college, as Facebook membership was restricted to individuals with email addresses issued by selected colleges, each of which was assigned a customized user ID space (e.g., registrants with an email address using the domain name "@uwaterloo.ca" were assigned a user ID in the space between 122,600,000 and 122,699,999). We identify user ID clusters of 2,362 colleges in the space ranging from zero to $3.5e8$.

if a significant percentage of the candidate's friends have attended a particular college or are residents of a certain city, the candidate itself may be inferred to have attended that college or be residing in that city. In addition to gathering the relevant data on the candidate, we also gather data to evaluate each particular candidate–target pair. For instance, we may determine the number of the candidate's friends who share a common affiliation attribute with the target. For example, if the particular target is an Alphabet board member, and the given candidate's friends include the user ID of a profile that we have already positively matched to another Alphabet board member, then the corresponding measure will record an increased likelihood for the candidate to match the target. Further, we weight certain measures with a confidence factor that indicates the likelihood of the measure being accurate. For example, if the alma mater of a candidate is inferred based on a large number of the user's friends having attended this institution, the confidence factor attached to the inferred attribute is determined to be high; otherwise, it is low. Some measures, depending on the dynamics of the values they generate, are set to be complementary to the match probability, so that they reflect the rarity of a positive match. For example, if we find the alma mater value "Coe College" of a candidate with the common name "James Miller" to match the alma mater of its target, we denominate the probability of the match by the number of Coe College graduates in our sample by the name of James Miller. Lastly, for every target whose portrait we observe during the data collection process (e.g., on the company website or on their LinkedIn profile), we employ a face recognition algorithm that compares the particular portrait to the Facebook profile pictures of the target's candidates.[6] Following the calculation of the above measures, we aggregate the values produced for each candidate–target identity pair into a single confidence score.

In the third and last step of the identification procedure, we uniquely identify a target's true profile from its given set of candidates, if applicable. To conserve human resources, from each set of candidates, we remove all candidates with a confidence score that does not exceed a predetermined threshold. The remaining candidates of a given target are then ranked based on their confidence scores, and matching is performed starting with the highest-ranking candidate and progressing to lower ranks. To avoid poor matching accuracy, all matching is done manually by hand.[7] For a match to be established, we require visual confirmation to ensure its validity. If the user's restrictive privacy settings render it impossible to establish a visual match because necessary matchmaking data is missing or hidden (e.g., photos, biographical data, friends lists, etc.), we endeavor to establish the match by forming a bridge

[6] We extract and compare facial features of the individuals' portraits using the dlib.net–implementation of the 68 facial landmarks localization algorithm proposed by Kazemi and Sullivan (2014).

[7] Six research assistants were paid and trained to assist in the validation of Facebook profiles.

between the particular candidate and the profile of an individual from the target's immediate environment (e.g., a family member). An example from our sample illustrating the matching of a fund manager profile with restrictive privacy settings through a less restrictive profile belonging to a family member is given in Appendix C.

C. *Facebook Friendship Ties*

In addition to determining the users' Facebook identities, we also determine friendship ties (connections) between their user profiles. Note that the Facebook network is organized as an undirected graph in which mutual consent is required for a connection to form between two users. Therefore, a connection between two users A and B can be disclosed with certainty either by disclosing that A is friends with B or by disclosing that B is friends with A. In this perspective, we can determine connections on the platform in two different ways.

First, by visiting the particular user profiles and collecting all users that populate the users' friends lists—if the respective friends list is publicly accessible. If a user's friends list is not publicly accessible, we may still be able to disclose the user's connections through "backlinks" (i.e., the opposite's friends list) from the friends' profiles. To enhance the backlink-based disclosure of our sample individuals' connections, we exploit Facebook's Mutual Friends function, which takes two users A and B as input (i.e., their user IDs) and returns a list of the two users' mutual friends if certain conditions are met. In particular, if A's friends list is private while B's friends list is public, the functionality will return all of B's friends that are friends with A and who disclose this connection on their end. To facilitate the procedure, we design a recursive iteration that pairs each particular target user with a set of other users (pivot users) and recursively uses all new friends returned for the target user at each particular step as pivot users for another iteration. The recursive procedure will proceed until all pivot users are paired with the target user and no new friends are returned by the function. In total, we query the Mutual Friends function four million times before it is shut down by Facebook in August 2021.

Second, we disclose connections between users based on their interactions on the platform. On Facebook, one way for users to interact with one another is through likes, comments, and tags that can be given to other users' content (e.g., posts, photos). Users may limit the audience that is allowed to see their content—including the possibility to engage with it or see who has engaged with it—to a selected few (e.g., only the user's friends), which hides the content from the public eye. However, on Facebook, the visibility of a limited number of items pertaining to a profile—content that Facebook classifies as "public information"—cannot be restricted. In addition to the user's screen name and gender, these items also include the user's current profile picture and current cover photo, if provided. Fortunately, while these two photos are also visible to non-friends, the audience of users that can engage with them (i.e., through likes, comments, or tags) is by default still limited to the user's friends. This unique setting enables us to disclose connections between two users who both hide their friends by examining user reactions received by their current profile picture and cover photo—provided that these photos fulfill certain additional conditions. For example, a photo is not eligible for this procedure if other users are tagged in it, because the audience (i.e., users enabled to engage via likes or comments) of such photos will automatically expand to also include the friends of the user that is tagged in the photo.

After determining the users' connections on the platform, we create a measure that captures the degree of visibility of a particular connection that we observe between a fund manager and a firm officer from our sample, depending on whether the friendship is publicly observable through the fund manager's friends list (*Visible*); whether it is not publicly observable through the fund manager's friends list, but observable through the backlink from the firm officer's friends list (*Invisible*); or whether it is not publicly observable through either the fund manager's friends list or through the firm officer's friends list (*DoublyInvisible*).

D. *Mutual Fund Sample*

We will now proceed to construct the sample of funds and fund holdings for our study. The universe of fund-month observations whose fund managers' Facebook profiles we are able to identify will naturally determine the universe of stock-month observations that are covered by the sample of funds, which in turn will span the universe of firm officers whose Facebook profiles we are interested to match.

The initial sample of funds contains the universe of U.S.-domiciled mutual funds covered by MS Direct. Although the large majority of previous studies in the mutual fund literature have used Thomson Reuters as their source of holdings data, our choice falls on Morningstar for several reasons. First, when comparing the holdings data from the Thomson Reuters Mutual Fund Holdings Database to the holdings data from MS Direct, we find that the latter are available at a considerably higher frequency (a brief comparison is detailed in Appendix D). Second, we confirm previous studies reporting that Morningstar fund holdings data are more complete in terms of reported stock holdings (see, e.g., Elton, Gruber, and Blake (2011)). Third, Morningstar is more accurate in reporting the funds' fund managers (see, e.g., Massa, Reuter, and Zitzewitz (2010) and Patel and Sarkissian (2017)). Finally, Morningstar assigns a unique identification number to every fund manager, which greatly facilitates the tracking of fund managers over time and across funds.

We begin our sample construction by including defunct and active fund share classes to overcome a potential survivorship bias. To ensure an equitable comparison basis for fund managers, we limit the sample to domestic and actively managed U.S. equity funds (i.e., we exclude index funds, international funds, money market funds, or funds that focus on bonds, commodities, nontraditional equity, and alternative asset classes). We follow standard practice and remove funds whose names contain the word "index" or "idx." For funds with multiple share classes, we aggregate all the observations pertaining to the different share classes into one observation, since these funds have the same portfolio composition. For each fund that passes the aforementioned filters, we obtain historical management data from MS Direct, which details the name(s) of the fund manager(s), the start and end dates of their management periods, brief vitae, and information on educational backgrounds. For the stocks held by our sample of funds, we obtain return data from the CRSP Monthly Stock Files. We merge the return data with the funds' holdings using historical CUSIP numbers.

From this starting point, our sample consists of 418,258 fund-month observations covering the period from January 1984 through December 2020. The sample includes 5,119 unique funds and averages 1,398 funds per calendar quarter. This is the sample we use when we construct the weights in our benchmark portfolios.

E. *Fund Manager Sample*

The 5,119 mutual funds that pass our initial filters are managed by the 10,029 fund managers.[8] Before matching the fund managers' Facebook profiles in line with the matching procedure outlined in Section I.B, we compile data on their biographical characteristics. We start by determining the version of a fund manager's most complete name (i.e., middle names, nicknames, birth names, family names adopted upon marriage, and suffixes) by using the Financial Industry Regulatory Authority's (FINRA's) BrokerCheck database, the Securities and Exchange Commission's (SEC's) Investment Adviser Public Disclosure database, and the CFA Institute's member directory. Next, we gather data on educational degrees, graduation year, work history, birthday, residence, portrait, and family members by conducting a cross-

[8]The reported number of fund managers is subject to two adjustments: 1. We identify and merge 251 cases in which two or more of the unique identification numbers that Morningstar assigns to each fund manager refer to the same sample individual. The majority of these duplicate assignments occur in events of name changes (e.g., earlier records refer to fund manager *Katherine Lieberman (née Buck)* as "Katherine Buck," while later records refer to her as "Katherine Lieberman"), or due to the usage of pseudonyms (e.g., different fund firms refer to fund manager *Langton C. "Tony" Garvin* either as "Langton C. Garvin" or as "Tony Garvin"). 2. We exclude 36 fund managers who we find to have died before the launch of Facebook in February 2004. We keep fund managers who died after this date, as these individuals might have created Facebook profiles which might be active to the present day (e.g., because Facebook was not notified about their passing or because a memorialized version of their profile deliberately remains online).

database search across multiple sources including LinkedIn profiles, Bloomberg executive profiles, profiles on The Wall Street Transcript, biographies published by fund firms, filings with the SEC, obituaries on legacy.com, alumni publications on ancestry.com, and newspaper articles on newspapers.com.

We then proceed to identifying the fund managers' identities on Facebook and successfully match the profiles of 3,984 (or 39.7%) of the 10,029 fund managers in the final sample. This coverage ratio compares well with common statistics on Facebook membership indicating that roughly six in ten U.S. American adults use or have used Facebook at some point in their lives. Figure 2 illustrates our coverage of Facebook-identified fund managers relative to the total number of fund managers in the Morningstar benchmark universe who satisfy the prior filters across the sample period. The share of Facebook-identified fund managers increases throughout the sample period peaking in 2018, where our sample includes the Facebook profiles of 45% of all then-active fund managers running the U.S-domiciled benchmark universe of actively managed U.S. equity mutual funds.

[Insert Figure 2 near here.]

Next, we limit the sample of mutual funds to those run by Facebook-identified fund managers. We include team-managed funds if we identify the Facebook profile of at least one fund manager in the team. Limiting the data to these observations reduces the sample to 262,380 fund-period observations. This final sample includes 4,094 of the 5,119 funds present in the initial sample.

F. Firm Officer Sample

For the firm officers heading the firms whose stocks are held by our sample of Facebook-identified funds, we obtain employment data and biographical information from BoardEx. The data purveyor collects and consolidates public domain information on management personnel of publicly quoted and large private companies in North America and around the world. BoardEx data come from a variety of different sources, including the SEC, press releases, first hand websites, and U.S. stock exchanges, and have been used to examine the role of social networks in a variety of economic papers (Cohen et al. (2008), Cohen, Frazzini, and Malloy (2010), Engelberg et al. (2012), and Chen, Cohen, Gurun, Lou, and Malloy (2020)). BoardEx provides detailed summaries of board compositions and/or the composition of senior management and has fully analyzed and collected data starting in 1999; however, individual company records typically have a deeper history. BoardEx details the firm officers' current and past roles at both active and inactive firms, the start and end dates of these roles, educational backgrounds, and affiliations with charitable or volunteer organizations. BoardEx assigns different seniority levels to different firm officer roles. Employees in management positions below board level are classified as "senior managers." Members of the board of directors who also occupy an executive position at the firm are classified as "executive directors." Members of the board of directors who are not employees of the firm (non-executive directors) are classified as "supervisory directors." We merge the BoardEx data with the funds' portfolio holdings using the linking table provided by Wharton Research Data Services (WRDS), which provides a link between the firm identifiers of BoardEx (companyid) and CRSP (permco). We drop employment records for which BoardEx does not specify the start date of the individual's employment at a company. If BoardEx provides no end date for an individual's role, we follow the purveyor in assuming that the individual still occupies the role. Next, we exclude individuals for whom the BoardEx records indicate that they were deceased before Facebook was launched in February 2004. From this starting point, the firms held by our sample of funds are directed by 267,106 firm officers whom we are interested to match on Facebook.

To allow for the matching of their Facebook profiles, we combine the firm officers' biographical information from various BoardEx files, including information on most comprehensive names, educational backgrounds, and work histories. With this data at hand we successfully match the Facebook profiles of 67,162 (or 25.1%) of the 267,106 firm officers in our sample.

G. Descriptive Statistics

Table I presents details on the Facebook data that we use in the paper. The sample includes data from the Facebook profiles of 3,984 fund managers and 67,162 firm officers.

[Insert Table I near here.]

Panel A of Table I provides an overview of the information that the fund managers and firm officers choose to disclose on their profiles. For each particular profile attribute, we report the share and the number of individuals from both groups that disclose the attribute. We find that 56% of all fund managers (N=2,228) and 51% of all firm officers (N=34,367) publish their friends. Approximately nine in ten individuals provide a profile picture, and the majority upload at least one additional photo. More generally, we observe that approximately

30% to 50% of the sample individuals in both groups reveal information pertaining to the less sensitive data categories (e.g., workplace, schools, resident city, hometown), while 20% to 30% disclose information pertaining to the more sensitive data categories (e.g., relationship status, spouse, or family members).

Panel B reports statistics on the data that we collect on friends, photos (including user reactions received by photos), and family members—the data categories that were the main focus of our data collection efforts. For each variable, we report the mean, median, standard deviation (SD), the total number of data items, and the number of individual profiles for which we collect the data. Statistics are computed for individuals conditional on nonmissing values. *Friends–All* is the total number of unique friends that we disclose per individual profile, irrespective of whether or not a profile's friends list was public or private. Based on the steps detailed in Section I.C, we are able to collect at least one friend for 97% of the fund managers (N=3,849) and for 99% of the firm officers (N=66,547) in our sample, even though approximately half of the individuals do not disclose friends on their profiles. In total, we collect 18 million friends with a median number of 163 and 118 friends per fund manager and firm officer, respectively. *Friends–Published* details the number of friends that we collect through publicly accessible friends lists (i.e., for the portion of profiles that disclose their friends list attribute—see Panel A). Here, we collect a median number of 210 friends per fund manager and 281 per firm officer. *Friends–Backlinks* details the number of friends that we collect via backlinks from friends' profiles. Here, we collect a median number of 75 friends per fund manager, and 4 per firm officer.[9] Finally, *Friends–Reactions* details the remaining number of friends that we collect by examining user engagements, through which we collect a median number if 61 friends per fund manager and 93 per firm officer.

Panel B further reports statistics on photos (i.e., profile pictures, cover photos, and miscellaneous photos) and reactions (i.e., likes, comments, and tags) received by and collected from these photos. From each profile, we collect all photos uploaded to its various photo albums and a short description of the photo along with all user reactions received by these photos. Taken together, we collect a total of 2 million photos and 17.8 million reactions.[10]

[9]The comparatively low number of firm officers friends disclosed through backlinks is owed to the shutdown of Facebook's Mutual Friends function in August 2021. Fortunately, at this point, we had already queried the function for all fund managers. Hence, the shutdown does not affect the total number of fund manager–firm officer connections that we disclose in this paper (refer to Section I.C for the function's mechanics).

[10]Facebook automatically generates photo descriptions for the visually impaired utilizing an object recognition algorithm that lists the items, people, and scenery that the given photo seems to show (e.g., "May be an image of 1 person, child, standing, smiling, outerwear, twilight, sky, beach, ocean, and car.").

The bottom part of Panel B presents statistics on the sample individuals' family member profiles. We identify family member profiles during the preliminary data collection process to support the matching of candidate profiles or to rule out the existence of an individuals' Facebook membership.[11] If not identified manually during the data collection process, the family member profiles stem from the sample individuals' family member profile section. In total, we collect at least one family member for 35% of the fund managers (N=1,383) and for 33% of the firm officers (N=22,396).

[Insert Table II near here.]

In Table II, we present summary statistics reflecting the average annual composition of our sample of funds, the funds' common stock holdings, and the firms' management personnel. Our sample of funds includes the 262,380 fund-month observations managed by Facebook-identified fund managers and covers the period 1984–2020. The benchmark universe of funds used to compute percentage coverages is the fund sample consisting of 418,258 fund-month observations whose construction is detailed in Section I.D (i.e., funds populating Morningstar's U.S.-domiciled universe of actively managed U.S. equity mutual funds). On average, our sample includes 1,118 funds per year, constituting an annual average coverage for the full sample period of 52% of the benchmark universe of funds, or 49% of the universe's total assets under management, respectively. The sample of Facebook-identified fund managers averages 898 individuals per year, constituting an annual average coverage of 34% of all managers active in the period 1984–2020. The full sample of firms whose stock is held by the funds averages 3,617 firms per year, which constitutes an annual average of 48% of all stocks in the CRSP universe, or 86% of the universe's total market capitalization. On average, these firms are headed by 57,729 firm officers, corresponding to an average of 94% of all firm officers present in the BoardEx universe. From these individuals, our matched sample of Facebook-identified firm officers covers an average of 14,449 individuals per year, or 20% of all firm officers whose firms are held by our sample of funds.

[Insert Table III near here.]

[11] If we are able to identify a public-friends Facebook profile belonging to one of the sample individual's immediate family members (i.e., spouses, parents, or children) and the sample individual is not among this profile's friends, we assume that the sample individual is not holder of a Facebook account.

Table III reports details on the Facebook friendships that we observe between the fund managers and firm officers in our sample. We disclose a total of 15,242 fund manager–firm officer connections involving 2,653 unique fund managers and 9,135 unique firm officers. We classify a total of 10,520 connections (or 70%) as "visible," 3,609 connections (or 24%) as "invisible," and 1,113 connections (or 6%) as doubly invisible (in the sense of our definition of visibility in Section I.C). Moreover, from the 15,242 disclosed connections, we classify 7,476 (or 49%) as potentially "tradable." We call a friendship "tradable" if the fund manager's tenure at the fund overlaps with the firm officer's tenure at the firm, and the firm's stock in the same month is held by at least one fund within the same Morningstar category. Of the 7,476 connections that we classify as tradable, we find 2,415 (or 32%) actually to be "traded," i.e., the fund manager's holdings of the stock overlap with the firm officer's tenure at the firm. Interestingly, while roughly 30% of all visible friendships are traded, the share of these traded connections increases to 36% and 45% when looking at invisible and doubly invisible friendships, respectively, suggesting that the more-hidden connections in our sample have a higher tendency to be activated.

[Insert Figure 3 near here.]

Importantly, our numbers also suggest that the sample of connected pairs does not stem from a few super-connectors, but involves a large number of sample individuals from both groups, fund managers and firm officers. We illustrate this data in Figure 3 using a network graph. The network graph includes the subsample of fund managers (blue colors) and firm officers (red colors) that form the subset of connected pairs that we classify as tradable. We denote traded fund manager–firm officer pairs within the set of tradable pairs with darker color shades. Each node represents an individual, and two nodes are connected by an edge representing a Facebook friendship between the two individuals. Individuals are clustered based on their current or most recent employer. In case of multiple affiliations to different firms, the individuals are assigned to the firm at which they occupy their most senior role.

[Insert Figure 4 near here.]

Before turning to the results, we report details on the roles of Facebook-identified firm officers in our sample. For this purpose, Figure 4 illustrates the breakdown of firm officer roles by seniority. Subplot A details the distribution of roles occupied by all 267,106 firm officers heading the public companies held by the sample of Facebook-identified funds. Subplot B details the distribution of roles occupied by the 67,162 Facebook-identified firm officers in our sample. Subplot C details the distribution of roles occupied by the 9,135 firm officers whose connection to a fund manager is classified as "tradable". Subplot D details the distribution of roles occupied by the 9,135 firm officers whose connection to a fund manager we actually find to be "traded" by the respective fund. Throughout our sample period, the numbers of connected and traded firm officers align well with the overall number of active firm officers.

II. Main Results

A. *Portfolio Weights*

In this section, we examine whether fund managers' hidden connections influence the funds' holdings. If fund managers perceive that they have an advantage through their connections with firm officers, we might expect them to overweight their friends' securities in their funds' portfolios. To test this possibility, for each fund-period observation, we calculate the portfolio weights in connected stocks as the dollar investment in these stocks divided by the fund's total dollar holdings in the reported period. We then estimate various forms of the regression equation

$$w_{i,k,t} = \alpha_0 + \beta' ConnectionVisibility_{i,k,t} + \Gamma' Controls_{i,k,t} + \epsilon_{i,k,t}, \tag{1}$$

where $w_{i,k,t}$ is the weight of fund i in stock k at time t; $ConnectionVisibility_{i,k,t}$ is a vector of four dummy variables capturing whether any of the team's fund managers and a firm officer of firm k are friends on the Facebook platform (*AllVisibilities*); whether the friendship is publicly observable through the fund manager's friends list (*Visible*); whether it is not publicly observable through the fund manager's friends list, but observable through the backlink from the firm officer's friends list (*Invisible*); or whether it is not publicly observable through either the fund manager's friends list or through the firm officer's friends list (*DoublyInvisible*). $\Gamma' Controls_{i,k,t}$ is a vector of control variables including *Style*, the percentage of the fund's total net assets invested in the style corresponding to the stock being considered (style is calculated as in Daniel, Grinblatt, Titman, and Wermers (1997)), market value of equity (*ME*), book to market (*BM*), and past 12-month return (*R12*). If fund managers tilt their portfolios toward the firms managed by their firm officer friends, then we would expect to find that β is positive and statistically significant.

In Table IV, we report the coefficient estimates and standard errors clustered at the fund level from Panel OLS estimations of various forms of Equation 1. All regressions include period fixed effects, and the unit of observation is stock-fund-period. The basic result is shown in columns 1–4, in which we include only an expression of $ConnectionVisibility_{i,k,t}$ and a constant in the regression. As seen in column 1, compared with the average weight of 74.6 basis points, mutual fund managers invest an additional 71.5 basis points in securities of firms managed by firm officers with whom they are friends on Facebook. From columns 2–4, we see that the additional allocations to securities of friends vary greatly depending on whether or not the friendship between a fund manager and a firm officer is publicly observable through their friends lists. Specifically, while fund managers allocate 49.9 additional basis points to securities of publicly observable friends, 95.80 additional basis points are allocated to securities of friends that are not publicly observable, and 136.47 additional basis points are allocated to securities of friends if these are doubly invisible. In column 5, we include both the *AllVisibilities* dummy and the *DoublyInvisible* dummy in the regression, showing that the on-top effect of *DoublyInvisible* over the other visibilities is 77.6 basis points. In columns 6 and 7, we estimate the regressions from columns 2 and 4 with fund fixed effects, relying solely on variation on the stock level (i.e., firm officer changes). While we find fund fixed effects to explain the variation in fund managers' portfolio allocations toward visible friends (allocations of fund managers who openly show their friends), the coefficient on doubly invisible friends remains statistically highly significant at 50.9 basis points. Finally, in columns 8 and 9, we estimate both specifications with firm fixed effects. These specifications controls for the average weight funds have in each stock and relies on variation on the fund level over time (i.e., fund manager changes) to explain portfolio weights. Controlling for firm fixed effects, fund managers allocate significantly more capital to securities of both visible and doubly invisible friends, with the latter effect being almost twice as large.

In summary, the different specifications tell a consistent story: Fund managers place larger bets on their friends' securities, and these allocations seem to be highly dependent on the particular connection's visibility.[12]

[12] In untabulated tests, we also control for industry fixed effects (based on the 48-industry classification used in Fama and French (1997)) and fund fixed effects (using the fund's Morningstar categories), both leading to more pronounced results than the specification in column 9.

B. Performance Tests

Our results thus far show that fund managers allocate significantly more money to firms managed by their hiddenly-connected firm officer friends. We now turn to exploring whether this pattern is also associated with increased performance; that is, whether fund managers' holdings of connected stocks outperform their holdings of nonconnected stocks, and if so, whether performance is associated with the connections' visibility. In contrast, if fund managers' allocations to friends' stocks are due to familiarity, for example, we would expect to see nonpositive results.

To investigate this question, we use a standard calendar time portfolio approach (see, e.g., Coval and Moskowitz (2001)) to create replicating portfolios of the funds' holdings. For each fund-period observation, we assign the stocks in a fund's portfolio into two sub-portfolios based on whether any of the fund's portfolio managers maintain a Facebook friendship with any of the firm's same-month firm officers. Our sample averages 318 connected funds per month, each holding an average of 2 connected stocks and 164 nonconnected stocks.

To compare the performance of the portfolios of connected and nonconnected holdings, we compute monthly portfolio returns for each fund under the assumption that funds did not change their holdings between two reporting dates:

$$R^N_{i,t} = \sum_{k \epsilon \mathcal{N}} \left(\frac{w_{i,k,t}}{\sum_{k \epsilon \mathcal{N}} w_{i,k,t}} \right) r_{k,t+1} \tag{2}$$

and

$$R^O_{i,t} = \sum_{k \epsilon \mathcal{O}} \left(\frac{w_{i,k,t}}{\sum_{k \epsilon \mathcal{O}} w_{i,k,t}} \right) r_{k,t+1} \tag{3}$$

where $\mathcal{N}$ is the set of stocks of a firm with an officer connected to at least one of fund i's fund managers, and $\mathcal{O}$ is the set of nonconnected stocks in fund i's portfolio. Following stock assignments into connected and nonconnected sub-portfolios, we keep stocks in the sub-portfolios until the next reporting date, when portfolios are rebalanced to reflect changes in holdings. We weight stocks by the fund's dollar holdings in the respective sub-portfolio. We then compute value-weighted averages of the returns in Equations 2 and 3 across funds at time t, weighting each fund's return by its total net assets under management (TNA). This approach effectively corresponds to a simple investment strategy of investing in the entirety of connected and nonconnected stocks in proportion to the amounts held by our sample of funds.

We assess portfolio performance using three different measures. In addition to simple raw returns, we compute monthly risk-adjusted returns based on the four-factor model of Carhart (1997), that is, as the intercept on a regression of monthly excess returns on explanatory variables that include the monthly returns from the three Fama and French (1993) factor-mimicking portfolios and Carhart (1997)'s momentum factor. To ensure that inferences do not depend on bias concerns stemming from previous research (see, e.g., Cremers, Petajisto, and Zitzewitz (2013)), we also employ characteristics-adjusted returns as in Daniel et al. (1997), hereafter DGTW. We compute a stock's DGTW-adjusted return as raw return minus the return on a value-weighted benchmark portfolio of all CRSP firms in the same size, book-to-market, and 1-year past return quintile.

[Insert Table V near here.]

Table V illustrates our main results. The table reports the average monthly performance of the funds' portfolio of Facebook-connected stocks and the portfolio of nonconnected stocks as well as returns yielded by a long-short (LS) portfolio strategy. We first note that the funds' connected portfolio performs significantly better relative to the nonconnected portfolio across all three performance metrics. From column 4 of the table we see that the connected portfolio earns, on average, a monthly four-factor alpha of 45 basis points compared with zero basis points for the nonconnected portfolio in column 5. Moreover, columns 7 and 8 of the table indicate that the connected portfolio outperforms its size, book-to-market, and momentum benchmark portfolio significantly by an average of 56 basis points per month, whereas the nonconnected portfolio exhibits no such outperformance. This first set of numbers suggests that fund managers with network ties to the firm officers heading the stocks that they invest in are better informed. At the same time, the evidence on the average return of the nonconnected portfolio indicates that the sample of Facebook-identified fund managers does not generally outperform.

Most interestingly, when forming connected portfolios sorted by fund manager–firm officer connection visibility, we find that the outperformance increases with the connection's hiddenness across all performance measures, and that the most-hidden connections (*DoublyInvisible*) are those associated with the largest and most significant abnormal returns accruing to fund managers—on average 135 basis points per month (over 16% alpha per year, t-stat = 3.54). Column 6 indicates that buying *DoublyInvisible*-connected holdings and selling short nonconnected holdings delivers a monthly four-factor alpha of 136 basis points on average (significant at the 1% level). The same long-short investment strategy involving invisibly connected stocks exhibits an alpha of 56 basis points per month (significant at the 10% level). In contrast, trading visibly connected stocks provides a positive but insignificant four-factor alpha of 17 basis points per month. Results are similar in magnitude when we look at DGTW-adjusted returns. Overall, our tests suggest that hidden connections on average are the most valuable connections in the fund manager–firm officer network.

We further explore the evolution of the connected portfolios sorted by friendship visibility using event time returns. Specifically, we compute value-weighted cumulative abnormal returns for the first 18 months following a fund's purchase of a connected stock. Consistent with the results in Table V, we find abnormal returns to increase with the level of connection hiddenness—reported in Figure 5. Over the course of 18 months, the portfolio of stocks formed based on doubly invisible connections does not fall below the portfolio formed based on invisible connections, which in turn does not fall below portfolio of visibly connected stocks. The figure further indicates that the returns accrue gradually over the course of the subsequent months and do not reverse.

[Insert Figure 5 near here.]

To gain a better understanding of the mechanisms behind the observed effects, we now investigate whether the strength of the fund manager–firm officer connection has implications on performance. If one assumes that return-relevant information in a network is more likely to flow between nodes that are more closely connected, we would expect that trading in the context of stronger friendship ties leads to increased outperformance.

By incorporating tie strength into the equation, we take into account that online social networks allow users to keep many different friends, some of which might be closer friends, while others might be more casual friends or acquaintances. From there on, given our data, many paths open up to measure tie strength. Drawing on a substantial body of research on social networks indicating that online interactions between individuals are diagnostic of stronger real world ties,[13] we here choose to assess tie strength by examining whether or not the fund managers and firm officers in our sample interact with each other on the Facebook platform. We explore alternative measures of tie strength in the robustness section.

[13] One may argue that strongly tied friends might be less likely to interact on Facebook, because strong ties often lead to other means of interaction (in-person, phone calls, texting, etc.). There is, however, a substantial body of research on social networks suggesting that more closely tied individuals use a greater variety of media to interact with each other online and offline rather than substituting these instruments (e.g., Haythornthwaite (2005)), further evidenced by findings that Facebook interactions can serve as an accurate proxy for real world friendship tie strength (Jones, Settle, Bond, Fariss, Marlow, and Fowler (2013)).

Note that the prevalent interaction modes on Facebook are likes, tags, and comments that users give to other users' profile content or that users receive on their own profile content (hereafter, reactions). For the 1,927 fund managers and 5,152 firm officers that form the 7,476 connections in our sample that we classify as tradable (see Table III), we collect 3.97 million reactions given to 309 thousand photos (including posts with photographic elements) uploaded by these particular individuals. Of these 3.97 million reactions, 10,318 have been exchanged between the particular fund manager–firm officers pairs. Taking a crude first look at the data, when we decompose the 7,476 tradable fund manager–firm officer connections into 2,415 traded and 5,061 nontraded pairs, we note that 29% of all traded pairs have mutually interacted with the other's profile content at least once, compared to 21% of the nontraded pairs. An example of the data on interactions between a fund manager and his firm officer friends is presented in Appendix E.

[Insert Table VI near here.]

In Table VI, we adjust our above performance analysis and construct portfolios sorted by friendship visibility and a reaction dummy. The "Reaction" portfolio includes the set of connected fund-month-stock observations for which we find the associated fund manager–firm officer pair to have mutually interacted with the other's profile content at least once. The "No Reaction" portfolio consists of the fund's connected stocks for which no interaction takes place between the particular fund manager–firm officer pair.

Consistent with our hypothesis, the results in Table VI indicate a relationship between the strength of a friendship and the funds' outperformance on connected stocks. For instance, the Reaction portfolio yields a monthly four-factor alpha of 115 basis points on average (significant at the 1% level), compared with statistically insignificant 31 basis points for the No Reaction portfolio (column 4 vs. 5). Columns 7 and 8 of the table show that the Reaction portfolio significantly outperforms its size, book-to-market, and momentum benchmark portfolio by an average of 96 basis points per month (significant at the 1% level), whereas the No Reaction portfolio exhibits 50 basis points (significant at the 5% level). To evaluate the on-top performance effect of interactions on Facebook, we form an investment strategy that buys the Reaction portfolio and sells short the No Reaction portfolio. When calculating returns of the long-short strategy, we require at least one connected holding with and one without Facebook interaction for each month. The average monthly four-factor alphas and DGTW-adjusted returns of the long-short strategy are 96 and 64 basis points per month, respectively, implying that trading fund manager–firm officer connections from the Reaction portfolio yields a significant outperformance over trading connections from the No Reaction-portfolio (columns 6 and 9). While we do not document a statistically significant on-top performance effect of reactions for visible connections, we do so for invisible connections.[14]

Before moving to the next section, we examine a further opportunity that our data offers to explore whether some fund manager–firm officer connections might be more important than others. Although unsubstantiated by theoretical predictions, we consider the question whether the performance of connected holdings may also depend on the respective firm officer's seniority level. For this empirical exercise we use BoardEx's categorization of role seniority, that is, the subdivision of roles occupied by management personnel into senior managers, executive directors, and supervisory directors (refer to Section I.F for the definitions of those roles). We then allocate fund holdings into portfolios based on whether any of the fund's current fund managers and a current firm officer of the given firm are friends on the Facebook platform (*AllSeniorities*); and whether the connected firm officer is a senior manager (*SM*); an executive director (*ED*); or a supervisory director (*SD*).

[Insert Table VII near here.]

The results shown in Table VII indicate that fund managers seem to possess more information about firms when they are friends with the firms' executive directors and supervisory directors, as opposed to when they are friends with the firms' senior managers. Trading fund managers' executive director and supervisory director connections yields an average monthly four-factor alpha of 80 and 102 basis points, respectively (significant at the 5% and 1% levels). More broadly, our results suggest that friendship ties to executive directors and supervisory directors are more advantageous for fund managers relative to friendship ties to senior managers.

C. *Connected Not Held Portfolios*

Since we are generally interested in testing the hypothesis of whether or not connected fund managers are better informed, and since mutual funds are restricted from short selling, the funds' active portfolio allocations may not reflect the funds' full information advantage. Given that our previous findings suggest that the funds' portfolio allocations reflect positive information about the fund managers' connected securities, we would expect that negative

[14] Note that we exclude doubly invisible connections from this assessment, as we identify these connections based on the sample individuals' interactions on the Facebook platform (see Section I.C).

information should manifest itself in the performance of the fund managers' connected stocks that are not held by the funds. Therefore, using a similar portfolio construction approach as in the prior subsection, we compute returns on the connected stocks that fund managers choose not to hold. Specifically, for each fund-period observation, the stocks in each fund portfolio are sorted into Connected Held (CH) and Connected Not Held (CNH) portfolios. We define Connected Not Held stocks as stocks that are not held by the particular fund and are headed by a fund manager's then-active firm officer Facebook friend while in the same month being held by at least one other fund from the same Morningstar category. Based on the assumption that funds did not change their holdings between two reporting dates, we construct monthly portfolios by keeping non held stocks in the portfolio until the next reporting date, when the actual portfolios are rebalanced to reflect changes in holdings. Within a given portfolio, we weight the non held stocks' returns by the stock's respective market capitalization. We then compute value-weighted returns by averaging across funds, weighting each fund portfolio return by the fund's total net assets value. The resulting sample includes 2,613 distinct funds and 177,156 fund-month observations covering the period from January 1984 through December 2020. The average monthly observation of a fund's Connected Not Held portfolio consists of 2.96 stocks pertaining to the fund managers' 2.25 connected firm officer friends.

[Insert Table VIII near here.]

Table VIII compares the average performance of the Connected Held and the Connected Not Held portfolios. The Connected Not Held portfolio exhibits no significant outperformance (columns 5 and 6). As shown in columns 8 and 9, the portfolio of connected stocks held by the fund managers tends to outperform the portfolio of connected stocks that fund managers choose not to hold. For invisible and doubly invisible connections, this outperformance amounts to a statistically significant monthly four-factor alpha of 57 and 119 basis points per month, respectively, with DGTW-adjusted returns being of a similar magnitude. These results suggest that fund managers do not simply weight all connected stocks at all times, as a familiarity explanation might suggest, but instead actively decide which connected stocks to hold and which not to hold. At the same time, we note that the results in Table VIII also provide strong evidence against potential endogeneity concerns.

D. Returns Around Corporate News

Having explored fund managers' returns on connected stocks, we now try to better understand the mechanisms behind these returns. If connected fund managers are informed, we would expect the funds' returns on connected stocks to be more concentrated around news announcements, i.e., when the information that possibly caused the fund manager to purchase the connected stock is eventually impounded into the stock price. Accordingly, we would expect returns to be comparatively less pronounced around news announcements for both the funds' nonconnected stocks and the set of connected stocks that the funds choose to avoid.

To construct the Connected/Nonconnected (Held) and Connected Not Held portfolios for this analysis, we modify the portfolio construction approaches introduced in Section II.B and Section II.C, respectively, by assigning to each stock in each fund portfolio its daily returns earned in the following month. Next, for each fund-day observation, we sort the stocks in each fund portfolio into news and no news sub-portfolios, based on whether or not the given stock was the subject of a news announcement on the particular day. We weight stock returns in the Connected/Nonconnected Held portfolios by the fund's dollar holdings, and stock returns in the Connected Not Held portfolios by the stock's respective market capitalization. Finally, we compute value-weighted returns by averaging across funds, weighting each fund portfolio return by the fund's total net asset value.

To obtain information on firm-specific news events, we use data available via the RavenPack Analytics database (RavenPack). The service provides real-time collection and analysis of entity-related news using natural language processing and machine learning techniques. The RavenPack data is extracted from Dow Jones Newswires, The Wall Street Journal, FactSet, and tens of thousands of other traditional and social media sources. To ensure that the news items that we use for our test actually convey material information about the firms rather than information about market movements, we follow Weller (2018) in excluding news reports on trading or prices (technical analysis signals, stock price movements, order imbalance reports) and news reports on investor relations themes (typically announcements of future information revelation dates). We filter the data down further to only include news in which RavenPack considers the related firm to be playing a key role (i.e., news items with an "event relevance" score of 100). To remove duplicated news reports, we isolate the first news item in chains of items that relate to the same subject (using RavenPack's "event similarity days" analytic). Following these preliminary data cleaning steps, we use the CUSIP bridge provided by RavenPack's entity mapping file to merge the RavenPack firm identifier (rp entity id) with the CRSP firm identifier (permco) and map the firms' news items to their stock returns. We align news items and stock returns using the New York Stock Exchange trading calendar. In this procedure, we follow a close-to-close rationale in accordance with CRSP's return formula.[15] Because the RavenPack data begin in 2000, this analysis runs from January 2000 to December 2020.

[Insert Table IX near here.]

Table IX compares the average daily performance of the Connected Held, Nonconnected Held, and Connected Not Held portfolios on days with and without news announcements. At first we note that the Connected Held portfolio earns significantly positive returns around news announcements across all measures of visibility, which are most pronounced in the doubly invisible specification with a daily four-factor alpha of 6 basis points (significant at the 1% level). By contrast, the returns of the Connected Held portfolio on days without news announcements are small and statistically indistinguishable from zero. These findings suggests that most of the return premium is generated on days with news headlines. The same pattern holds true for stocks in the Nonconnected Held portfolio, but importantly, a long-short strategy that buys connected stocks on news days and sells short nonconnected stocks on news days yields a daily four-factor alpha of 2.2 basis points (significant at the 10% level). This outperformance almost doubles to 4 basis points (significant at the 1% level) in the doubly invisible specification. A similar picture emerges when looking at the Connected Not Held portfolio: Again we find positive returns that are concentrated around news announcements, however, the average return of a long-short portfolio that buys the portfolio of connected stocks and sells short the portfolio of connected not held stocks reveals that the Connected Held portfolio experiences news returns significantly greater on average than those of the Connected Not Held portfolio, corroborating the evidence presented in section Section II.C.

[15] For example, if a news item becomes public during Friday evening after market hours, we map it to the stock's next Monday return to take into account that CRSP-reported daily stock returns are calculated based on a stock's closing price on a given date and the most recent valid closing price prior to this date.

III. Robustness

A. Alternative Stock-Level Performance Test

We now supplement the sorted-portfolio approaches employed in Section II using multivariate cross-sectional Fama-MacBeth regressions (Fama and MacBeth (1973)) to check for the persistence of returns earned on the fund managers' hiddenly connected stocks. This allows us to control for several other firm- and stock-level characteristics that have been found to contain relevant pricing information and are commonly used in the literature. These control variables include firm size (*ME*), book-to-market ratio (*BM*), momentum (*MOM*), short-term reversal (*STR*), industry momentum (*IMOM*), and standardized unexpected earnings (*SUE*). The dependent variable in the Fama-MacBeth regressions is next month's stock excess returns. We calculate the main regressor of interest, $DiffWeight_{k,t}$, for each month t and stock k as the difference between the average weight that Facebook-connected funds invest in the stock and the average weight that all other funds invest in the stock. To make results comparable across all models, we standardize $DiffWeight_{k,t}$ by dividing it by its cross-sectional standard deviation each month.

[Insert Table X near here.]

Coefficient estimates for the average risk premia are presented in Table X. Consistent with the results in Table V, stocks that are more heavily held by fund managers who are connected to a firm officer at the respective firm exhibit a significant and positive outperformance. The coefficient estimate of $DiffWeight_{k,t}$ in column 1 is 0.0181, implying that a one standard deviation increase in the weight difference predicts an increase in monthly stock returns by 181 basis points. Further, the results in columns 2 to 4 corroborate our findings in Table V implying that outperformance largely increases with the connection's hiddenness. While the coefficient estimate of $DiffWeight_{k,t}$ is insignificant for visible friendships, it is 171 and 228 basis points for invisible and doubly invisible friendships, respectively.

B. Potential Selection Bias Concerns

By selecting only fund managers who we find to have a Facebook account, we are likely introducing aspects of selection. For fund-month observations prior to Facebook's widespread adoption in the 2005–2010 period, the fund managers whose Facebook profiles we are able to identify must have been comparatively young at their time of active management. Here, a possible concern is that the Facebook-identified fund managers who have managed money in the early years are ex post successful by design, have a lot of connections, and may therefore dominate our identification of connected versus nonconnected holdings. These fund managers may have a large high-profile network because they were successful, not because the network helped them to be successful. This is true for every time period (including today), but it might be expected to have the largest impact in the earlier sample observations (as the more sparser Facebook sample might be more dominated by these selected fund managers).

Indeed, when comparing the characteristics of Facebook-identified and non-identified fund managers, we find the Facebook-identified fund managers to be significantly younger on average in the earlier years of our sample.[16] The data are presented in Figure 6, which compares the average age of all fund managers in the universe of domestic actively managed U.S. equity mutual funds across our sample period (solid line) to both the average age of Facebook-identified fund managers (dotted line) and the average age of non-identified fund managers (dashed line).

[Insert Figure 6 near here.]

While Facebook-identified fund managers on average are up to eight years younger in the earlier years of our sample, we note that the age gap converges to become statistically indistinguishable from zero in the later years of our sample (post-2010). However, by selecting on age, we may also select on sophistication. This may even hold true for the post-2010 period (in a time when there was widespread adoption of Facebook by the demographic of the average fund manager in our sample) and up to the present day because in our study we are selecting fund managers who choose to have a Facebook account. It could be that the choice not to join Facebook is deliberate; that is, these fund managers may have the scope or ability to have a Facebook account, but deliberately choose not to. Or, some fund managers may not have the need to use Facebook in any part of their lives because they have different ways of connecting to others (e.g., they substitute usage of Facebook with a more exclusive network tool or better technology for connecting with people they find it optimal to stay connected to).

[16]Interestingly, when comparing other characteristics of Facebook-identified and non-identified fund managers, we find no systematic differences in gender, nor in dimensions that are negatively (or positively) related to fund performance, including MBA degrees, Ivy League enrollment, CFA certifications, or the colleges' SAT percentile ranks.

However, when comparing Facebook-identified and non-identified funds, we do not find any statistical differences in performance between the two groups of funds, implying that our Facebook matching does not introduce a selection bias toward more sophisticated fund managers. Figure 7 illustrates the fund performance of Facebook-identified (dashed line) and non-identified funds (solid line) across our sample period. For this comparison, fund performance is calculated as annualized four-factor alpha using funds' monthly net returns.

[Insert Figure 7 near here.]

C. *Additional Tests*

Having already examined the persistence of returns earned on hidden connections in a multivariate regression framework, we now turn to a battery of additional robustness exercises to examine the general consistency of returns earned on connected stocks across different subsamples. To this end, we rerun the analysis of fund managers' holdings of connected stocks as in the first row of Table V. We report results in Table XI, measured as average monthly four-factor alphas. In Panel A we use alternative approaches to assessing tie strength of fund manager–firm officer connections. In Panel B we examine the robustness of our analyses across various subperiods of our initial sample. In Panel C we investigate robustness to including additional fund characteristics. In Panel D we undertake tests to further abate potential reverse causality concerns. The starting point to building subsamples are the 2,415 traded fund manager–firm officers pairs reported in Table III for which we find a fund manager's holdings of the stock to overlap with the firm officer's tenure at the firm.

[Insert Table XI near here.]

The specifications (1) through (3) in Panel A assess tie strengths of the observed fund manager–firm officer connections by exploring each particular individual's friendship ties with the other's family members. These specifications are motivated by the assumption that connected individuals that are acquainted with members of each other's family may be more closely tied. To disclose such connections, we use data collected from the roughly 59 thousand Facebook profiles belonging to our sample individuals' family members.[17] Specification (1) indicates a connection premium of 84 basis points (significant at the 5% level) for the

[17] Refer to Panel B of Table I for a more detailed breakdown of the family member profiles. The profiles of family members undergo the same treatment as the profiles of our sample individuals.

subsample of pairs for which we find one or both individuals in a connected pair also to be connected to at least one member of the other's family. In specification (2), we find trades pertaining to the subsample of connected pairs for which we find one or both individuals in a pair to be connected to the other's spouse to yield a return of 93 basis points (significant at the 5% level). Interestingly, the subsample of connected pairs in specification (3) for which we find the pair's respective spouses to be connected to one another yields a premium of 128 basis points (significant at the 1% level). The three remaining specifications in Panel A proxy crudely for physical propinquity, which is classically regarded as a necessary condition for a friendship tie to form (e.g., Festinger, Schachter, and Back (1950)). For instance, subsamples formed for the connected fund manager–firm officer pairs that were either classmates in high school (specification (4)) or attended the same college (specification (5))[18] both produce large and significant results (at the 5% level). The connection premium is smaller in magnitude for a subsample of connected pairs with matching hometowns (that also are in the same age group by no more than a one year difference), but loses significance. Overall, these results in Panel A corroborate our findings in Table VI.

In Panel B, we reestimate the returns on connected holdings for two more subperiods, one of which excludes fund-month observations during the dot-com bubble (1999–2001), and the other excluding fund-month observations during the financial crisis (2007–2008). In both cases, we find that our results are robust to the exclusion of these observations (at the 10% level), suggesting that returns are not driven by these episodes.

The subsamples for specifications (9) and (10) in Panel C are constructed by separating fund-month observations into those that are single-managed by a sole fund manager and those that are team-managed, respectively. We find both subsamples to produce results very similar to those in Table V. Furthermore, specifications (11) and (12) imply that our results are not likely driven neither by connected holdings of large firms (funds with Morningstar categories in the large blend, large growth, or large value spectrum) nor by connected holdings of small-cap firms (small-cap blend, small-cap growth, small-cap value).

The non positive outperformance of nonconnected stocks held (reported in Table V) and the returns of connected stocks not held (reported in Table VIII) are hard to reconcile with a reverse causality story. It is conceivable but unlikely that fund managers' past outperformance in specific stocks and time periods is related to forming subsequent Facebook

[18]The following data-cleaning steps were taken in this process: First, in dealing with universities with multiple campuses, we treat each satellite campus as a separate institution (e.g., we treat the University of Texas campuses at Austin and Arlington as separate institutions). Second, we assign all business schools to their corresponding universities or hosting institutions (e.g., we treat the McCombs School of Business and the University of Texas at Austin as the same institution). Third, if no campus is specified for a university that has multiple campuses, we assign the particular graduate to the university system's main campus (e.g., we assign graduates of Texas A&M University to the university's main campus in College Station).

connections with the respective firm officers but no connections with other firm officers. However, to ensure with a fair degree of certainty that tie formation is independent of later success in the professional career, in Panel D, we form two more subsamples. In specification (13), in order to limit the sample of fund-month observations to investment decisions that occurred after the friendship tie was most likely formed, we restrict it to observations pertaining to all fund manager–firm officer pairs that meet the criteria of specifications (4) through (6), i.e., fund manager–firm officer pairs that were high school classmates, attended the same college and overlapped in the pursuit of their degrees, or that come from the same hometown and matching age bucket. In addition, in specification (14), we build a subsample of fund-month observations following the earliest Facebook connection date that we are able to identify.[19] We find the outperformance of connected pairs in both subsamples to remain large and statistically significant (at the 5% level), suggesting that most of the correlation that we uncover between fund manager–firm officer connections and stock performance is driven by network effects, rather than the other way around.

IV. Conclusion

This paper explores hidden connections derived from a sample of 71,000 fund managers and firm officers using data from the world's largest social networking platform, Facebook. Making use of unique aspects of Facebook's functionality, we are able to measure the extent to which the network ties among fund managers and firm officers are visible versus hidden. We find that the more hidden a network tie is, the more valuable the information that appears to be associated with the trading across it. The premium on hidden connections remains strong and significant through the present day. It seems to be neither driven by a familiarity or selection story—as fund managers seem to be correctly timing when to hold (and when to avoid) stocks of the firms to which they are hiddenly tied to—nor by any industry, firm type, time period, or style criteria.

Stepping back from our setting, the costs of establishing and maintaining connections across network structures continue to decrease. As they do, we are observing that networks across all aspects of behavior, influence, and information transfer are largely becoming richer and more complex, heightening the need to understand their hidden aspects. Future research should explore the impact of these nodes in greater depth, potentially even estimating the impact of biased inference based on failing to account for hidden ties. This could be done, for instance, by identifying a small subsample of a network in which all nodes are "fully

[19] To identify a pair's earliest connection date, we combine data from two sources. First, based on the date when we first observed the friendship. Second, based on timestamps associated with the individuals' interactions on the Facebook platform.

revealed," comparing it to the remainder of the network, comprising both transparent and shrouded nodes, and estimating the different dynamics therein. Richer inferences derived from these types of comparisons have the potential to alter optimal responses in complex networked system dynamics and the understanding of economy-wide shock propagation.

Appendix A. Variable Definitions

Table A.I. Descriptions of Main Variables and Sources
This table provides descriptions and sources of variables used in our study. The following abbreviations are used: AE – Author's estimations, BO – BoardEx, CS – Compustat, CRSP – Center for Research in Security Prices, FB – Facebook.com, KF – Kenneth R. French's website, MS – Morningstar Direct, RP – RavenPack.

Variables	Description	Source
Panel A: Portfolio Sorts		
Connected	A fund-month-stock observation is added to the Connected/Connected Held portfolio if any of fund i's fund managers in period t and a firm officer of stock k in period t are friends on the Facebook platform; otherwise, it is added to the nonconnected portfolio. **Note:** For reasons of distinguishability, we call the connected and nonconnected portfolio sorts "Connected Held" and "Nonconnected Held" in Tables VIII and IX, respectively.	MS, CRSP, FB
AllVisibilities	A fund-month-stock observation is added to the AllVisibilitiesportfolio if any of fund i's fund managers in period t and a firm officer of stock k in period t are friends on the Facebook platform—irrespective of the visibility of the connection between the individuals.	MS, CRSP, FB
Visible	A fund-month-stock observation is added to the Visible portfolio if any of fund i's fund managers in period t and a firm officer of stock k in period t are friends on the Facebook platform, and the friendship is publicly observable through the fund manager's friends list.	MS, CRSP, FB
Invisible	A fund-month-stock observation is added to the Invisible portfolio if any of fund i's fund managers in period t and a firm officer of stock k in period t are friends on the Facebook platform, and the friendship is not publicly observable through the fund manager's friends list, but observable through the backlink of the firm officer's friends list.	MS, CRSP, FB

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Table A.I – continued from previous page.

Variables	Description	Source
DoublyInvisible	A fund-month-stock observation is added to the DoublyInvisible portfolio if any of fund i's fund managers in period t and a firm officer of stock k in period t are friends on the Facebook platform, and the friendship is not publicly observable through either the fund manager's friends list or through the firm officer's friends list.	MS, CRSP, FB
Reaction	A fund-month-stock observation is added to the Reaction portfolio if any of fund i's fund managers in period t and a firm officer of stock k in period t are friends on the Facebook platform, and the individuals mutually react to the other's content on the Facebook platform; otherwise, it is added to the No Reaction portfolio.	MS, CRSP, FB
AllSeniorities	A fund-month-stock observation is added to the AllSeniorities portfolio if any of fund i's fund managers in period t and a firm officer of stock k in period t are friends on the Facebook platform—irrespective of the firm officer's role.	MS, CRSP, FB, BO
SM	A fund-month-stock observation is added to the SM (Senior Manager) portfolio if any of fund i's fund managers in period t and a firm officer of stock k in period t in the role of a senior manager are friends on the Facebook platform.	MS, CRSP, FB, BO
ED	A fund-month-stock observation is added to the ED (Executive Director) portfolio if any of fund i's fund managers in period t and a firm officer of stock k in period t in the role of an executive director are friends on the Facebook platform.	MS, CRSP, FB, BO
SD	A fund-month-stock observation is added to the SD (Supervisory Director) portfolio if any of fund i's fund managers in period t and a firm officer of stock k in period t in the role of a supervisory director are friends on the Facebook platform.	MS, CRSP, FB, BO
Connected Not Held	A fund-month-stock observation is created and added to the Connected Not Held portfolio if any of fund i's fund managers in period t and a firm officer of stock k in period t are friends on the Facebook platform, and stock k is not held by the fund i in period t, while stock k is held by at least one other fund from fund i's Morningstar category.	MS, CRSP, FB

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Table A.I – continued from previous page.

Variables	Description	Source
News	A fund-day-stock observation is added to the News portfolio if any of fund i's fund managers in period t and a firm officer of stock k in period t are friends on the Facebook platform, and stock k was the subject of a news announcement on day t; otherwise, it is added to the No News portfolio.	MS, CRSP, FB, RP
Panel B: Weight Regressions		
Stock Weight $w_{f,s,t}$	Fund i's net assets invested in stock k at time t divided by the total net assets of fund i's equity portfolio at time t.	MS, CRSP, CS
Style$_{i,k,t}$	Percentage of net assets that fund i invests in period t in stock k's 5x5x5 portfolio bucket, determined as in Daniel et al. (1997).	MS, CRSP, CS
pME$_{i,k,t}$	Market value of equity of stock k, held by fund i, in time t.	CRSP, CS
pBM$_{i,k,t}$	Book value of stock k relative to market value of stock k, held by fund i, in time t.	CRSP, CS
R12$_{i,k,t}$	Stock k's return from the end of month $t-12$ to the end of month t.	CRSP
Panel C: Fama-Macbeth Regressions		
ExcessRet$_{k,t}$	Stock k's excess return in period t. ExcessRet$_{k,t}$ is stock k's raw return in period t obtained from CRSP. RiskFree$_t$ is the U.S. risk free rate in period t obtained from Kenneth R. French's website.	CRSP, KF, AE
DiffWeight$_{k,t}$	The difference between the average weight that FB-connected (or FB-interacted, depending on the specification) funds in period t simultaneously invest in stock k (i.e., stock buys) and the average weight that all other funds invest in stock k in period t.	MS, FB, AE
ME$_{k,t}$	Stock k's market equity in month t, calculated as stock k's price at the end of month t times its shares outstanding at the end of month t. If $ME_{k,t}$ is non-positive, the observation is considered to be missing. The variable is log-transformed.	CRSP, AE

Continued on next page.

Table A.I – continued from previous page.

Variables	Description	Source
$BM_{k,t}$	Stock k's book-to-market ratio at the end of month t, calculated as the firm's book equity from the last fiscal year (ending at least six months and less than 18 months ago) divided by stock k's ME at the end of the month of the last fiscal year ending. If either book equity or ME is non-positive, the observation is considered to be missing. The variable is log-transformed.	CRSP, CS, AE
$MOM_{k,t}$	Stock k's momentum at the end of month t, calculated as stock k's return from the end of month $t-12$ to the end of month $t-1$.	CRSP, AE
$STR_{k,t}$	Stock k's short-term reversal at the end of month t, calculated as stock k's return from the end of month $t-1$ to the end of month t	CRSP, AE
$IMOM_{k,t}$	Stock k's industry momentum at the end of month t, calculated as the value-weighted return of stock k's Fama-French-48 industry from the end of month $t-1$ to the end of month t.	CRSP, CS, KF, AE
$SUE_{k,t}$	Stock k's standardized unexpected earnings measure at the end of month t, calculated as in Livnat and Mendenhall (2006).	CRSP, CS, AE

Appendix B. Facebook Search Query Strings

Here we describe our approach to issuing a large number of search queries to Facebook's search engine. First, note that Facebook allows organizations to create a "Facebook page" where they can share content, engage with their audience, or link with their customers. This in turn enables Facebook users to signal their association with the particular organization on their user profiles (e.g., attendance of a college or working for a company). If the user does not explicitly restrict the audience with whom this biographical detail is shared, Facebook's search engine will return the user's profile when queried accordingly. Note further that every Facebook page is automatically assigned a numeric identifier (PageID) upon registration, which can be extracted from the page's source code. By embedding the PageID into a customized query string and appending it to Facebook's URL, one can automatically assign desired parameters to the search engine's filters and pass these to the server. For illustration, suppose that we want to search for "James Smith," educated at Harvard University (Facebook page fb.com/Harvard with PageID 105930651606; thus also accessible at fb.com/105930651606), and working at Citigroup (PageID 152431441489088). Next, we embed the PageIDs into a JSON string, which may be composed of up to three nested name-argument pairs corresponding to the engine's search filters (city, education, and work). To embed the PageIDs matching Facebook's syntax, we write:


```
{"school":"{\"name\":\"users_school\",\"args\":\"105930651606\"}",
"employer":"{\"name\":\"users_employer\",\"args\":\"152431441489088\"}"}
```


Next, we convert the JSON string into the Base64 format (using a Base64 encoder):


```
eyJzY2hvb2w6MCI6IntcIm5hbWVcIjpcInVzZXJzX3NjaG9vbFwiLFwiYXJnc1wiOlw
iMTA1OTMwNjUxNjA2XCJ9IiwKImVtcGxveWVyOjAiOiJ7XCJuYW1lXCI6XCJ1c2Vyc1
9lbXBsb3llclwiLFwiYXJnc1wiOlwiMTUyNDMxNDQxNDg5MDg4XCJ9fQ==
```


This Base64-encoded JSON string can then be used as *filter* parameter value in a query string together with a *q* parameter that takes the name of the individual.[20]

$$\overbrace{\text{https://facebook.com}}^{\text{Base URL}}\overbrace{\text{/search/people}}^{\text{Path}}\overbrace{\text{?q=}\underbrace{\text{James\%20Smith}}_{\text{Screen Name}}\text{\&filters=}\underbrace{\text{eyJzY2hvb2w6M(...)}}_{\text{Base64-encoded JSON}}}^{\text{Query String}}$$

[20] Note that the name must be separated by "%20," the percent-encoded value for the space character.

Appendix C. Matching Profiles Through Backlinks

Facebook users may implement restrictive privacy settings to disallow access to personal information on their profiles (e.g., photos, biographical data, friends lists, etc.). Such data is needful to establish a direct match between a profile and the user's real world identity. However, matches may be established by forming a bridge between the particular profile and the profile of an individual from the identity's immediate environment (e.g., a family member)—if the latter has less restrictive privacy settings. Figure C.I provides an example of the procedure. Given a restricted user profile that we consider a candidate profile for one of our sample individuals (subfigure A). Using information on the individual's family members, we can identify the user profile of the sample individual's son (subfigure B). The son's profile includes a photo that has his father tagged in it (subfigure C). By comparing the photo to his portrait on the fund firm's website (subfigure D), we can visually identify the sample individual. The backlink created by the tag shown in subfigure C leads to the user profile shown in subfigure A. It is therefore said to belong to the sample individual (i.e., we consider the identity behind the profile and the target identity to be the same person).

(A) (B) (C) (D)

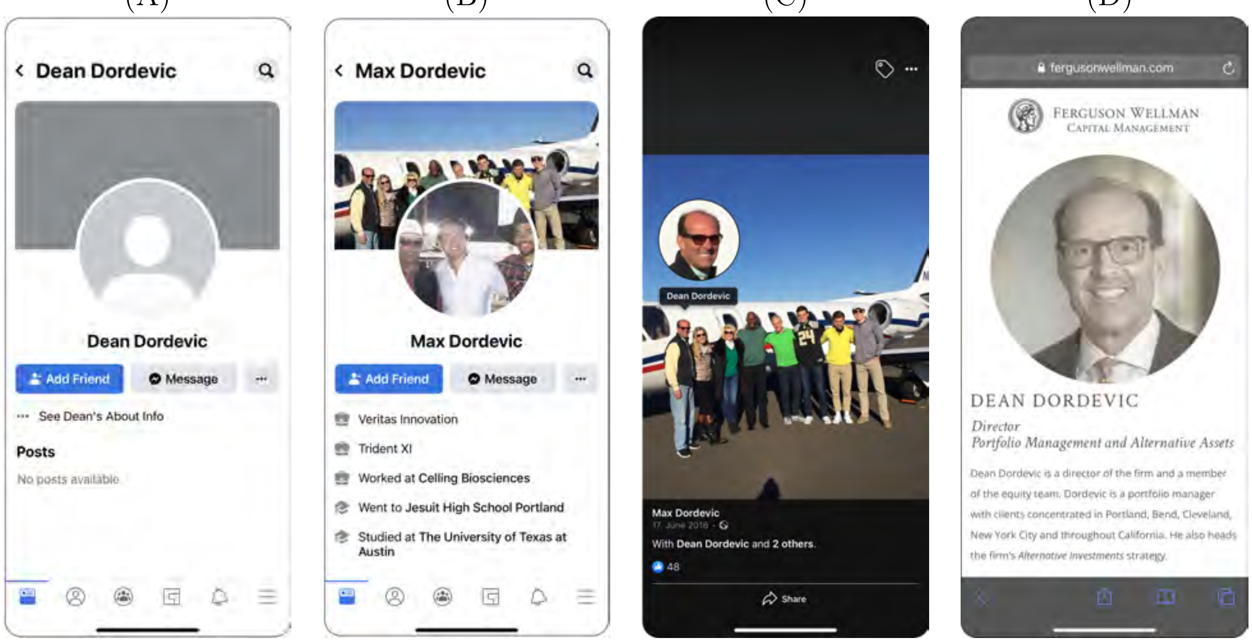

Fig. C.I. Matching Profiles with Restrictive Privacy Settings. This figure presents the restricted profile of one of our sample individuals (subfigure A); the profile of the sample individual's son (subfigure B); a photo of the sample individual on the son's profile (subfigure C); and a portrait of the sample individual on the website of the fund firm (subfigure D).

Appendix D. Frequency of Fund Holdings

Unlike the overwhelming majority of articles in the mutual fund literature (who turn to Thomson Reuters to obtain data on fund holdings) our study uses Morningstar. Here we compare the frequency of fund holdings from MS Direct (the construction of the MS Direct sample is detailed in Section I.D) to the frequency of fund holdings from the Thomson Reuters Mutual Fund Holdings Database (TR Holdings). To construct the TR Holdings/CRSP MF sample, we obtain information on fund share class characteristics from the CRSP Survivor-Bias-Free U.S. Mutual Fund Database (CRSP MF). We merge this data with TR Holdings using the WRDS MFLINKS product by following the data appendix provided by Doshi, Elkamhi, and Simutin (2015). We include defunct and active fund share classes and limit the sample to domestic actively managed U.S. equity funds. Lastly, since studies that use TR Holdings/CRSP MF as their source of holdings data typically obtain information on the fund management structure from MS Direct, we establish a match between CRSP MF and MS Direct by following the data appendix provided by Pástor, Stambaugh, and Taylor (2015). The comparison is detailed in Figure D.I. The figure compares the average time span between two consecutive holdings observations in months and the number of available funds in the period 1983–2017, indicating that the frequency of Morningstar holdings is better starting as early as 1991.

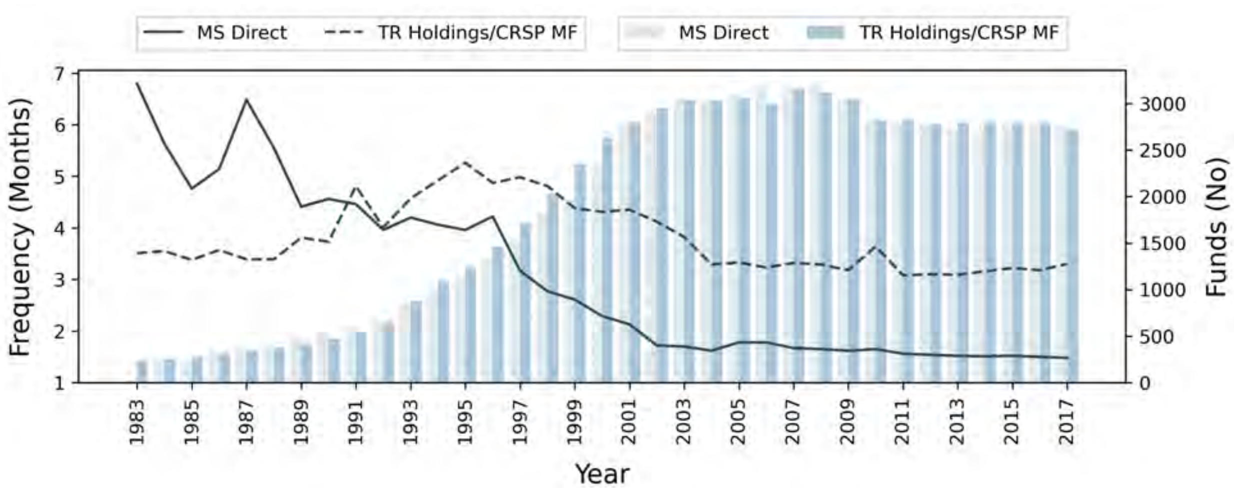

Fig. D.I. Comparison of Holdings from Morningstar and Thomson Reuters. This figure compares the average time span between two consecutive fund holding observations in months (lines) and the number of funds (bars) for fund holdings of U.S.-domiciled mutual funds obtained from MS Direct relative to fund holdings obtained from Thomson Reuters.

Appendix E. Facebook Interactions

date	interaction_id	firm_officer_id	firm_officer_name	firm_officer_role	reaction	direction	comment
2016-12-28-01:32	10102840642002933	494231	Jason Doris	{'Nuance Communications': 'Division VP Sales'}	comment	received	Cabernet rouge for me please
2017-05-16-00:26	10103047446301083	640739	Tom Smegal	{'California Water': 'VP/CFO/Treasurer'}	like	received	nan
2017-07-20-07:40	10103274744378843	830199	Tiffany R. Warren	{'Omnicom': 'SVP/Chief Diversity Officer'}	like	received	nan
2017-07-20-07:40	10103274744378843	1090714	Steve Jurvetson	{'Tesla': 'Supervisory Director'}	comment	received	Warren and Astro were there as well... Oh; and at ou…
2017-07-20-07:40	10103274744378843	1090714	Steve Jurvetson	{'Tesla': 'Supervisory Director'}	tagged	received	nan
2017-10-17-02:16	10177940467764274	989141	Greg Sands	{'Quinstreet': 'Supervisory Director'}	like	given	nan
2017-10-17-22:43	10103463627693143	1252489	Lenny Stein	{'Splunk': 'SVP/Chief Legal Officer'}	comment	received	They are just ducking with you.
2018-06-02-05:39	10103926617243293	1260853	Steve Vassallo	{'Sunrun': 'Supervisory Director'}	like	given	nan
2018-11-18-03:06	10104233970687803	1090711	Ira Ehrenpreis	{'Tesla': 'Supervisory Director'}	like	received	nan
2018-12-04-22:57	10104264379336703	830199	Tiffany R. Warren	{'Omnicom': 'SVP/Chief Diversity Officer'}	comment	received	They are awesome
2018-12-26-03:26	10104336430804903	1090711	Ira Ehrenpreis	{'Tesla': 'Supervisory Director'}	like	received	nan
2018-12-28-18:49	10104343300274263	1475596	Christopher M. Schroeder	{'Mexco Energy': 'Supervisory Director'}	comment	received	See you shortly
2019-04-17-16:41	10104743739072893	1591402	Chris Fralic	{'Meet Group': 'Supervisory Director'}	comment	received	I'll never forget meeting a young David Hornik at the TEDdrive Laguna Seca race track...
2019-04-30-16:29	10104607412907413	1090711	Ira Ehrenpreis	{'Tesla': 'Supervisory Director'}	like	received	nan
2019-09-06-14:57	10104443077347063	1090714	Steve Jurvetson	{'Tesla': 'Supervisory Director'}	like	received	nan
2019-09-27-06:30	10104489342047943	1328447	Greg Bohlen	{'Beyond Meat': 'Supervisory Director'}	comment	received	What a great night. Thanks for all the food; booze and great conversation
2020-04-03-18:01	10107320370791763	1299599	Laurie Yoler	{'Church & Dwight': 'Supervisory Director'}	like	received	nan
2021-03-14-09:21	10226194896940647	1912436	Caroline Shin	{'Thayer Ventures': 'Supervisory Director'}	comment	given	You both look great!
2021-07-28-14:49	10106222330496603	494231	Jason Doris	{'Fastly': 'Vice President Sales'}	comment	received	Are you headed back to West coast? I'll be in NYC we…
2021-10-12-09:06	10106317944449713	1090711	Ira Ehrenpreis	{'Tesla': 'Supervisory Director'}	like	received	nan

Fig. E.I. Interactions of a Fund Manager with Firm Officer Friends. This figure shows a screenshot of interactions from our database between a fund manager and his firm officer Facebook friends. The data includes interactions (reactions on photos) exchanged between the fund manager and different firm officers from our sample in the period December 2016 to December 2021. Data types include the date associated with the profile content, the firm officers' names, the role(s) that they occupied on the particular day, the reaction type (like, comment, tag), its direction (received by the fund manager vs. given to), and the reaction's content, if applicable.

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Table I. Summary Statistics: Facebook Data

This table provides details on the Facebook data that we collect for this paper. The sample includes the manually identified Facebook profiles of 3,984 fund managers and 67,162 firm officers. Panel A details the information that the sample individuals disclose on their Facebook profiles. For each particular profile attribute, we report the percentage share (% Share) and the number of sample individuals (N Profiles) from each group (fund managers and firm officers) that disclose the attribute. Panel B reports statistics on the data collected on friends, photos (including reactions received by these photos), and family member profiles. Statistics are computed conditional for profiles with nonmissing values. For each variable, we report the mean, median, standard deviation (STD), total number of data items (N Items), and number of profiles for which we collect the data item (N Profiles). *Friends–All* details the number of friends that we disclose per profile, irrespective of whether or not the profile's friends list was publicly accessible. *Friends–Published* details the number of friends that we collect through publicly accessible friends. *Friends–Backlinks* details the number of friends that we collect via backlinks from friends' profiles. *Friends–Reactions* details the remaining number of friends that we collect by examining user engagements (reactions). The panel further reports statistics on photos collected from the profiles and details the number of reactions received by these photos. At the bottom of the panel, we report statistics on profiles of family members that we collect for the sample individuals. These are manually collected during the preliminary data collection process, and are also obtained from the family member section of sample individuals' positively identified profiles.

	Fund Managers (N Profiles = 3,984)		Firm Officers (N Profiles = 67,162)	
	% Share	N Profiles	% Share	N Profiles
Panel A: Disclosed Attributes				
Friends List	.56	2,228	.51	34,367
Profile Picture	.91	3,609	.93	62,697
Other Photos	.66	2,615	.33 [a)]	21,930
Work	.32	1,286	.36	33,869
College	.45	1,797	.50	33,641
High School	.39	1,566	.43	29,171
Current City	.53	2,116	.53	35,409
Hometown	.43	1,706	.47	31,336
Other Places Lived	.11	444	.11	7,609
Relationship Status	.20	802	.23	15,469
Family Members	.23	920	.29	19,710
Life Events	.25	987	.31	25,088

Continued on next page.

Table I. – continued from previous page.

	Fund Managers (N Profiles = 3,984)					Firm Officers (N Profiles = 67,162)				
	Mean	Median	STD	N Items	N Profiles	Mean	Median	STD	N Items	N Profiles
Panel B: Collected Data [b]										
Friends Section										
Friends–All	250	163	349	960,809	3,849	261	118	451	17,359,479	66,547
Friends–Published	302	210	409	671,890	2,228	434	281	515	14,901,429	34,367
Friends–Backlinks	117	75	147	182,046	1,562	8	4	17	268,967	31,649
Friends–Reactions	99	61	127	131,822	1,337	183	93	376	2,001,496	10,963
Photo Section										
Photos	44	6	155	138,048	3,168	80	10	223	2,040,734	25,485
Reactions	512	100	1,781	1,527,923	2,982	778	107	2,681	16,308,324	20,975
Likes	459	92	1,563	1,348,524	2,940	701	101	2,379	14,632,087	20,886
Comments	66	13	254	149,923	2,264	147	32	484	1,449,935	9,842
Tags	31	5	114	29,476	956	37	7	138	226,302	6,190
Family Section										
Family–All	2.09	1	1.77	3,390	1,383	2.49	2	2.47	55,842	22,396
Spouses	1.00	1	0.05	860	680	1.00	1	0.03	8,842	8,835
Children	1.57	1	0.78	821	358	1.47	1	0.74	8,660	5,902
Parents	1.13	1	0.32	187	142	1.08	1	0.28	1,940	1,790
Other	1.99	1	1.76	1,522	747	2.33	1	2.29	36,400	15,628

[a] Note that the collection of photos is computationally expensive, and 40% of the firm officers' photos were outstanding at the time of writing.
[b] Note that while Panel A reports statistics on data disclosed by the sample individuals on their Facebook profiles, Panel B reports statistics on Facebook data that—even though it is associated with the individuals' profiles—must not necessarily have been gathered from these profiles (e.g., while from Panel A it becomes apparent that 920 fund managers disclose profiles of their family members, Panel B indicates that the data include family member profiles belonging to 1,383 fund managers, because we also collect these profiles manually during the data collection process).

Table II. Summary Statistics: Facebook-identified Sample of Funds
This table presents annual summary statistics for the "Facebook-identified" sample of mutual funds, the funds' common stock holdings, and the stocks' firm management personnel. For each variable, we report its mean, median, minimum, maximum, and standard deviation (STD). The sample of funds consists of 262,380 fund-month observations covering the period 1984–2020. It includes domestic actively managed U.S. equity mutual funds from MS Direct for which we identify the Facebook profile of at least one of the fund's portfolio managers. The benchmark universe of funds used to compute percentage coverages is the fund sample consisting of 418,258 fund-month observations whose construction is detailed in Section I.D. The sample of stocks includes the Facebook-identified funds' holdings in common stocks covered by the CRSP stock universe. The data on firm management personnel are obtained from BoardEx and include firm officers heading the Facebook-identified funds' stock holdings.

	Mean	Median	Min.	Max.	STD
Facebook-identified funds per year	1,118	1,483	24	1,985	754
% of funds in benchmark universe	.52	.58	.15	.73	.19
% of total net assets in benchmark universe	.49	.51	.08	.78	.21
Facebook-identified fund managers per year	898	1,113	23	1,521	589
% of fund managers in benchmark universe	.34	.36	.13	.45	.10
Firms held by funds per year	3,617	3,963	341	5,234	1,332
% of stocks in CRSP universe	.48	.54	.05	.65	.17
% of market cap in CRSP universe	.86	.97	.34	.99	.18
Firm Officers of firms held by funds per year	57,729	62,084	1,183	111,058	43,125
% of firm officers in BoardEx sample	.94	.99	.57	1.	.10
Facebook-identified firm officers per year	14,449	13,568	88	31,465	12,193
% of firm officers held by funds	.20	.22	.07	.28	.07

Table III. Fund Manager–Firm Officer Facebook Friendships
This table provides details on the fund manager–firm officer friendships that we observe in this study. The table compares the total number of fund manager–firm officer friendships (Friendships–All), the number of tradable fund manager–firm officer friendships (Friendships–Tradable), and the number of traded friendships (Friendships–Traded), broken down by friendship visibility. We call a friendship "tradable" if the fund manager's tenure at the fund overlaps with the firm officer's tenure at the firm, and the firm's stock in the same month is held by at least one fund within the same Morningstar category. We call a friendship "traded" if the fund manager's holdings of the stock overlap with the firm officer's tenure at the firm. We denote the visibility of a Facebook friendship depending on whether the friendship is publicly observable through the fund manager's friends list (*Visible*); whether it is not publicly observable through the fund manager's friends list, but observable through the backlink from the firm officer's friends list (*Invisible*); or whether it is not publicly observable through either the fund manager's friends list or through the firm officer's friends list (*DoublyInvisible*).

	N Pairs	N Fund Managers	N Firm Officers
Friendships–All	15,242	2,653	9,135
Visible	10,520	1,648	7,098
Invisible	3,609	931	2,634
DoublyInvisible	1,113	519	951
Friendships–Tradable	7,476	1,927	5,152
Visible	5,213	1,204	3,931
Invisible	1,742	658	1,428
DoublyInvisible	521	318	476
Friendships–Traded	2,415	933	1,789
Visible	1,548	582	1,272
Invisible	631	300	511
DoublyInvisible	236	131	190

Table IV. OLS Regressions: Portfolio Weights in Connected Stocks by Visibility

This table reports the coefficient estimates and standard errors from Panel OLS estimations of mutual funds' portfolio weights in stocks managed by fund managers' firm officer Facebook friends. The dependent variable w is the fund's dollar investment in a stock as percentage of the fund's total net assets. The independent variables capture the degree of visibility of the fund manager's friendship with the firm officer(s) of the given firm. These are categorical variables indicating whether any of the fund's current fund managers and a current firm officer of the given firm are friends on the Facebook platform (*AllVisibilities*); whether the friendship is publicly observable through the fund manager's friends list (*Visible*); whether it is not publicly observable through the fund manager's friends list, but observable through the backlink from the firm officer's friends list (*Invisible*); or whether it is not publicly observable through either the fund manager's friends list or through the firm officer's friends list (*DoublyInvisible*). The control variables included where indicated are *Style*, the percentage of the fund's total net assets invested in the style corresponding to the stock being considered (style is calculated as in Daniel et al. (1997)), and *pME*, *pBM*, and *R12*, which are percentiles of market value of equity, book to market, and past 12-month return, respectively. Each regression includes period fixed effects. Fund and firm fixed effects are included where indicated. The sample period is 1984–2020. Units of observation are fund-stock-period. Standard errors are adjusted for clustering at the period level and are reported in brackets. Significance levels are denoted by *, **, and ***, which correspond to the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Constant	74.59***	74.59***	74.59***	74.59***	74.59***	1.42*	1.43*	-24.80***	-24.83***
	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.79]	[0.79]	[1.03]	[1.02]
AllVisibilities	71.47***				58.89***				
	[1.18]				[1.17]				
Visible		49.93***				1.20		11.38***	
		[1.46]				[0.80]		[0.98]	
Invisible			95.80***						
			[1.55]						
DoublyInvisible				136.47***	77.59***		50.94***		21.64***
				[2.68]	[2.47]		[2.06]		[2.91]
Controls	No	No	No	No	No	Yes	Yes	Yes	Yes
Fixed effect	Period	Period	Period	Period	Period	Period	Period	Period	Period
Fixed effect						Fund	Fund	Firm	Firm
Adj. R squared	0.01	0.01	0.01	0.01	0.01	0.36	0.36	0.40	0.40

Table V. Portfolio Sorts: Monthly Returns on Connected Stocks by Visibility

This table reports monthly calendar time portfolio returns sorted by friendship link visibility. We denote the visibility of a friendship link using four dummy variables capturing whether any of the fund's current fund managers and a current firm officer of the given firm are friends on the Facebook platform (*AllVisibilities*); whether the friendship is publicly observable through the fund manager's friends list (*Visible*); whether it is not publicly observable through the fund manager's friends list, but observable through the backlink from the firm officer's friends list (*Invisible*); or whether it is not publicly observable through either the fund manager's friends list or through the firm officer's friends list (*DoublyInvisible*). For each fund-period observation, the stocks in each fund portfolio are sorted into portfolios of connected and nonconnected stocks. We define connected stocks as firms that are headed by one of the fund manager's then-active firm officer Facebook friends. Based on the assumption that funds did not change their holdings between two reporting dates, we construct monthly portfolios by keeping the stocks in the portfolio until the next reporting date, when portfolios are rebalanced to reflect changes in holdings. Within a given portfolio, stock returns are weighted by the fund's dollar holdings. Finally, we compute value-weighted returns by averaging across funds, weighting each fund portfolio return by the fund's total net asset value. Long-Short (LS) is the monthly return of a zero cost portfolio that buys the portfolio of connected stocks and sells short the portfolio of nonconnected stock. We report raw returns, four-factor alphas, and DGTW-adjusted returns in the period 1984–2020. Four-factor alpha is the intercept on a regression of monthly excess returns on explanatory variables that include the monthly returns from the three Fama and French (1993) factor-mimicking portfolios and Carhart (1997)'s momentum factor. DGTW-adjusted returns are defined as raw returns minus the returns on a value-weighted benchmark portfolio of all CRSP firms in the same size, book-to-market, and one-year past return quintile. t-statistics are shown below the coefficient estimates in brackets. Significance levels are denoted by *, **, and ***, which correspond to the 10%, 5%, and 1% levels, respectively.

	Raw Return			Four-Factor Alpha			DGTW-Adjusted		
	Connected	Nonconn.	LS	Connected	Nonconn.	LS	Connected	Nonconn.	LS
AllVisibilities	1.44***	0.97***	0.47*	0.45*	0.00	0.45*	0.56***	0.03	0.53***
	(4.09)	(4.08)	(1.94)	(1.85)	(0.15)	(1.84)	(2.82)	(0.73)	(2.73)
Visible	1.13***	0.98***	0.15	0.16	-0.01	0.17	0.27*	0.03	0.25
	(3.86)	(3.96)	(0.84)	(0.88)	(-0.23)	(0.92)	(1.69)	(0.59)	(1.56)
Invisible	1.53***	0.95***	0.57*	0.56*	-0.00	0.56*	0.71***	0.03	0.69***
	(3.73)	(3.99)	(1.87)	(1.81)	(-0.02)	(1.83)	(2.80)	(0.67)	(2.74)
DoublyInvisible	2.40***	0.93***	1.48***	1.35***	-0.00	1.36***	1.39***	0.03	1.37***
	(5.02)	(3.62)	(3.88)	(3.54)	(-0.16)	(3.57)	(3.84)	(0.57)	(3.80)

Table VI. Portfolio Sorts: Monthly Returns on Connected Stocks with Interactions by Visibility
This table reports monthly calendar time portfolio returns sorted by friendship visibility and a reaction dummy. The "Reaction" portfolio includes the set of a fund's connected stocks where the fund's portfolio manager(s) and any of the stock's firm officers mutually interact with the other's content on Facebook (i.e., like, comment, or tags given to the other's content). The "No Reaction" portfolio consists of the fund's connected stocks where no such reactions take place between the particular individuals. To construct the connected held portfolios for this analysis, we use the portfolio construction approach detailed in Table V. Long-Short (LS) is the monthly return of a zero cost portfolio that buys the Reaction portfolio and sells short the No Reaction. Portfolios are sorted by friendship visibility as defined in Table V, which includes the expressions *AllVisibilities*, *Visible*, *Invisible*, and *DoublyInvisible*. We report raw returns, four-factor alphas, and DGTW-adjusted returns in the period 1984–2020. Four-factor alpha is the intercept on a regression of monthly excess returns on explanatory variables that include the monthly returns from the three Fama and French (1993) factor-mimicking portfolios and Carhart (1997)'s momentum factor. DGTW-adjusted returns are defined as raw returns minus the returns on a value-weighted benchmark portfolio of all CRSP firms in the same size, book-to-market, and one-year past return quintile. t-statistics are shown below the coefficient estimates in brackets. Significance levels are denoted by *, **, and ***, which correspond to the 10%, 5%, and 1% levels, respectively.

	Raw Return			Four-Factor Alpha			DGTW-Adjusted		
	Reaction	No Reaction	LS	Reaction	No Reaction	LS	Reaction	No Reaction	LS
AllVisibilities	2.19***	1.29***	1.04***	1.15***	0.31	0.96***	0.96***	0.50**	0.64**
	(5.17)	(3.67)	(2.96)	(3.56)	(1.24)	(2.67)	(4.63)	(2.53)	(2.42)
Visible	1.42***	1.26***	0.09	0.55*	0.26	0.18	0.19	0.23	-0.05
	(3.32)	(3.91)	(0.23)	(1.86)	(1.17)	(0.48)	(0.89)	(1.60)	(-0.20)
Invisible	2.16***	1.53***	0.76*	1.09***	0.56*	0.71*	1.02***	0.59**	0.46*
	(4.66)	(3.59)	(1.71)	(3.13)	(1.66)	(1.68)	(3.76)	(2.51)	(1.73)
DoublyInvisible	2.40***			1.35***			1.39***		
	(5.02)			(3.54)			(3.84)		

Table VII. Portfolio Sorts: Monthly Returns on Connected Stocks by Seniority

This table reports monthly calendar time portfolio returns sorted by friendship visibility and firm officer seniority. We denote firm officer seniority using BoardEx's categorization of role seniority (see Section I.F). We allocate fund holdings into portfolios based on whether any of the fund's current fund managers and a current firm officer of the given firm are friends on the Facebook platform (*AllSeniorities*); and whether the connected firm officer is a senior manager (*SM*); an executive director (*ED*); or a supervisory director (*SD*). To construct the connected held and nonconnected held portfolios for this analysis, we use the portfolio construction approach detailed in Table V. Long-Short (LS) is the monthly return of a zero cost portfolio that buys the portfolio of connected stocks and sells short the portfolio of nonconnected stock. Portfolios are sorted by friendship visibility as defined in Table V, which includes the expressions *AllVisibilities*, *Visible*, *Invisible*, and *DoublyInvisible*. We report raw returns, four-factor alphas, and DGTW-adjusted returns in the period 1984–2020. Four-factor alpha is the intercept on a regression of monthly excess returns on explanatory variables that include the monthly returns from the three Fama and French (1993) factor-mimicking portfolios and Carhart (1997)'s momentum factor. DGTW-adjusted returns are defined as raw returns minus the returns on a value-weighted benchmark portfolio of all CRSP firms in the same size, book-to-market, and one-year past return quintile. t-statistics are shown below the coefficient estimates in brackets. Significance levels are denoted by *, **, and ***, which correspond to the 10%, 5%, and 1% levels, respectively.

	Raw Return			Four-Factor Alpha			DGTW-Adjusted		
	Connected	Nonconn.	LS	Connected	Nonconn.	LS	Connected	Nonconn.	LS
AllSeniorities	1.44***	0.97***	0.47*	0.45*	0.00	0.45*	0.56***	0.03	0.53***
	(4.09)	(4.08)	(1.94)	(1.85)	(0.15)	(1.84)	(2.82)	(0.73)	(2.73)
SM	1.29***	0.98***	0.31	0.28	-0.01	0.29	0.47***	0.03	0.44***
	(4.03)	(3.96)	(1.63)	(1.41)	(-0.23)	(1.46)	(2.77)	(0.59)	(2.63)
ED	1.88***	0.97***	0.91***	0.80**	0.00	0.80**	0.97***	0.03	0.94***
	(4.42)	(4.08)	(2.77)	(2.43)	(0.15)	(2.43)	(3.40)	(0.73)	(3.34)
SD	1.93***	0.95***	0.98***	1.02***	-0.01	1.03***	1.11***	0.02	1.09***
	(4.49)	(3.81)	(2.84)	(2.86)	(-0.56)	(2.92)	(3.96)	(0.46)	(3.94)

Table VIII. Portfolio Sorts: Monthly Returns on Connected Not Held Stocks by Visibility

This table reports monthly calendar time portfolio returns for the funds' connected and connected not held portfolios, sorted by friendship link visibility. For each fund-period observation, the stocks in each fund portfolio are sorted into Connected Held (CH) and Connected Not Held (CNH) portfolios. We define Connected Not Held stocks as stocks that are not held by the particular fund and are headed by a fund manager's then-active firm officer Facebook friend while in the same month being held by at least one other fund from the same Morningstar category. Based on the assumption that funds did not change their holdings between two reporting dates, we construct monthly portfolios by keeping non held stocks in the portfolio until the next reporting date, when the actual portfolios are rebalanced to reflect changes in holdings. Within a given portfolio, we weight the non held stocks' returns by the stock's respective market capitalization. We then compute value-weighted returns by averaging across funds, weighting each fund portfolio return by the fund's total net assets value. Long-Short is the monthly return of a zero cost portfolio that buys the CH portfolio and sells short the CNH portfolio. We report raw returns (Raw), four-factor alphas (Alpha), and DGTW-adjusted returns (DGTW) in period 1984–2020. Four-factor alpha is the intercept on a regression of monthly excess returns on explanatory variables that include the monthly returns from the three Fama and French (1993) factor-mimicking portfolios and Carhart (1997)'s momentum factor. DGTW-adjusted returns are defined as raw returns minus the returns on a value-weighted benchmark portfolio of all CRSP firms in the same size, book-to-market, and one-year past return quintile. t-statistics are shown below the coefficient estimates in brackets. Significance levels are denoted by *, **, and ***, which correspond to the 10%, 5%, and 1% levels, respectively.

	Connected Held (CH)			Connected Not Held (CNH)			Long CH/Short CNH		
	Raw	Alpha	DGTW	Raw	Alpha	DGTW	Raw	Alpha	DGTW
AllVisibilities	1.44***	0.45*	0.56***	1.08***	0.10	0.11	0.36	0.35	0.45**
	(4.09)	(1.85)	(2.82)	(3.72)	(0.84)	(1.18)	(1.37)	(1.35)	(2.06)
Visible	1.13***	0.16	0.27*	1.12***	0.07	0.13	0.01	0.09	0.14
	(3.86)	(0.88)	(1.69)	(3.50)	(0.50)	(1.01)	(0.04)	(0.41)	(0.74)
Invisible	1.53***	0.56*	0.71***	0.98***	-0.02	0.01	0.54	0.57*	0.71**
	(3.73)	(1.81)	(2.80)	(2.93)	(-0.09)	(0.05)	(1.60)	(1.66)	(2.57)
DoublyInvisible	2.40***	1.35***	1.39***	1.10**	0.16	0.20	1.30***	1.19**	1.20***
	(5.02)	(3.54)	(3.84)	(2.41)	(0.49)	(0.67)	(2.75)	(2.59)	(2.73)

Table IX. Portfolio Sorts: Daily Returns on Connected Stocks by Visibility and News Announcements
This table reports daily calendar time portfolio returns on corporate news for the funds' connected held, nonconnected held, and connected not held portfolios, sorted by friendship visibility. To construct the connected held (CH)/nonconnected held (NCH) and connected not held (CNH) portfolios for this analysis, we modify the portfolio construction approaches used in Tables V and VIII, respectively, by assigning to each stock in each fund portfolio its daily returns earned in the following month. Next, for each fund-day observation, we sort the stocks in each fund portfolio into news and no news sub-portfolios, based on whether or not the given stock was the subject of a news announcement on the particular day. We weight stock returns in the Connected/Nonconnected Held portfolios by the fund's dollar holdings, and stock returns in the Connected Not Held portfolios by the stock's respective market capitalization. Finally, we compute value-weighted returns by averaging across funds, weighting each fund portfolio return by the fund's total net asset value. Long-Short is the monthly return of a zero cost portfolio that buys the Connected Held portfolio and sells short the Nonconnected Held portfolio, respectively, that sells short the Connected Not Held portfolio. Portfolios are sorted by friendship visibility as defined in Table V, which includes the expressions *AllVisibilities*, *Visible*, *Invisible*, and *DoublyInvisible*. We report daily four-factor alphas in the period 2000–2020. Four-factor alpha is the intercept on a regression of monthly excess returns on explanatory variables that include the monthly returns from the three Fama and French (1993) factor-mimicking portfolios and Carhart (1997)'s momentum factor. t-statistics are shown below the coefficient estimates in brackets. Significance levels are denoted by *, **, and ***, which correspond to the 10%, 5%, and 1% levels, respectively.

	Connected Held (CH)		Nonconnected Held (NCH)		Connected Not Held (CNH)		Long CH/ Short NCH		Long CH/ Short CNH	
	News	No News	News	No News	News	No News	News	No News	News	No News
AllVisibilities	0.041***	0.004	0.019***	0.004	0.021***	-0.002	0.022*	-0.000	0.020*	0.008
	(2.75)	(0.64)	(3.97)	(1.08)	(2.70)	(-0.41)	(1.71)	(-0.03)	(1.67)	(1.13)
Visible	0.033*	0.006	0.019***	0.004	0.018**	-0.005	0.014	0.001	0.015	0.012
	(1.77)	(0.78)	(4.00)	(1.08)	(2.16)	(-0.73)	(1.11)	(0.21)	(1.14)	(1.46)
Invisible	0.043**	0.007	0.019**	0.004	0.020***	-0.009	0.024**	0.002	0.023*	0.017*
	(2.06)	(0.79)	(3.92)	(1.08)	(2.69)	(-1.20)	(2.04)	(0.29)	(1.94)	(1.70)
DoublyInvis.	0.060***	0.005	0.020***	0.004	0.023*	-0.005	0.040***	0.001	0.037**	0.011
	(2.87)	(0.48)	(4.27)	(1.08)	(1.67)	(-0.44)	(2.69)	(0.08)	(2.39)	(0.81)

Table X. Returns: Cross-sectional Fama-Macbeth Regressions by Visibility
This table reports risk premium estimates from monthly cross-sectional Fama and MacBeth (1973) regressions in the period 1984–2020. The main independent variable of interest is $DiffWeight_{k,t}$, the difference between the average weight that Facebook-connected funds invest in the stock and the average weight that all other funds invest in the stock. Other independent variables include firm size (ME), book-to-market ratio (BM), momentum (MOM), short-term reversal (STR), industry momentum ($IMOM$), and standardized unexpected earnings (SUE). The dependent variable in the Fama-MacBeth regressions are next month's stock excess returns ($ExcessRet$), calculated as raw return minus the risk free rate. All dependent and independent variables are in each month winsorized at the 1st and 99th percentile. Regressions are run separately for *AllVisibilities*, *Visible*, *Invisible*, and *DoublyInvisible*, the different expressions of a friendship's degree of visibility as defined in Table IV. Standard errors are adjusted for clustering at the period level and are reported in brackets. Significance levels are denoted by *, **, and ***, which correspond to the 10%, 5%, and 1% levels, respectively.

	AllVisibilities	Visible	Invisible	DoublyInvisible
	(1)	(2)	(3)	(4)
Constant	0.0101***	0.0105***	0.0124***	0.0111***
	[0.0038]	[0.0038]	[0.0038]	[0.0039]
DiffWeight	0.0181**	0.0147	0.0171**	0.0228***
	[0.0079]	[0.0089]	[0.0085]	[0.0083]
ME	-0.0006**	-0.0006**	-0.0008**	-0.0007**
	[0.0003]	[0.0003]	[0.0003]	[0.0003]
BM	0.0005	0.0005	0.0005*	0.0004
	[0.0003]	[0.0003]	[0.0003]	[0.0003]
MOM	0.0003	0.0003	0.0002	0.0002
	[0.0023]	[0.0023]	[0.0023]	[0.0024]
STR	-0.0236***	-0.0241***	-0.0230***	-0.0238***
	[0.0057]	[0.0057]	[0.0057]	[0.0058]
IMOM	0.0876***	0.0837***	0.0826***	0.0839***
	[0.0186]	[0.0187]	[0.0190]	[0.0190]
SUE	-0.0010	-0.0010	-0.0006	-0.0011
	[0.0013]	[0.0013]	[0.0012]	[0.0013]
Adj. R squared	0.0744	0.0682	0.0783	0.0814
N	1,262,650	1,264,503	1,235,862	1,233,925
N Months	294	294	289	288

Table XI. Additional Robustness Tests

This table reports monthly calendar time portfolio returns for a battery of robustness tests. To construct the connected portfolios, we rerun the analysis of fund managers' holdings of connected stocks as in the first row of Table V. Specifications (1) and (2) include fund manager–firm officers pairs for which one or both individuals in a connected pair are also connected (1) to at least one member of the other's family, respectively, (2) to the other's spouse. Specification (3) includes connected pairs for which we also find the pairs' respective spouses to be connected among one another. Specifications (4) through (6) include pairs that (4) were classmates in high school, (5) graduated from college together, or (6) come from the same hometown and age bucket. Specifications (7) and (8) exclude fund-month observations during (7) the dot-com bubble, respectively, (8) the financial crisis. Specifications (9) through (12) include (9) only single-managed funds, (10) only team-managed funds, (11) only large-cap funds, or (12) only small-cap funds. Specification (13) includes only pairs whose tie formation can be plausibly reasoned through physical propinquity, i.e., specifications (4) through (6) combined. Specification (14) includes fund-month observations of pairs following the earliest proof of their tie formation (based on observations of friends lists and interactions). We report monthly four-factor alphas in the period 1984–2020, if not otherwise specified. Four-factor alpha is the intercept on a regression of monthly excess returns on explanatory variables that include the monthly returns from the three Fama and French (1993) factor-mimicking portfolios and Carhart (1997)'s momentum factor. Significance levels are denoted by *, **, and ***, which correspond to the 10%, 5%, and 1% levels, respectively.

	Four-Factor Alpha	N Pairs
Panel A: Tie Strength		
(1) Connected with family	84**	188
(2) Connected with spouse	93**	91
(3) Interconnected spouses	128***	32
(4) High school classmates	78**	26
(5) Same college graduates	71**	237
(6) Same hometown	36	43
Panel B: Subperiods		
(7) Excluding financial crisis (2007–2008)	49*	2,261
(8) Excluding dot-com bubble (1999–2001)	52*	2,303
Panel C: Fund Characteristics		
(9) Single-managed funds	50*	463
(10) Team-managed funds	43*	2,197
(11) Large-cap funds	42*	1,098
(12) Small-cap funds	47*	627
Panel D: Endogeneity Concerns		
(13) Physical propinquity	69**	258
(14) Evidence of tie formation	104**	435

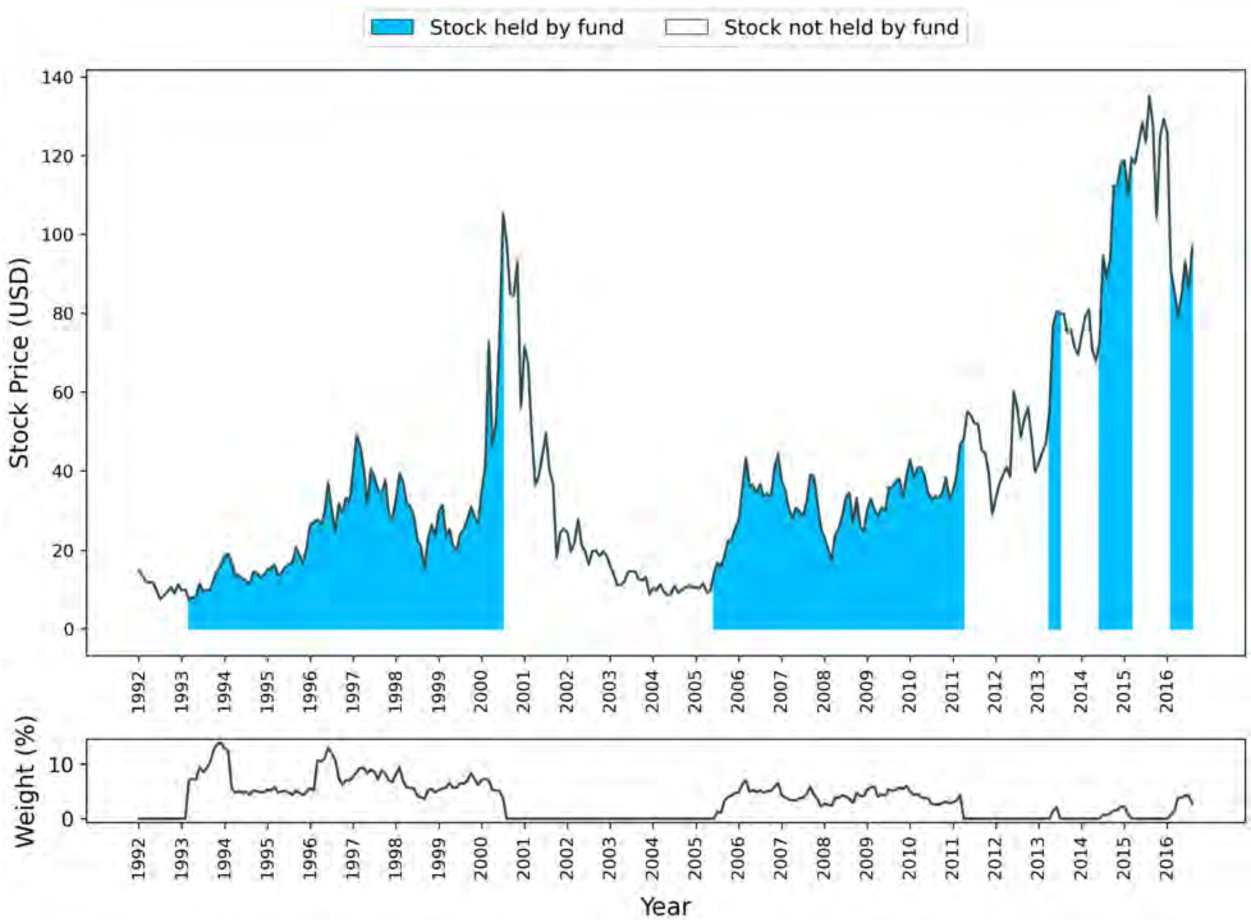

Fig. 1. Fund Manager Bergelmir's Holdings in Ananke's Firm. The upper chart of this figure plots the evolution of the stock price of CEO Ananke's stock in the period 1992–2016. The blue shaded area indicates the time period during which Ananke's stock was held by Bergelmir's fund. The white shaded area indicates the time period during which Bergelmir's fund had no position in Ananke's stock. The lower chart of this figure plots Bergelmir's fund weights (in %) in Ananke's stock over the same time period.

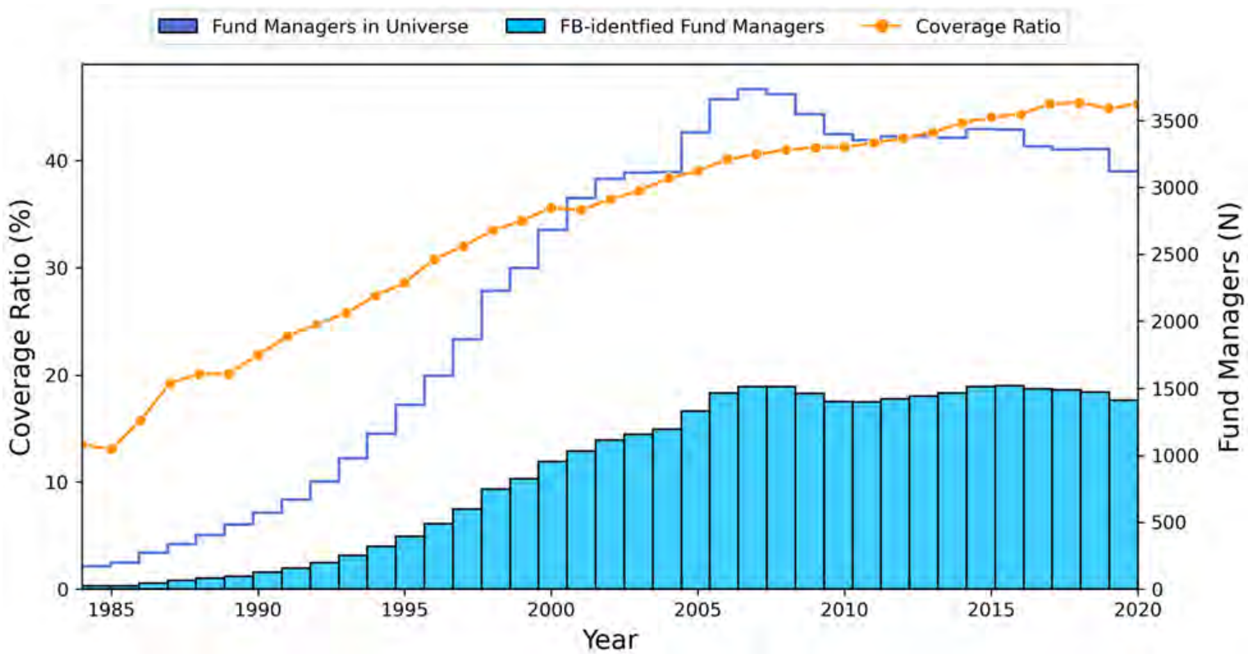

Fig. 2. Coverage of Facebook-identified Fund Managers. This figure illustrates our sample coverage (orange dotted line) of Facebook-identified (FB-identified) fund managers (blue bars, absolute values) relative to all fund managers serving in the U.S-domiciled benchmark universe of actively managed U.S. equity mutual funds (blue line, absolute values) in the period 1984–2020. The sample of Facebook-identified fund managers includes 3,984 of the 10,029 fund managers in the benchmark universe.

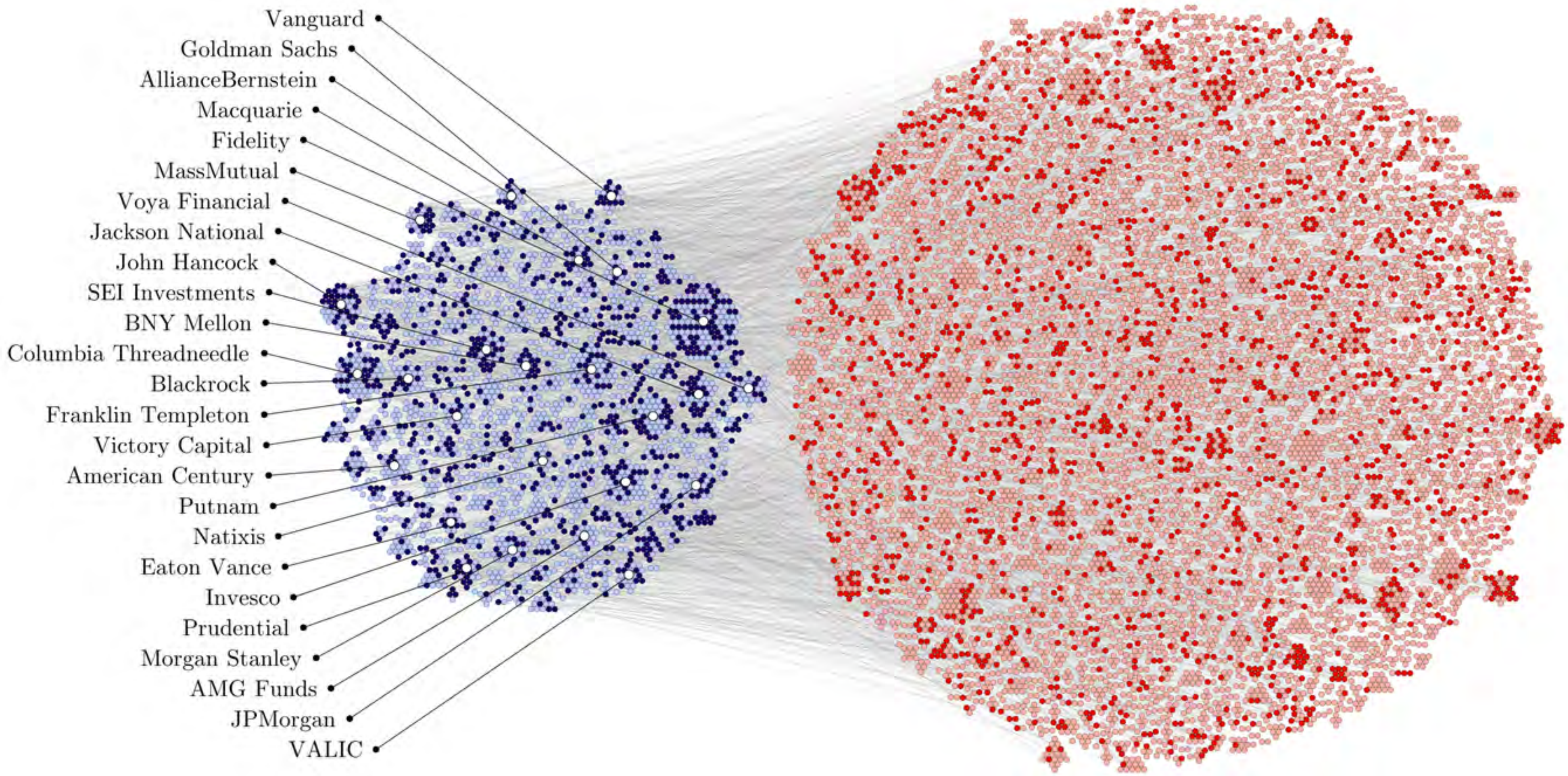

Fig. 3. Graph of Connected Fund Manager–Firm Officer Pairs. This graph illustrates the subsample of fund managers (blue colors) and firm officers (red colors) that form the subset of connected pairs that we classify as tradable. We denote traded fund manager–firm officer pairs within the set of tradable pairs with darker color shades. Each node represents an individual, and two nodes are connected by an edge representing a Facebook friendship between the two individuals. Individuals are clustered based on their current or most recent employer. In case of multiple affiliations to different firms, the individuals are assigned to the firm at which they occupy their most senior role. We call a friendship "tradable" if the fund manager's tenure at the fund overlaps with the firm officer's tenure at the firm, and the firm's stock in the same month is held by at least one fund within the same Morningstar category. We call a friendship "traded" if the fund manager's holdings of the stock overlap with the firm officer's tenure at the firm. Distances between nodes have no economic interpretation. The graph is created using a circle packing algorithm.

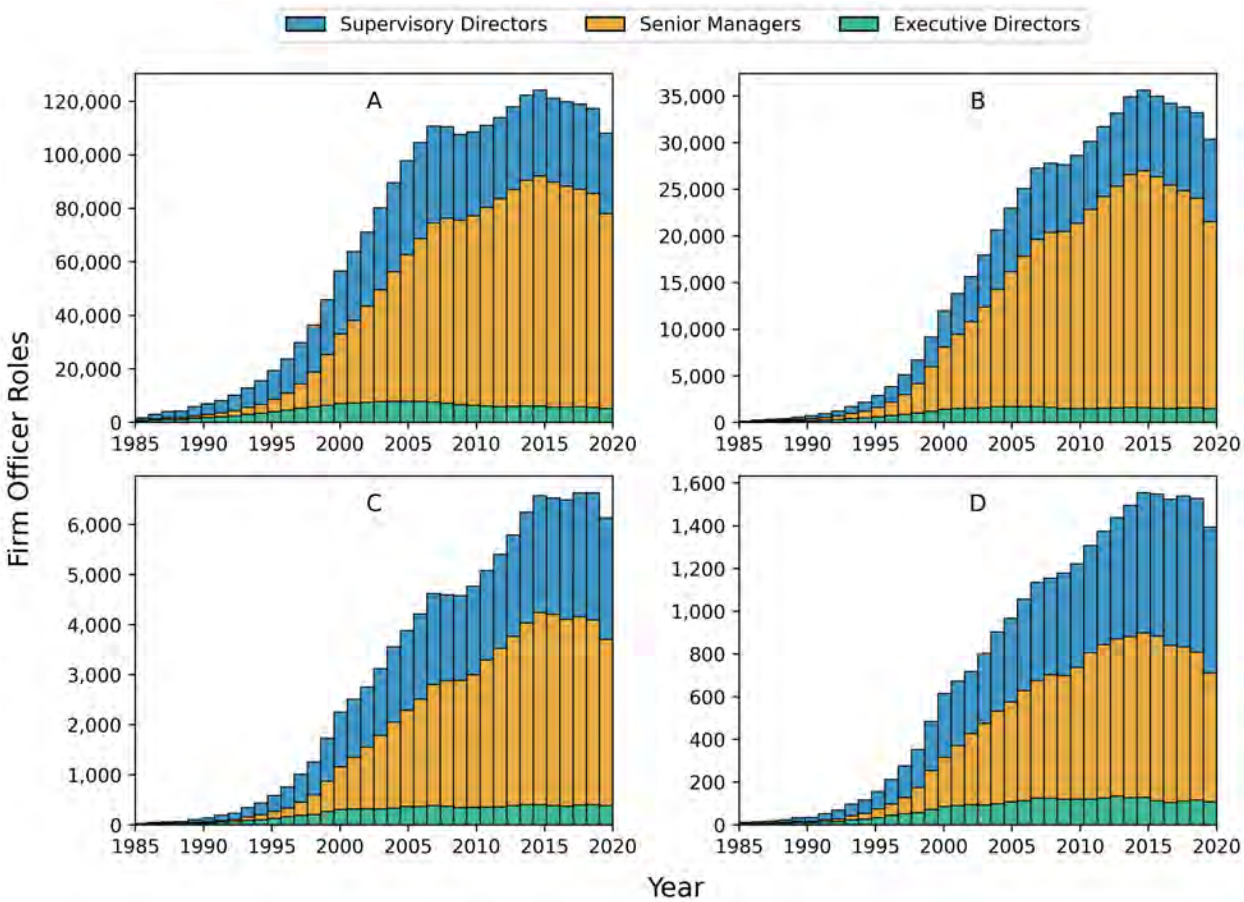

Fig. 4. Distribution of Firm Officer Roles by Seniority. This figure illustrates the distribution roles occupied by the sample of firm officers heading the firms held by Facebook-identified funds, broken down by seniority level. Subplot A details the distribution of roles occupied by all 267,106 firm officers heading the public companies held by the sample of Facebook-identified funds. Subplot B details the distribution of roles occupied by the 67,162 Facebook-identified firm officers in our sample. Subplot C details the distribution of roles occupied by the 9,135 firm officers whose connection to a fund manager is classified as "tradable". Subplot D details the distribution of roles occupied by the 9,135 firm officers whose connection to a fund manager we actually find to be "traded" by the respective fund. BoardEx assigns different seniority levels to different firm officer roles. Employees in management positions below board level are classified as "senior managers." Members of the board of directors who also occupy an executive position at the firm are classified as "executive directors." Members of the board of directors who are not employees of the firm (non-executive directors) are classified as "supervisory directors." We call a friendship "tradable" if the fund manager's tenure at the fund overlaps with the firm officer's tenure at the firm, and the firm's stock in the same month is held by at least one fund within the same Morningstar category. We call a friendship "traded" if the fund manager's holdings of the stock overlap with the firm officer's tenure at the firm.

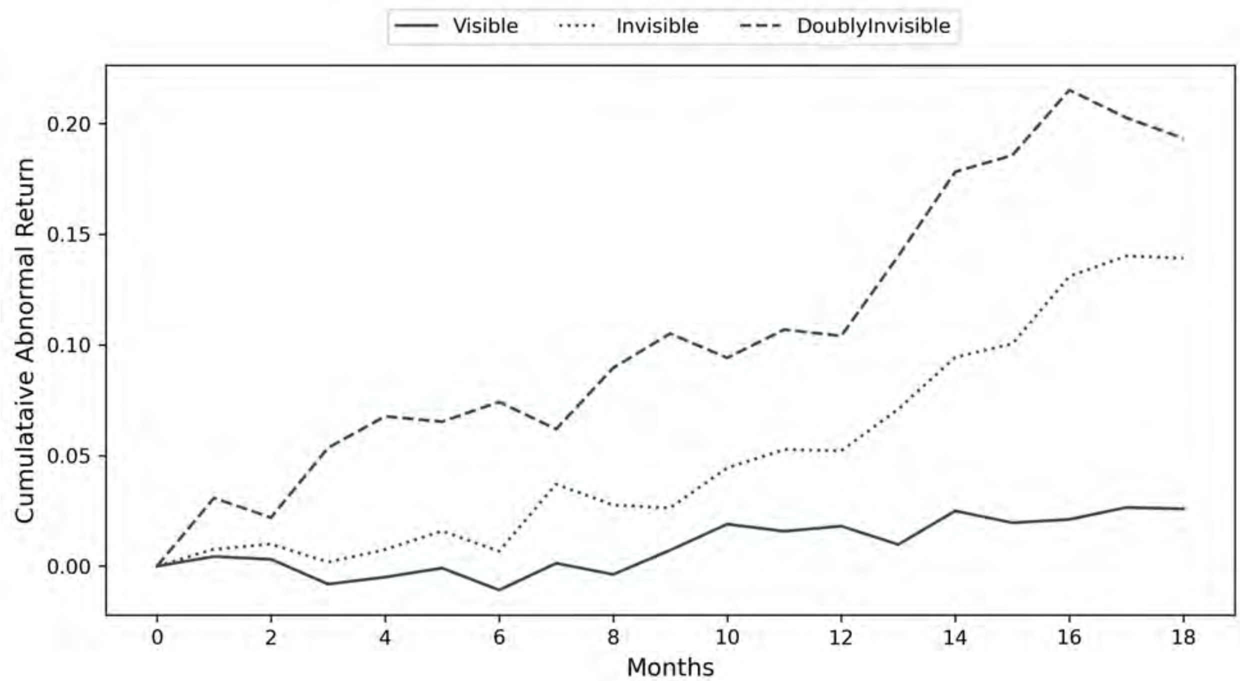

Fig. 5. Cumulative Abnormal Returns on Connected Stocks. This figure presents weighted-average cumulative abnormal returns for the first 18 months following a fund's purchase of a connected stock. We define connected stocks as firms that are headed by one of the fund manager's then-active firm officer Facebook friends. We divide funds' purchases of connected stocks into three groups, depending on the degree of visibility of the particular fund manager–firm officer Facebook friendship. We distinguish three degrees of visibility, depending on whether the friendship is publicly observable through the fund manager's friends list (*Visible*); whether it is not publicly observable through the fund manager's friends list, but observable through the backlink from the firm officer's friends list (*Invisible*); or whether it is not publicly observable through either the fund manager's friends list or through the firm officer's friends list (*DoublyInvisible*). If the stock position is sold and the stock is repurchased at a later point in time, we count this purchase as a new event. Observations are at the fund-month level. Abnormal returns are adjusted for market returns. Values of stock positions are adjusted for inflation.

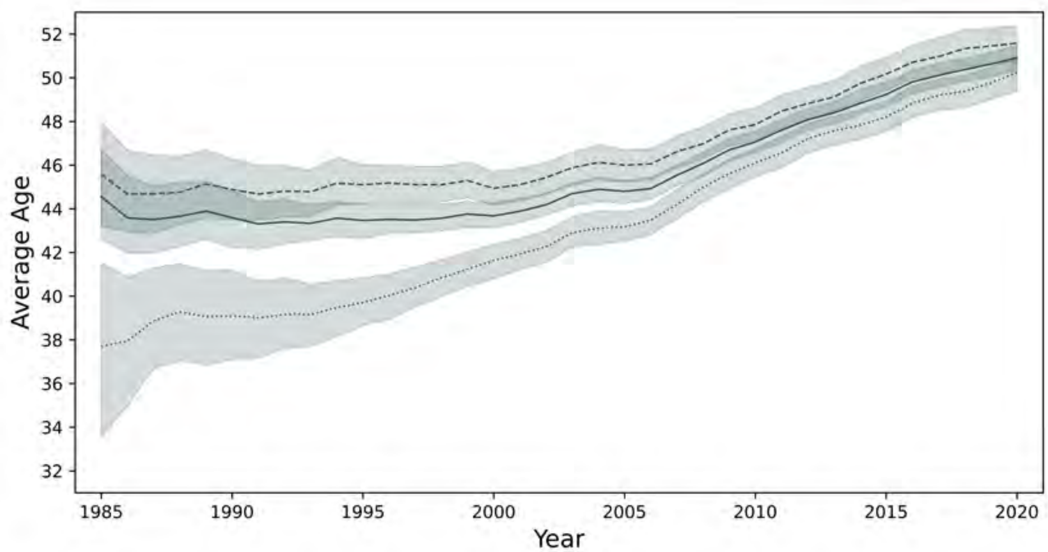

Fig. 6. Age of Facebook-identified and Non-identified Fund Managers. This figure compares the average age of all fund managers (solid line) in the initial sample of domestic actively managed U.S. equity mutual funds covering the period 1984–2020 to both the average age of Facebook-identified fund managers (dotted line) and the average age of non-identified fund managers (dashed line). The shaded area represents the 99% confidence interval. In case data on a fund manager's birth year are not available, we follow Chevalier and Ellison (1999) in using the fund manager's undergraduate degree to proxy for age (assuming that the undergraduate degree was completed at age 21).

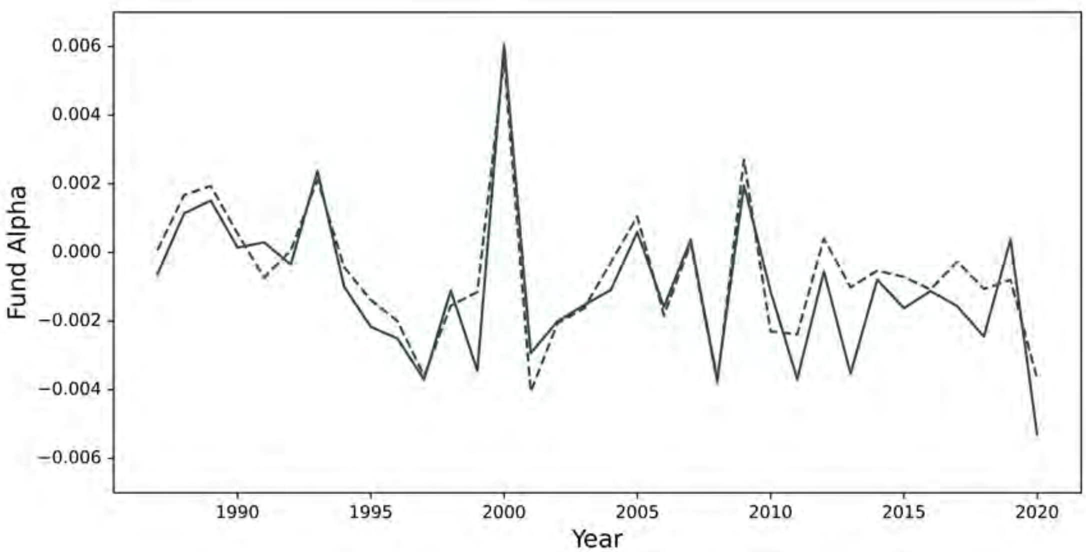

Fig. 7. Performance of Facebook-identified and Non-identified Funds. This figure compares the performance of funds run by Facebook-identified fund managers (dashed line) and the performance of the funds run by non-identified fund managers (solid line) across the sample period 1984–2020. Fund performance is calculated as annualized four-factor alpha using funds' monthly net returns over the past 36 months, and a minimum window of 24 observations. Fund return data are obtained from MS Direct.