Hidden Alpha*

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ABSTRACT

Using the setting of financial agents—in particular, network ties among mutual fund managers and firm officers—we explore the importance of hidden network connections relative to all other network ties. We find that hidden network ties are those associated with the largest and most significant abnormal returns accruing to the fund managers—on average 135 basis points per month (over 16% alpha per year, t-stat = 3.54) across the universe of fund managers and public firms. This is relative to insignificant abnormal returns accruing on average to all of their other trades, including those to trades of 'visible' ties in the fund manager-firm officer network. The hidden network premium does not appear to be driven by a familiarity or characteristic selection story, as fund managers seem to be correctly timing exactly when to hold (and when not to hold) the firms to which they have hidden network ties. Further, the more hidden the network tie is, the more valuable the information that appears to be associated with the trading across it. This hidden network connection premium is not driven by any industry, style, time period, or firm type, remaining strong and significant through the present day. More broadly, the findings highlight the importance of missing or hidden nodes and connections when understanding the true nature of shock propagation in complex network systems.

*We are grateful for helpful comments and suggestions from Andres Almazan, Martin Brown, Jonathan Cohn, Amit Goyal, Tobias Hemauer, Markku Kaustia, Angelo Ranaldo, Clemens Sialm, Laura Starks, Sheridan Titman, and Scott Yonker. We also thank seminar and conference participants University of St. Gallen, Harvard Business School, HEC Lausanne, University of Texas at Austin, Texas A&M University, the 22nd EdukCircle International Convention on Business, and the 2021 New Zealand Finance Meeting. Stephan Heller gratefully acknowledges funding from the Swiss Institute of Banking & Finance Sponsors Association at University of St. Gallen and the SWITCH Foundation Zurich.

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The study of social networks pervades all of economics—both from theoretical and empirical perspectives. Networks form the structural foundation underpinning all groups of individuals, from small assemblies up through complex societies. Consequently, various types of networks among countries and firms and down to the level of individuals have been used to develop a better understanding of patterns and themes observed 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 (edge) among those nodes, then inference can be reliably carried out. Unfortunately, for many real-world networks, this is not the case. Importantly, the presence of nodes and edges that are "hidden" to observers—either intentionally or unintentionally—can have profound impacts on estimations of how information, shocks, or other phenomena are transmitted within the network structure itself.

In this paper, we provide novel evidence on the powerful impact of one such "hidden network" among influential agents in financial markets. In particular, we explore hidden ties between mutual fund managers and firm executives of the publicly traded companies that the funds invest in. To this end, our study makes 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 roughly 70,000 manually identified Facebook profiles of fund managers and firm officers active between 1984 and 2020. Using publicly accessible data on their connections and interactions on the Facebook platform, we classify friendships that are public versus those that hidden by one (or even both) sides of a connected pair.

Facebook connections provide a number of additional advantages relative to past work on connections in financial markets. In particular, the data allow us to not only establish the timing and currentness of a given connection, but also measure its intensity (e.g., "likes" of current content) and the connectivity of other related nodes (e.g., significant others, siblings, or children connected to the same or a closely related node). More centrally, we are also able to uncover hidden nodes and to find rich, substantive information above and beyond what can be observed from the existing, visible nodes in the network. In fact, the hidden nodes are on average the most valuable nodes in the network by some measures. Thus, ignoring them leads to an incomplete and potentially even deceptive view of network structure and impulse 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 well-developed social network on Facebook. Her Facebook friends included Mr. Bergelmir, a fund 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 tie (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 very successful 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% annualized abnormal return. This was over 18% larger than Bergelmir's abnormal returns on all other stocks in her portfolio over the same time period. Moreover, Bergelmir was Facebook friends with a number of other firm officers, and he actively traded their firms' stock over this time period. His average abnormal performance on the entire set of these Facebook friend connections was 185 basis points in monthly alpha (t-stat = 2.68), or over 22% per year. This again was over 14% higher than the performance of all other stocks that Bergelmir 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 friendship links depending on whether or not they are hidden. This example involves a connection between Ms. Calypso—a fund manager of multiple large and active mutual funds over our sample period—and Mr. Deimos, a firm officer serving at a large international retail firm. Unlike the friend connection between Ananke and Bergelmir (observable from both sides of the connections' Facebook profiles and friends lists), we classify the friendship between Calypso and Deimos as "invisible." The reason for this classification is that although they grew up in the same hometown and graduated from high school together, their friendship tie cannot be seen on Calypso's Facebook profile because she opted to "hide" her friends list. However, Deimos did not make that same decision, and all of his connections and so forth can be seen

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

by anyone with knowledge of his Facebook profile. Thus, in spite of the hidden features of Calypso's node, we are able to identify their Facebook friendship, along with the common high school class attendance, pictures taken together over the years, and so forth. In Section I we show that we are also in fact able to identify and unearth what we call "doubly invisible" friendship relations by examining specific profile content.

With regard to performance, we find that Calypso does remarkably well on his trades in Deimos's firm. Calypso has alphas of over 300 basis points per month (t-stat = 1.91) trading in Deimos's firm versus insignificant and even slightly negative alphas in point estimate by -6 basis points per month (t-stat = -0.32) over the same time period trading in all of his other positions. In fact, beyond this, while Calypso does have holdings in Deimos's firm beforehand, he substantially increases his holdings following Deimos's appointment (from 4 to 16 times across the active funds he manages). Moreover, like Ananke, Calypso also broadly outperforms on all firms he trades to that he has a Facebook friendship connection with (although these are all hidden connections from Calypso's side, as described above). Calypso's average alphas trading these hidden Facebook friend connections were over 13% per year (t-stat = 2.20) and more than 10% higher than his average performance trading all other firms over the same period.

We find these patterns to be valid on average across the entire universe of fund managers and firms throughout our sample period. In particular, using data from 1984 to 2000, we find that hidden connections between fund managers and firm officers result in abnormal, risk-adjusted returns of 135 basis points per month on average (t-stat = 3.54). This translates to a four-factor alpha of over 16% per year. Moreover, managers hiding their network connections are not simply better average performers, as shown by the risk-adjusted return on all other holdings to which they do not have a connection being statistically zero (t-stat = -0.16). Further, these returns appear uncorrelated with known return determinants, as the value-weighted long-short raw portfolio return is 148 basis points per month (t-stat = 3.88), which is nearly identical to the value-weighted risk-adjusted alpha of 136 basis points per month (t-stat = 3.57).

Consistent with these hidden networks being unique, important, and information-rich nodal connections within the network structure, we find that the abnormal returns to connections between fund managers and firm officers monotonically increase with the level of this hiddenness. Specifically, perfectly "visible" connections are associated with abnormal returns that are small and statistically indistinguishable from zero (16 basis points per month,

t-stat = 0.88). In contrast, one-sided invisible connections (hidden by the fund manager) are associated with abnormal returns of 56 basis points per month (t-stat = 1.81), while doubly invisible network connections generate an outperformance of over 16% (t-stat = 3.54) in risk-adjusted returns per year.

We also explore the investment behavior of fund managers vis-à-vis their connections—from visible to invisible network links. In particular, we examine the holding and weighting decisions of these managers in firms they trade based on the hiddenness of the connection to the firm. We find that the most hidden connections are again those with the most significant over-weighting by fund managers. In particular, while we see a roughly 65% higher weight in stocks to which a manager has dual-sided visible connections, that overweighting rises to almost a 200% overweighting in doubly invisible network connections and is highly statistically significant. Moreover, the significant portfolio overweighting in doubly network-connected stocks also holds when controlling for time and firm fixed-effects, for example, when looking at two fund managers trading over the same time period and comparing the fund managers that do (vs. do not) have a doubly invisible connection among the current firm officers. In addition, it holds with fund fixed-effects, for example, when looking at a given fund manager's portfolio over a period and solely comparing those firms that are (and are not) connected to that fund manager by a doubly invisible connection.

To explore the mechanism in more depth, we examine the extent to which our results could be driven by either a simple familiarity or a selection mechanism. For instance, fund managers may simply prefer to invest in their friends' ventures, not because of information passed along the connected nodes (hidden or not) but because of a homophily or familiarity bias toward these connected nodes. However, this pure familiarity explanation could not explain the outperformance or why it increases along with the hiddenness of the connection. A more nuanced version that includes selection (e.g., high-types select or are more likely to jointly match) might generate some dispersion in average performance between the observed returns of hidden network connections versus other nonconnected firms (or those with fewer hidden connections). To test this explanation, we examine the sample of firms that are hidden-connected stocks of fund managers but that the fund manager nevertheless chooses not to hold. If the story is one of an unobserved characteristic causing hidden network connections to simply select on better-quality fund-stock pairs, we should see the returns of the following two groups as being identical because they sort on the same hidden-connection characteristic: currently hidden connected stocks the fund manager chooses to invest in versus currently hidden connected stocks the fund manager actively chooses not to hold. In contrast, when we run exactly this test in our sample, we find that the hidden-connection stocks that managers choose to hold significantly outperform those that they choose not hold. In particular, hidden-network-held stocks outperform not-held stocks by 119 basis points per month (t-stat = 2.59) in abnormal returns, or over 14% per year. This finding is consistent with the doubly invisible network of connections being information-rich sources for fund managers, and it is less consistent with a pure familiarity or selection explanation.

To explore the mechanism further, if the hidden networks we identify are truly driving the empirical patterns we see in the abnormal returns generated by the fund managers, varying the strength of the network links should alter the abnormal returns that can be generated from the network link. To test this possibility, we proxy for friendship tie strength using a unique aspect of the Facebook data itself. In particular, participants on Facebook can actively engage with others' content through interactions such as liking, commenting, sharing, or tagging. This feature allows us to sort connections by the extent to which mutual fund managers actively engage with the user content of their firm officer connection. Using this engagement as a proxy for the strength of the network tie, we find that, across all connection types that we are able to measure, stronger ties result in larger returns associated with the given connection.

Lastly, we run a number of additional tests, subsample analyses, and sample specifications to explore the robustness of the return effects and the relationships we find. First, we find that the results do not seem to be concentrated in any given industry, investment style, or sub-period; they are instead large and significant across all of them. In addition, the results are not concentrated solely in small stocks—all of the results we report in the paper are value-weighted returns and within the universe of firms traded by active mutual funds (structurally), which biases even further toward larger and more liquid firms. Next, we also test the relationship in a multivariate regression framework in which we can control for more return determinants–with the relationship remaining large and significant.

More broadly, we find that the abnormal returns accruing to the hidden-network returns continue to accrue for an extended period following the trading.Further, and importantly, we observe no sign of any return reversal in the future for these returns, suggesting that the information associated with these trades is information important for fundamental firm value and is eventually incorporated into it. Lastly, we show that the effects and hidden-network dynamics we find remain strong and significant to the present day.

Our paper contributes to the growing literature concerned with the role of social networks in the transfer of information into securities prices. Most closely related to our work, Cohen, Frazzini, and Malloy (2008) find that mutual fund managers place bigger bets and make more profitable trades on firms that have management personnel with whom they share educational commonalities. Engelberg, Gao, and Parsons (2012) provide evidence that firms that have social connections 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. Results from Cai and Sevilir (2012) suggest that social connections between board directors of target and acquirer firms lead to better merger performance. Engelberg, Gao, and Parsons (2013) find that CEOs with social connections to outsiders bring valuable information into the firm through these connections and receive higher compensation.

Empirically identifying the networks among funds and firms is challenging because direct observations of social interactions among individuals are rare. Instead, existing evidence relies on indirect proxies of social connections, such as geographic proximity (e.g., Coval and Moskowitz (2001)) and common school ties (e.g., Cohen et al. (2008)). Unlike all prior studies, our paper is the first to directly observe whether fund managers and firm officers indeed know and interact with each other. Although prior results are consistent with the hypothesis that information is transmitted socially, our Facebook connection measure provides major advantages. As noted by other authors (e.g., Pool, Stoffman, and Yonker (2015)), prior proxies for social connection are noisy at best and likely fail to capture the true magnitude of the effects of social connectedness. Specifically, they have a high chance to wrongly classify individuals as connected to one another. The richness of the data collected from Facebook allows us to classify connections into different categories based on presumed friendship origin and intensity.

The remainder of the paper proceeds as follows. Section I presents our data collection procedures 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.

[2] Appendix A describes the full set of variables and data sources used in this paper.

A. Collecting Facebook Data

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 an "about" section. The about section 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.

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.

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) in our sample, we retrieve a plurality of users (candidate users) whose profiles hold attributes similar to the target identity's known attributes. In the second step, we determine each candidate user's probability of matching its corresponding target identity by calculating a confidence score based on different similarity

[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, which has strongly limited the capacity of researchers to access user-generated Facebook data.

and proximity measures. In the third step, we rank each target identity's candidate users based on their confidence scores and try to manually match the target identity's true profile from its given set of candidate users. We illustrate these details of the procedure using the following description.

In the first step of the identification procedure, for each target identity in our sample, we populate a list of candidate users that we retrieve from different sources. We start by querying each target identity using Facebook's internal search engine, which takes a name and a set of search parameters as input and returns a list of candidate users 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 collecting of the search parameters' identifiers and the syntax of the query strings in Appendix B. However, since the search engine will only search the subset of users that have added (and publicly shared) a value for the queried attribute, we compensate for the potential scarcity of publicly disclosed information by relying on a range of other sources to retrieve candidate users, most notably the friends lists of successfully matched target entities.

In the second step, for each candidate associated with a target identity, we calculate a confidence score indicating the likelihood of the identity behind the candidate user being equivalent to the target identity. The score is calculated based on a range of measures representing similarities between the candidate user and the target identity. With each measure, we focus on capturing a different aspect of potential similarity. Using semantic measures, we analyze a candidate user's various profile attributes (e.g., screen name, username, education, workplace, location) and compare their values to those held by the target identity. Before the comparison of attributes, we selectively augment the target identity'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 example, owing to the added middle name initial, the candidate user fb.com/teresa.l.white.16 finds a more confident match with the target identity's name "Teresa Lynne Malone (née White)." For several

[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.

measures, we use attributes that are not observed but inferred from information associated with the user. For instance, for candidates with a userID value in the space between zero and $3.5e8$, we infer the educational institution attended by the user from the numeric value of the userID, irrespective of whether or not the education attribute can be observed from the user's profile. For example, when evaluating the similarity of candidate user fb.com/manu.sekhri.9 to the given target identity "Manu K. Sekhri," a 1996 graduate of University of Waterloo (Canada), even though the candidate user's education attribute is not disclosed on his profile, we are able to infer it from the value of the candidate's userID ("122,614,211"), which matches the customized userID 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 user (i.e., friends) and determine the number of friends who share a certain attribute. For example, if a significant percentage of the candidate user's friends have attended a particular college or are residents of a certain city, the candidate user 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 user, we also gather data to evaluate each particular candidate user–target identity pair. For instance, we may determine the number of the candidate user's friends who share a common affiliation attribute with the target identity. For example, if the particular target identity is a Facebook board member, and the candidate user's friends list includes the userID of another Facebook board member (that we have already positively identified), then the corresponding measure will record an increased likelihood for this candidate user to match its target identity. 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 user 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 user with the common name "James Miller" to match the alma mater of its target

[5] A unique numeric userID 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 the finding that userIDs 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, and each college was assigned a customized userID space (e.g., registrants with an email address using the domain name "@uwaterloo.ca" were assigned a userID in the space between 122,600,000 and 122,699,999). We identify the userID clusters of 2,362 colleges in the space ranging from zero to $3.5e8$.

identity, we denominate the probability of the match by the number of Coe College graduates in our sample that go by the name of James Miller. Also, for every target identity 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 identity's candidate users.[6] Lastly, for each candidate user–target identity pair, we aggregate the values produced by the various measures into a single confidence score.

In the third and last step of the identification procedure, we uniquely identify a target identity's true profile from its given set of candidate users. To conserve human resources, from each set of candidate users, we remove all candidate users with a confidence score that does not exceed a predetermined threshold. The remaining candidate users of a given target identity are then ranked based on their confidence scores, and matching is performed starting with the highest-ranking candidate user 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 match because the user's personal information (e.g., photos, biographical data, friends lists, etc.) cannot be accessed, we try to establish the match by forming a bridge between the particular candidate profile and the user profile belonging to an individual from the target identity's immediate environment (e.g., a family member). An example is given in Appendix C.

B. *Disclosure and Visibility of Facebook Friendships*

Following the identification of their user profiles, we proceed to disclose friendship links between the individuals. Note that Facebook is organized as an undirected graph in which mutual consent is required for a friendship link to form. Therefore, a friendship 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. We collect friendship links in three different ways.

First, by visiting each particular profile and collecting all users that populate the user's friends list, if the friends list is publicly accessible.

Second, if the user's friends list is concealed, because the two users on each side of a friendship link can separately control the visibility of their friends lists, we may disclose friendship links through backlinks (i.e., friends lists) from friends' profiles. We enhance the disclosure of friendship links through backlinks by exploiting Facebook's Mutual Friends

[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.

API, which takes two userIDs as input and returns a list of their common friends, if certain conditions are met. Specifically, if a user with hidden friends (target user) is paired with another user with nonhidden friends (pivot user), the API will return the fraction of the two users' mutual friends who also disclose their friends. To facilitate the procedure, we design a recursive iteration that pairs each target user with its pivot users and recursively uses all new friends returned at each particular step as input to another iteration. The recursive iteration proceeds until all friends are paired with the target user and no new friends are returned by the API.

Third, we disclose friendship links between two users who both hide their friends lists by examining their interactions on the platform. Although Facebook users are given the option to limit the visibility of most pieces of content that they share or that is shared on their profiles to specific audiences, users cannot limit the visibility of profile content that Facebook classifies as "public information." This includes the user's current profile picture and the profile's current cover photo. By default, the audience of users able to react to these items is limited to the user's friends.

This unique setting allows us to disclose friendship links between two users that both hide their friends. When disclosing friendships based on reactions received by a user's profile pictures and cover photos, we exclude reactions given to photographs in which third parties are tagged, as the audience of such photos automatically expands to include the friends of the user who is tagged (and may receive reactions from them).

Following the collection of the individuals' friendship links, we distinguish between three degrees of visibility of a fund manager–firm officer 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 of 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*).

C. *Mutual Fund Sample*

The initial sample of funds contains the universe of U.S.-domiciled mutual funds covered by MS Direct. Although most 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 has been shown to be more accurate in reporting the funds' fund managers (see, e.g., Massa, Reuter, and Zitzewitz (2010) and Patel and Sarkissian (2017)). Lastly, 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 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 418,300 fund-month observations covering the period from January 1984 through December 2020. The sample includes 5,119 unique funds and averages 1,399 funds per calendar quarter. This is the sample we use when we construct the weights in our benchmark portfolios.

D. *Fund Manager Sample*

The 5,119 mutual funds passing our initial filters are managed by 10,031 fund managers.[8] Before we can match the fund managers' Facebook profiles by following the matching procedure outlined in Section I.A, we must compile data on their biographical characteristics. To this end, we first determine the version of the fund manager's most complete name (i.e.,

[8] The reported number of fund managers is subject to two adjustments: (1) Morningstar assigns a unique identification number (UIN) to each fund manager. Nonetheless, we identify and merge 245 cases in which two or more UINs refer to the same individual. The majority of duplicate assignments occur in the event 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 Langton C. "Tony" Garvin either as "Langton C. Garvin" or as "Tony Garvin"). (2) We exclude 36 fund managers whom we find to have died before the launch of Facebook in February 2004. Note that we keep individuals who have died after the Facebook launch (169 individuals as of October 2021), because the Facebook profiles of deceased persons may still be active (e.g., because Facebook has not been notified about their passing, or because a memorialized version of the profile remains online).

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-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 the main stage in our data collection—identifying the fund managers' Facebook profiles. In this process, we match the Facebook profiles of 3,981 (or 39.7%) of the 10,031 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 Facebook or have used it 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. From the figure we can see that the share of Facebook-identified fund managers increases throughout the sample period, with the coverage ratio peaking in 2018 where we cover 45% of all fund managers in the U.S-domiciled universe of actively managed U.S. equity funds.

[Insert Figure 2 near here.]

We limit our 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 fund-month observations run by fund managers with identified Facebook profiles reduces the sample of funds to 262,241 fund-period observations. This final sample includes 4,094 of the 5,119 funds in the initial sample.

E. Firm Officer Sample

For the firm officers heading the firms whose stock is held by our sample of 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 the 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 BoardEx 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 261,796 firm officers whom we are potentially interested in.

To enable the matching of the firm officers' Facebook profiles, we combine the firm officers' biographical information from various BoardEx files, including information on their most comprehensive name, educational background, and work history. We again follow the procedure outlined in Section I.A to identify the individuals' Facebook profiles. In total, we match the Facebook profiles of 65,756 of the 261,796 firm officers in our sample.

F. Descriptive Statistics

Table 1 provides details on the Facebook data that we use in this paper. The final sample includes data from the Facebook profiles of 3,981 fund managers and 65,756 firm officers.

[Insert Table 1 near here.]

Panel A provides an overview of the information that the fund managers and firm officers in our sample choose to disclose on their Facebook profiles. For each particular profile attribute, we report the share and the number of individuals from both groups that disclose the attribute. A total of 2,226 (or 56%) of the 3,981 fund managers and 34,187 (or 52%) of the 65,756 firm officers publish their friends lists on their profiles. Approximately nine in ten individuals from each group provide a (non-blank) profile picture (90% and 94%, respectively), and the majority of individuals add at least one additional photograph (66% and 31%, respectively). We observe that 30%–50% of the individuals reveal non-sensitive information (e.g., workplace, schools, resident city, hometown), while 20%–30% of the individuals disclose more sensitive information on their relationship or family members.

Panel B reports statistics on the data that we collect on friends, photos, 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), total number of data items, and number of individual profiles for which we collect the data. Statistics are conditional on nonmissing values. *Friends–Total* is the total number of friends that we disclose per individual profile, irrespective of whether or not a profile's friends list is publicly accessible. In this perspective, we disclose at least one Facebook friend for 3,843 fund managers (97%) and for 65,170 firm officers (99%). We collect a total of 18.0 million friends connected to the fund managers and firm officers, with a median number of 162 and 118 friends per fund manager and firm officer, respectively. The *Friends–Public* figure details the number of friends that we collect from profiles with publicly accessible friends lists (i.e., from the portion of profiles that disclose their friends list attribute, see Panel A). The median number of friends collected from the profiles with public friends lists is 210 for fund managers and 280 for firm officers. *Friends–Hidden* is the number of friends collected for profiles with nonpublic friends lists. We collect nonpublic friends for 1,617 of the 1,755 fund managers who do not disclose their friends lists, and for 30,983 of the 31,552 nondisclosing firm officers. For the fund managers and firm officers with nonpublic friends lists, we reconstitute a median number of 111 and 7 friends, respectively. As outlined in Section I.B, one of the two sources that we rely on to collect nonpublic friends is the locating of a particular user in other users' friends lists (*Friends–Backlinks*). The reason for the relatively low number of hidden friends disclosed for firm officers is the shutdown of the Facebook's Mutual Friends API that we have been exploiting to enhance the disclosure of friends through backlinks.[9] The *Friends–Reactions* figure represents our second source of nonpublic friends—i.e., the collecting of user reactions received by certain content on a user's profile. From this source, we collect a median number of 58 and 91 friends for fund managers and firm officers, respectively.

Panel B further reports statistics on photos (i.e., profile pictures, cover photos, and miscellaneous photos) and collected reactions received by these photos. For instance, from each profile that we observe, we collect all photos uploaded to the profile's photo album(s), a short description of the photo,[10] and all user reactions (i.e., likes, comments, and tags) associated with each particular photo. From the fund managers' and firm officers' profiles, we collect a total number of 2.0 million photographs, with a median number of 6 and 10 photos for fund managers and firm officers, respectively. From these photos, we collect a total of 17.7 million reactions, with a median number of 100 and 107 reactions per fund manager and firm officer, respectively. A majority of 90% of the reactions that we observe are likes, while 9% are comments, and 1% are tags.

The bottom part of Panel B presents statistics on the collected family member profiles pertaining to our sample individuals. We identify the profiles of the individuals' family members during the preliminary data collection process to support the matching of candidate profiles or—if we cannot identify an individual's profile—to rule out the existence of a Facebook membership so that no more comparison needs to be performed for the particular individual.[11] In addition, we may obtain further profiles of family members from the family member section of the profiles that we successfully match to our sample individuals. In total, we collect family member profiles pertaining to 1,382 (or 35%) of the fund managers and to 22,174 (or 34%) of the firm officer.

[Insert Table 2 near here.]

[9] Following the depreciation of Facebook's Graph API's *Mutual Friends* feature in April 2018, the browser-based version of this endpoint was deprecated in August 2021. At this point, we had queried the API for the fund managers' friends but were still in the progress of fetching the firm officers' friends.

[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 might show (e.g., "May be an image of 1 person, child, standing, smiling, outerwear, twilight, sky, beach, ocean, and car.").

[11] By examining the Facebook profiles of their immediate family members (i.e., profiles of spouses, parents, siblings, or children), we rule out the existence of a Facebook membership for 790 nonmatched fund managers with a fair degree of certainty.

In Table 2, we present summary statistics reflecting the average annual composition of our sample of funds, their common stock holdings, and the firms' management personnel. The sample of funds includes the 262,241 fund-month observations managed by Facebook-identified fund managers and covers the period from 1984 to 2020. The benchmark universe of funds used to compute percentage coverages is the fund sample consisting of 418,300 fund-month observations whose construction is detailed in Section I.C (i.e., funds that populate Morningstar's actively managed U.S. equity fund universe). On average, our sample includes 1,117 funds per year, constituting an annual average coverage 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, which constitutes an annual average coverage of 34% of all managers active in the period 1984–2020. The 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 an annual average of 86% of the universe's total market capitalization. On average, these firms are headed by 57,110 firm officers, covering an average of 94% of all firm officers present in the BoardEx universe. From these individuals, our matched sample of Facebook-identified firm officers averages 14,235 individuals per year, or an annual average of 20% of all active firm officers whose firms are held by the sample of funds.

[Insert Table 3 near here.]

Table 3 reports details on the Facebook friendships that we observe between the fund managers and firm officers in our sample. We disclose a total of 14,865 connected fund manager–firm officer pairs involving 2,625 unique fund managers and 8,872 unique firm officers. Of these pairs, we classify a total of 10,306 (or 70%) as visible in the sense of our definition in Section I.B, while 3,585 (or 24%) and 974 (or 6%) are invisible and doubly invisible, respectively. Moreover, we classify 7,301 (or 49%) of the 14,865 connections as "tradable." We define a friendship as (potentially) 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 in the same Morningstar Category. Of the 7,301 connections that we classify as tradable, we find 2,373 (or 33%) to be "traded" by the fund managers. We define a friendship as traded if the fund manager's fund's holding of the firm's stock overlap with the firm officer's tenure at the firm.

Interestingly, while roughly 30% of all visible friendships are traded, the share of traded friendships increases to 36% and even 48% when looking at invisible and doubly invisible friendships, respectively, suggesting that more-concealed connections have a higher tendency to be activated. 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 both fund managers and firm officers. We illustrate the data in Figure 3 using a network graph.

[Insert Figure 3 near here.]

The network graph includes subsample of fund managers (blue) and firm officers (red) that form connected pairs categorized as tradable. Traded pairs within the tradable pairs are denoted with a darker color shade. Each node represents an individual; two nodes are connected by an edge representing a 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 of their most senior role.

Figure 4 shows the breakdown of firm officers by the seniority of their roles over time and compares the full sample of firm officers held (subplot A) with firm officers identified on Facebook (subplot B). It further compares the sample of firm officers connected to fund managers (subplot C) with the sample of traded firm officers (subplot D). Over our sample period, the number of connected and traded firm officers aligns well with the overall number of firm officers. We notice that supervisory directors and executive directors are overrepresented in the sample of traded firm officers in comparison with the full sample of firm officers held.

[Insert Figure 4 near here.]

II. Main Results

A. Portfolio Weights

If fund managers gain an informational advantage through their friendships with firm officers, we would expect them to overweight their friends' securities in their funds' portfolios. To test this possibility, for each fund holding observation, we calculate the portfolio weight 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 of 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 should find that β is positive and statistically significant.

In Table 4, 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. 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. This specification 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 specifications tell a consistent story: Fund managers place larger bets on their friends' securities, and their portfolio allocations are highly dependent on the visibility of the friendships.[12]

B. Performance Tests

Our results thus far show that fund managers invest significantly more in securities that are managed by friends. Next, we address the question of whether fund managers do so because they have a comparative advantage in generating information about their friends' firms. If so, we should expect the returns that fund managers earn on friends' securities to reflect this information; that is, their portfolios of friend securities should outperform their other holdings. In contrast, if their allocations to friends are due to familiarity, for example, we should see nonpositive results. To investigate this, we use a standard calendar time portfolio approach (see, e.g., Coval and Moskowitz (2001)) to examine 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. The sample averages 319 connected funds per month, each holding an average of two connected stocks and 165 nonconnected stocks.

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

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

and

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

[12] In untabulated analyses, we control for industry fixed effects (Fama-French 48) and fund fixed effects (Morningstar Category), both leading to more pronounced results than the specification in column 9.

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 the stocks in the sub-portfolios until the next reporting date, when the portfolios are rebalanced to reflect changes in holdings. Stocks are weighted 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 portfolios in proportion to the amounts held by our sample of mutual 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 our 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.

Table 5 illustrates our main result. We report the average monthly performance for the connected and nonconnected portfolios and the difference between these averages (LS). The table shows that when we allocate stocks into portfolios based on whether the fund manager is friends with a then current firm officer at the firm, the connected portfolio performs significantly better compared with the nonconnected portfolio across all three performance metrics. The connected portfolio exhibits a monthly four-factor alpha of 45 basis points on average, compared with zero basis points for the nonconnected portfolio (column 4 vs. 5). Columns 7 and 8 of the table show that the connected portfolio significantly outperforms its size, book-to-market, and momentum benchmark portfolio by an average of 56 basis points per month, whereas the nonconnected portfolio exhibits no outperformance. Performance numbers on the connected portfolio suggest that fund managers possess information about their friends' firms. At the same time, our evidence on the nonconnected portfolio indicates that our sample of Facebook-identified fund managers does not generally outperform.

[Insert Table 5 near here.]

Most importantly, when we form connected portfolios sorted by the visibility of the fund manager–firm officer connection, we find that outperformance increases with the friendship's hiddenness across all performance measures. An investment strategy that buys connected holdings of doubly invisible friendships and sells nonconnected holdings delivers a monthly four-factor alpha of 136 basis points on average (significant at the 1% level). The same long-short strategy involving invisible friendships exhibits an alpha of 56 basis points (significant at the 10% level), whereas trading involving visible friendships provides a positive but insignificant alpha of 17 basis points. Results are similar in magnitude when we look at DGTW-adjusted returns.

We explore the evolution of the connected portfolios sorted by friendship visibility using event time returns in Figure 5. 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 5, abnormal returns increase with the level of friendship hiddenness. As seen in Figure 5, over the course of 18 months, the portfolio of stocks involving doubly invisible friendships does not fall below the invisible friendship portfolio, which in turn does not fall below the visible friendship portfolio. The figure also 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 next investigate whether the strength of the fund manager–firm officer friendship tie 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 higher 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 rather casual friends or acquaintances. From there on, 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 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.

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). Taking a crude first look at the data, when we decompose the 7,301 fund manager–firm officer connections that we classify as tradable (see Table 3) into 2,373 traded and 4,928 nontraded pairs, we note that 29% of all traded pairs have mutually reacted to the other's profile content at least once, compared to 21% of nontraded pairs.[14] An example of the data on interactions is shown in Appendix E.

[Insert Table 6 near here.]

In Table 6, 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 reacted to 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 6 indicate a strong 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 interaction on Facebook, we form an investment

[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 communication means (e.g., Haythornthwaite (2005)), further evidenced by findings that Facebook interactions serve as an accurate proxy for real world friendship tie strength (Jones, Settle, Bond, Fariss, Marlow, and Fowler (2013)).

[14]For the 1,901 fund managers and 5,022 firm officers that form the 7,301 tradable connections we collect a total of 3,355,916 reactions given to 254,305 uploaded by these particular individuals. 18,528 of the observed reactions have been exchanged between the particular fund manager–firm officers pairs.

strategy that buys reaction holdings and sells no reaction holdings. 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 basis points and 64 basis points, respectively, implying that trading-reaction fund manager–firm officer friendships yields a significant outperformance over trading-no reaction friendships (columns 6 and 9). While we do not document a statistically significant on-top performance effect of reactions for visible friendships, we do so for invisible friendships.[15]

Our data offer a further opportunity to explore which fund manager–firm officer connections are important. In particular, we consider the question whether the performance of fund managers' connected stocks is related to the firm officers' seniority. For this empirical exercise, we use BoardEx's categorization of firm officer role seniority, that is, the subdivision of roles into senior managers, executive directors, and supervisory directors (for descriptions of roles see Section I.E). 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*); whether the connected firm officer is a senior manager (*SM*); whether the connected firm officer is an executive director (*ED*); or whether the connected firm officer is a supervisory director (*SD*).

[Insert Table 7 near here.]

Results in Table 7 suggest that fund managers possess more information about firms when they are friends with the firms' executive directors and supervisory directors, as opposed to the firms' senior managers. Trading fund managers' executive director and supervisory director friendships yield an average monthly four-factor alpha of 80 and 102 basis points, respectively (significant at the 5% and 1% levels). Our findings also indicate that executive directors and supervisory directors are either more likely to share return-relevant information with their fund manager friends or that they possess more return-relevant information about their firm, compared with senior managers.

[15] Note that all doubly invisible friendships in our sample are stemming from reactions, as we identify those friendships through mutual interaction on Facebook.

C. Connected Not Held Portfolios

Since we are interested in testing the hypothesis that fund managers have an informational advantage in securities within their network of firm executives, and since mutual funds are generally restricted from short selling, the funds' active portfolio allocations may not reflect their 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 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. Connected not held stocks are defined as stocks that are not held by the fund and that are managed 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 the stocks in the portfolio until the next reporting date, when portfolios are rebalanced to reflect changes in holdings. Within a given portfolio, we weight the stock returns of the not held stocks by the stock's respective market capitalization, and we 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 2.97 stocks pertaining to 2.25 connected firm officer friends.

[Insert Table 8 near here.]

Table 8 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 fund managers tends to outperform the portfolio of connected stocks that managers choose not to hold. For invisible and doubly invisible friendships, this outperformance amounts to a statistically significant monthly four-factor alpha of 57 basis points and 119 basis points, respectively, with DGTW-adjusted returns being of a similar magnitude. These results suggest that 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, the results in Table 8 provide strong evidence against potential endogeneity concerns.

D. Returns Around Corporate News

Having explored fund managers' earn substantial returns on connected stocks, we now turn to exploring 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 the 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 firm rather than 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 items in which RavenPack considers the related firm to be playing a key role in the underlying news report (i.e., news items with an "event relevance" score of 100). In addition, to remove duplicated news reports, we isolate the first news item in chains of news 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.[16] Because the RavenPack data begin in 2000, this analysis runs from January 2000 to December 2020.

[Insert Table 9 near here.]

Table 9 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 four-factor alpha of 6 basis points (significant at the 1% level). By contrast, the connected held portfolio's returns 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.

[16] 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

In addition to the sorted-portfolio approach in Section II, we use multivariate cross-sectional Fama-MacBeth regressions (Fama and MacBeth (1973)) to evaluate the performance impact of social connections between fund managers and firm officers. 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 10 near here.]

Coefficient estimates for the average risk premia are presented in Table 10. Consistent with the results in Table 5, stocks that are more heavily held by fund managers who are friends with a firm officer at the respective firm exhibit a significant and positive outperformance. In column 1, the coefficient estimate of $DiffWeight_{k,t}$ is 0.0181, implying that a standard deviation increase in the weight difference predicts an increase in monthly stock returns by 181 basis points. Results in columns 2 to 4 also corroborate our findings in Table 5 regarding the visibility of fund manager–firm officer friendships. 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. Addressing Potential Selection Bias Concerns

By selecting only fund managers who end up having a Facebook account, we are introducing several aspects of selection. In the post-2010 period—that is, once there was widespread adoption of Facebook by the demographic of our average mutual fund managers in the sample—we are only selecting fund managers who choose to have a Facebook account. It could be that the choice not to join Facebook is deliberate; the manager may have the knowledge, scope, and ability to have an account, but deliberately chooses not to. Or, it could be that some fund managers (even post-2010 and up to the present) do not have the knowledge, ability, or need to use Facebook in any part of their lives, including managing their portfolios. Thus, this second group could be composed of both fund managers who are less technically sophisticated and those who are very sophisticated but who have different (maybe better) ways of connecting to others (e.g., more private social networks) or have different technologies for generating abnormal returns (e.g., "quantitative" fund managers). Consequently, we may be selecting on fund manager age, sophistication, and funds' overall strategy (quantitative vs. fundamental). For years prior to 2010—that is, before Facebook's widespread use and before it was launched in 2004—fund managers whose Facebook profiles we are able to identify must have been comparatively young at their time of active management.

Similarly, there is also a selection of the firm officers who have information available on Facebook whom we can classify as connected by our measure, as opposed to those who do not have a Facebook presence. Not having a Facebook presence could be for strategic reasons (e.g., a firm officer does not want to have any information on the firm or his connections even inadvertently leaked through Facebook). Such choice could also be a similar proxy for sophistication versus lack of sophistication with the technology, or the opposite as above (e.g., high-profile CEOs are part of a more exclusive network tool or have better technologies for connecting with people they find it optimal to stay connected to).

Do the fund managers we identify on Facebook, especially the ones who were managing in the beginning of our sample period, differ from the ones without Facebook? 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. This also raises reverse-causality concerns. These fund managers may have a large and high-profile network because they were successful, not that the network helped them to be successful. This is true for every time period (even today), but it might be expected to have the largest impact in the earlier years (as the more sparser Facebook portfolio might be more dominated by these selected fund managers).

[Insert Figure 6 near here.]

Figure 6 illustrates the average age of Facebook-identified and non-identified fund managers across our sample period. We find that in the earlier years of our sample, Facebook-identified fund managers are significantly younger on average (up to eight years). However, this age gap converges to become statistically indistinguishable from zero in later sample periods.

[Insert Figure 7 near here.]

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

IV. Conclusion

To explore hidden networks, we construct a sample of over 70,000 fund managers and firm officers using the world's largest social media network, Facebook. Utilizing unique aspects of Facebook's network, 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 the network tie is, the more valuable the information that appears to be associated with the trading across it. Moreover, this hidden-network connection premium is not driven by any industry, style, time period, or firm type, and it remains strong and significant through the present day. The hidden-network premium does not appear to be driven by a familiarity or characteristic selection story underlying hidden-network ties, as fund managers seem to be correctly timing when to hold (and when not to hold) stocks of the firms to which they have hidden-network ties.

Stepping back from our setting, the cost of establishing and maintaining connections across network structures continues to decrease. As it does, 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 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, from the understanding of shock propagation economy-wide, to optimal targeting for advertising and promotion and the adoption of pro-social views and behaviors, and to optimal vaccine roll-out to control disease spread.

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/ Connected Held	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/Nonconnected Held portfolio.	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 friend connection; otherwise, it is added to the Nonconnected/Nonconnected Held portfolio.	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

Continued on next page.

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; otherwise, it is added to the Nonconnected portfolio.	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

Continued on next page.

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 Regression Variables		
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	Percentage that fund i invests in period t in stock k's DGTW bucket.	MS, CRSP, CS
$\text{pME}_{i,k,t}$	Market value of equity of stock k, held by fund i, in time t.	CRSP, CS
$\text{pBM}_{i,k,t}$	Book value of stock k relative to market value of stock k, held by fund i, in time t.	CRSP, CS
$\text{R12}_{i,k,t}$	Stock k's return from the end of month $t-12$ to the end of month t.	CRSP
Panel C: Fama-Macbeth Regressions		
$\text{ExcessRet}_{k,t}$	Stock k's excess return in period t. $\text{ExcessRet}_{k,t}$ 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
$\text{DiffWeight}_{k,t}$	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
$\text{ME}_{k,t}$	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
$\mathrm{BM}_{k,t}$	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
$\mathrm{MOM}_{k,t}$	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
$\mathrm{STR}_{k,t}$	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
$\mathrm{IMOM}_{k,t}$	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
$\mathrm{SUE}_{k,t}$	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 an alternative approach to conduct searches based on Facebook's internal search engine. First, note that on Facebook an organization can create a "Facebook page" to engage with their audience. This in turn enables individuals to signal their association with this organization on their profiles (e.g., attendance of a college). If the user shares this detail with a public audience, 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 the string to Facebook's URL, one can automatically assign desired parameters to the search engine's filters and pass these to the server. The procedure enables us to execute a large number of Facebook searches. For illustration, suppose that we wanted to search for "James Smith," educated at Harvard University (fb.com/Harvard, PageID 105930651606), and working at Citigroup (fb.com/citi, PageID 152431441489088). The PageIDs must be embedded into a JSON string, which can be composed of up to three nested name-argument pairs corresponding to the engine's search filters (city, education, and work). Here, 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==
```


The 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.[17]

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

[17] Note that the name needs to 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 necessary to establish a direct match between a profile and the user's real world identity. However, it may be possible to establish the match 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)

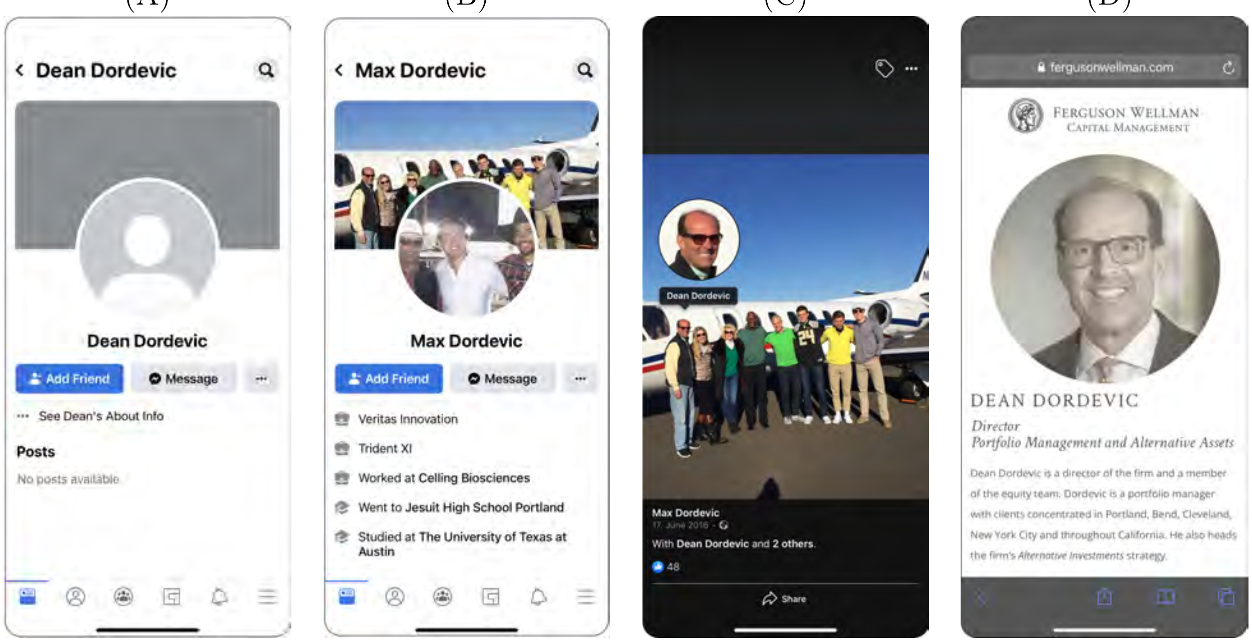

Fig. C.I. Matching Profiles with Restrictive Privacy Settings
This figure presents the restricted profile of one of our sample individuals (subfigure A); the profile of the sample individual's son (subfigure B); a photo of the sample individual on the son's profile (subfigure C); and a portrait of the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

Appendix D. Frequency of Fund Holdings

For future reference, we compare the frequency of fund holdings from MS Direct (the construction of the MS Direct sample is detailed in Section I.C) to 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. In this procedure, we closely follow the data appendix provided by Doshi, Elkamhi, and Simutin (2015). We drop funds that are not covered by the linking table. We include defunct and active fund share classes and limit the sample to domestic and actively managed U.S. equity funds. As mentioned in Section I.C, MS Direct is known to more accurately capture the funds' manager details, which is why studies that use the TR Holdings–CRSP MF merge as their source of holdings data still turn to MS Direct to obtain information on fund managers. Therefore, we establish a match between CRSP MF and MS Direct by following the data appendix provided by Pástor, Stambaugh, and Taylor (2015). We use both the CUSIP and Ticker of each fund share class to create a one-to-one concordance between the fund share class identifiers of CRSP (fundno) and MS Direct (secid). Figure D.I compares the average time span between two consecutive holding observations in months and the number of available funds in the period 1983–2017.

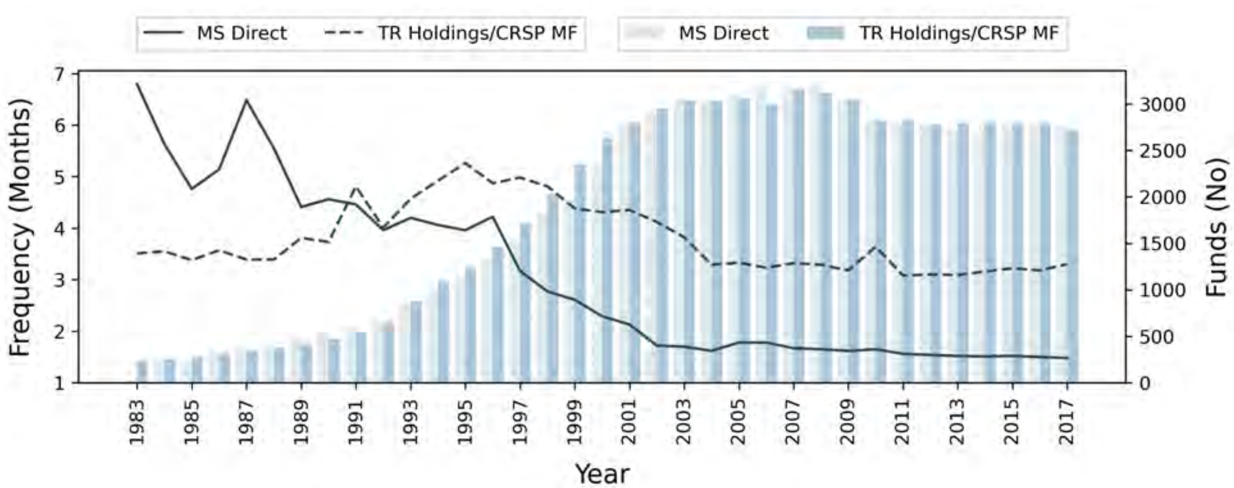

Fig. D.I. Comparison of Holdings from MS Direct and TR Holdings/CRSP MF
This figure compares the average time span between two consecutive fund holding observations in months (lines) and the number of funds (bars) for fund holdings of U.S.-domiciled mutual funds obtained from MS Direct and through the TR Holdings/CRSP MF merge.

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 between a Fund Manager and his Firm Officer Friends
This figure shows a screenshot of interactions from our database between a fund manager and the fund manager's firm officer friends on Facebook. The data includes reactions that firm officers have given to the fund manager's profile content (i.e., photos) and reactions that the fund manager has given to the firm officers' profile content, in the period between December 2016 and December 2021. Data columns 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 1. Summary Statistics: Facebook Data

This table provides details on the Facebook data that we collect for this paper. The sample includes the Facebook profiles of 3,981 fund managers and 65,756 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–Total* is the number of friends that we disclose per profile, irrespective of whether or not the profile's friends list was publicly accessible. *Friends–Public* is the number of friends collected for profiles with publicly accessible friends lists. *Friends–Hidden* is the number of friends collected for profiles with nonpublic friends lists. We collect nonpublic friends by locating users in other users' friends lists *(Friends–Backlinks)* and by examining reactions given to certain profile content *(Friends–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 = 3,981)		Firm Officers (N Profiles = 65,756)	
	% Share	N Profiles	% Share	N Profiles
Panel A: Disclosed Attributes				
Friends List	.56	2,226	.52	34,187
Profile Picture	.90	3,602	.94	61,982
Other Photos	.66	2,612	.31	20,429
Work	.32	1,287	.36	33,296
College	.45	1,797	.49	32,421
High School	.39	1,560	.43	28,596
Current City	.53	2,114	.53	35,012
Home Town	.43	1,703	.47	30,980
Other Places Lived	.11	440	.11	7,489
Relationship Status	.20	802	.23	15,358
Family Members	.23	891	.29	17,282
Life Events	.25	988	.31	24,840

Continued on next page.

Table 1. – continued from previous page.

	Fund Managers (N Profiles = 3,981)					Firm Officers (N Profiles = 65,756)				
	Mean	Median	STD	N Items	N Profiles	Mean	Median	STD	N Items	N Profiles
Panel B: Collected Data [a)]										
Friends										
Friends–Total	248	162	349	954,753	3,843	262	118	452	17,090,940	65,170
Friends–Public	302	210	409	671,456	2,226	433	280	515	14,808,649	34,187
Friends–Hidden	168	111	201	271,973	1,617	68	7	239	2,093,611	30,983
Friends–Backlinks	116	74	147	181,822	1,563	9	4	17	262,933	30,480
Friends–Reactions	96	58	124	125,876	1,306	184	91	386	1,854,089	10,077
Photos & Reactions										
Photos	44	6	154	137,880	3,162	78	10	221	1,862,521	23,794
Reactions	513	100	1,781	1,528,291	2,982	776	107	2,677	16,163,731	20,833
Likes	459	92	1,563	1,348,855	2,940	699	101	2,375	14,500,596	20,744
Comments	66	13	254	149,959	2,265	147	32	483	1,439,696	9,770
Tags	31	5	114	29,477	957	36	7	139	223,439	6,139
Family Members										
Family Profiles	2.09	1	1.77	3,389	1,382	2.49	2	2.47	55,281	22,174
Spouses	1.00	1	0.05	859	679	1.00	1	0.03	8,736	8,729
Children	1.57	1	0.78	821	358	1.47	1	0.74	8,599	5,860
Parents	1.13	1	0.32	187	142	1.08	1	0.28	1,910	1,763
Other	1.87	1	1.57	1,206	640	2.14	1	2.07	29,414	13,713

[a)] Note that while Panel A reports statistics on data disclosed by the sample individuals on their Facebook profiles, the statistics in Panel B provide information on Facebook data that—even though it is associated with the individuals' profiles—must not necessarily have been obtained from these profiles (e.g., while from Panel A we can see that 891 fund managers disclose at least one family member profile, Panel B indicates that the data includes family member profiles pertaining to 1,382 fund managers, as we also collect these profiles manually during the data collection process).

Table 2. 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 262,241 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 418,300 fund-month observations whose construction is detailed in Section I.C. 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	1,117	1,484	24	1,986	753
% 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	1,114	23	1,519	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	57,110	61,750	1,178	109,791	42,561
% of firm officers in BoardEx sample	.94	.99	.57	1.	.10
Facebook-identified firm officers per year	14,235	13,485	88	30,975	11,973
% of firm officers held by funds	.20	.22	.07	.28	.07

Table 3. 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, the number of tradable fund manager–firm officer friendships, and the number of traded fund manager–firm officer friendships, broken down by friendship visibility. We define a friendship as (potentially) 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 in the same Morningstar Category. We define a friendship as traded if the fund manager's fund's holding of the firm's 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 of 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
All Friendships	14,865	2,625	8,872
Visible	10,306	1,637	6,925
Invisible	3,585	928	2,611
DoublyInvisible	974	474	834
Tradable Friendships	7,301	1,901	5,022
Visible	5,115	1,191	3,842
Invisible	1,729	657	1,417
DoublyInvisible	457	289	417
Traded Friendships	2,373	920	1,765
Visible	1,533	578	1,261
Invisible	621	298	506
DoublyInvisible	219	121	174

Table 4. 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 sample period is 1984–2020, and the units of observation are fund-stock-period. 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 of interest measure the degree of visibility of the fund manager's friendship with the firm officer(s) of a 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 of 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. 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 5. 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 of 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 connected and nonconnected portfolios. We define connected stocks as firms that are managed 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. 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 6. Portfolio Sorts: Monthly Returns on Connected Stocks by Visibility and Reactions

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 react to the other's content on Facebook (i.e., like, comment, or tags on the other's content). The nonreaction portfolio consists of the fund's connected stocks where no such reactions take place between the particular individuals. We denote the visibility of a friendship 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 of 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*). To construct the connected held portfolios for this analysis, we use the portfolio construction approach detailed in Table 5. 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*	1.10***	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 7. 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.E). 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*); whether the connected firm officer is a senior manager (*SM*); whether the connected firm officer is an executive director (*ED*); or whether the connected firm officer is 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 5. 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 8. 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. 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 of 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 connected held (CH) and connected not held (CNH) portfolios. Connected not held stocks are defined as stocks that are not held by the fund and that are managed 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 the stocks in the portfolio until the next reporting date, when portfolios are rebalanced to reflect changes in holdings. Within a given portfolio, we weight the stock returns of the not held stocks by the stock's respective market capitalization, and we compute value-weighted returns by averaging across funds, weighting each fund portfolio return by the fund's total net assets value. We report raw returns (Raw), four-factor alphas (Alpha), and DGTW-adjusted returns (DGTW) 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 9. 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 5 and 8, 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 the 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. 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 10. 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 each visibility type as defined in Table 5. 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.

	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

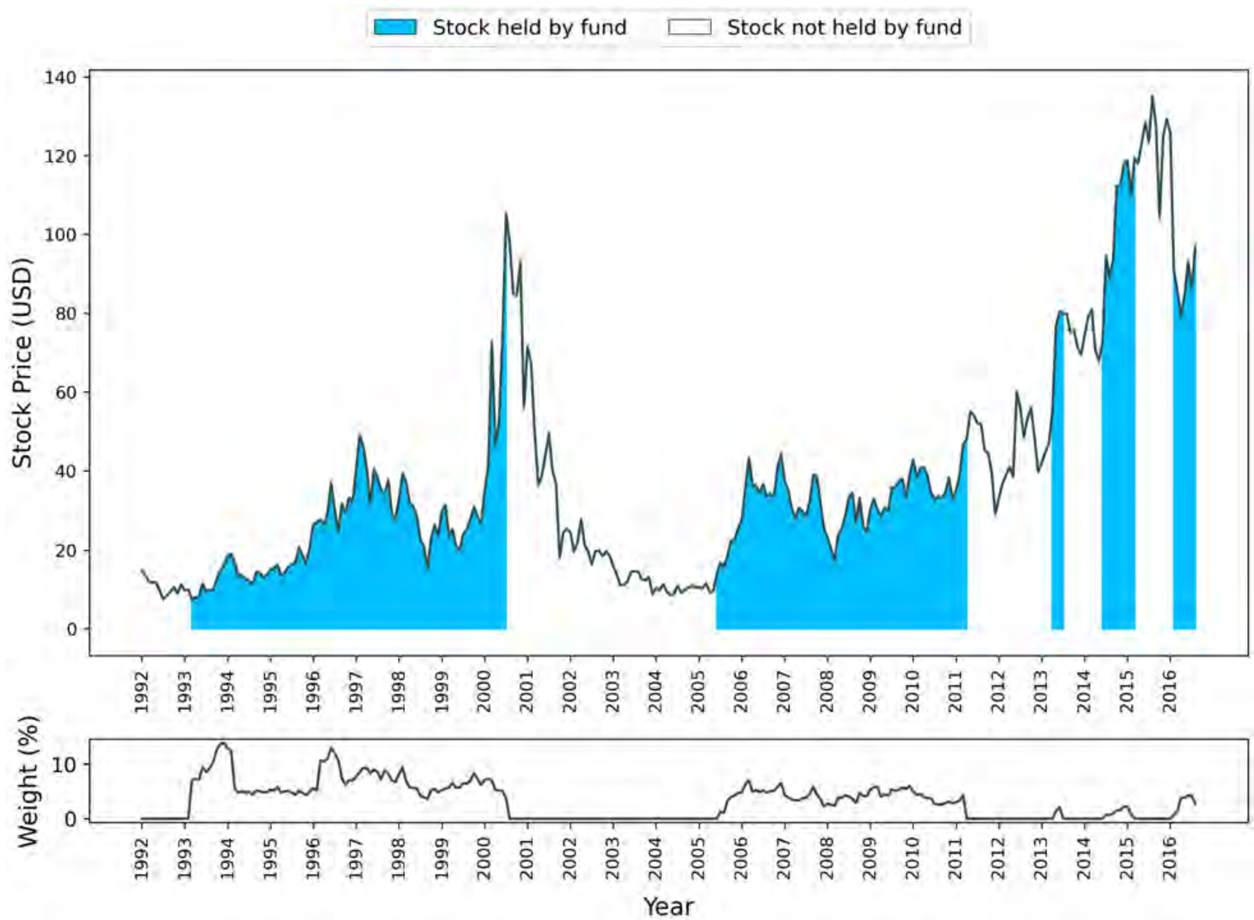

Fig. 1. Fund Manager Bergelmir's Holdings in Ananke's Firm
The upper chart plots the evolution of the stock price of CEO Ananke's stock in the period 1992–2016. The blue shaded area indicates the time period during which Ananke's stock was held by Bergelmir's fund. The white shaded area indicates the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

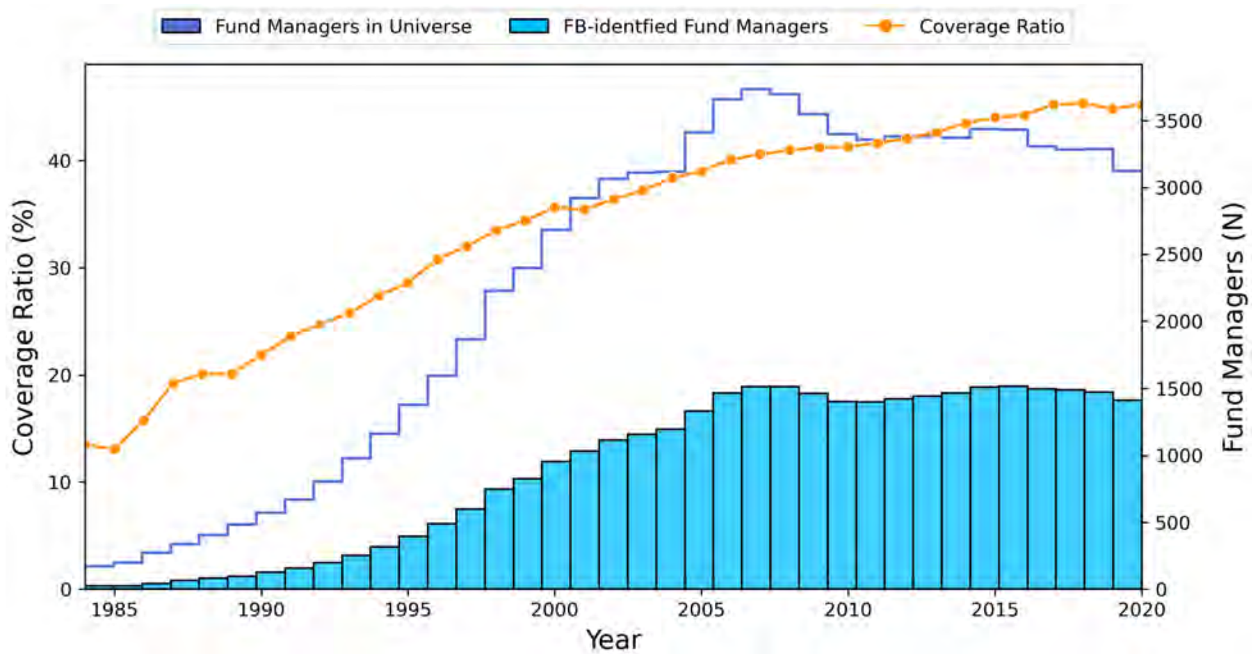

Fig. 2. Coverage of Facebook-identified Fund Managers
This figure illustrates our sample coverage (orange dotted line) of Facebook (FB)-identified fund managers (blue bars, absolute values) relative to all fund managers serving in the U.S-domiciled benchmark universe of actively managed U.S. equity funds (blue line, absolute values) in the period period 1984–2020. The sample of FB-identified fund managers includes 3,981 of the 10,031 fund managers in the benchmark universe.

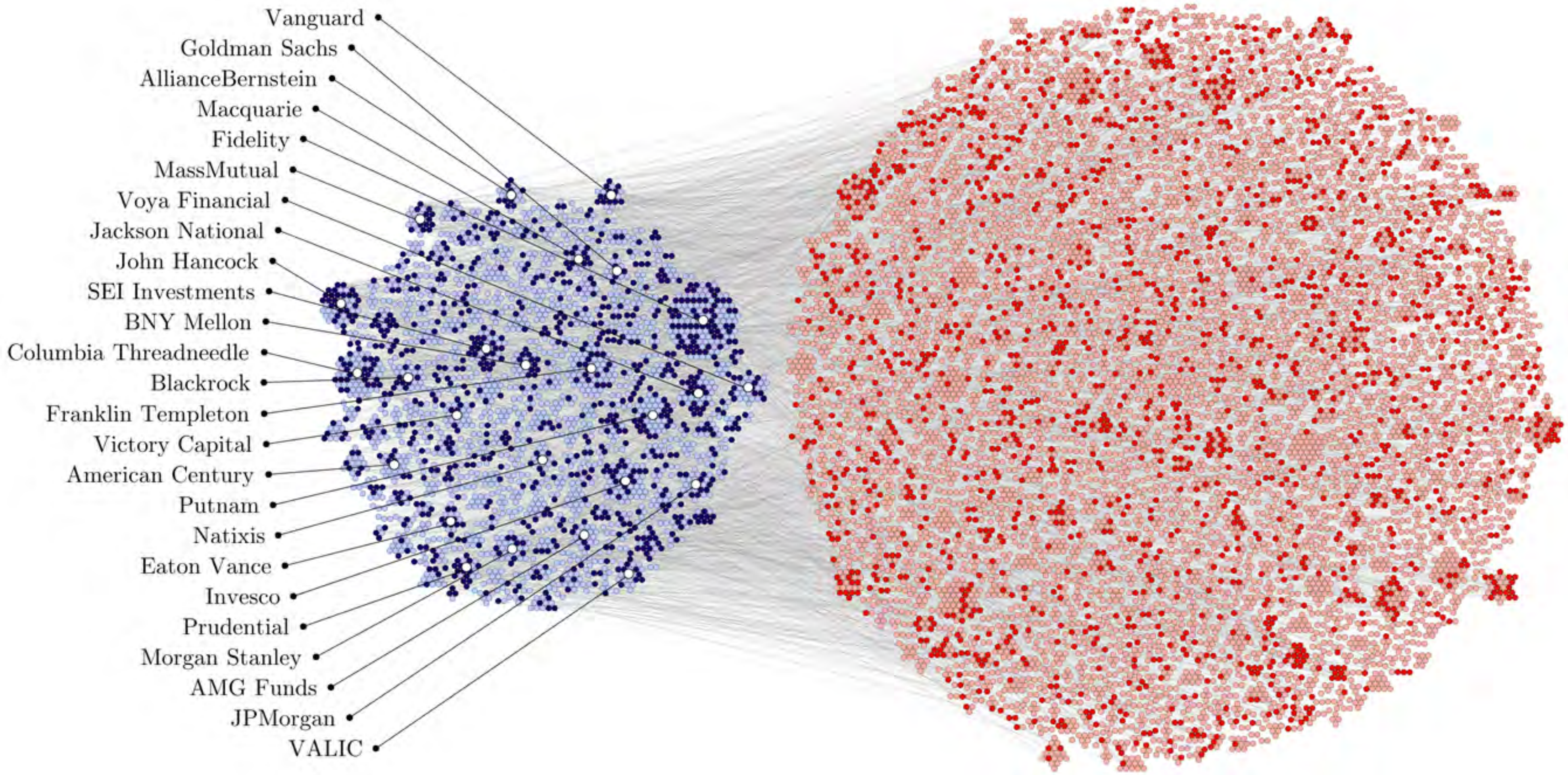

Fig. 3. Graph of Connected Fund Manager–Firm Officer Pairs

This graph includes subsample of fund managers (blue) and firm officers (red) that form connected pairs categorized as tradable. Traded pairs within the tradable pairs are denoted with a darker color shade. Each node represents an individual; two nodes are connected by an edge representing a 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 of their most senior role. We define a friendship as (potentially) 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 in the same Morningstar Category. We define a friendship as traded if the fund manager's fund's holding of the firm's 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.

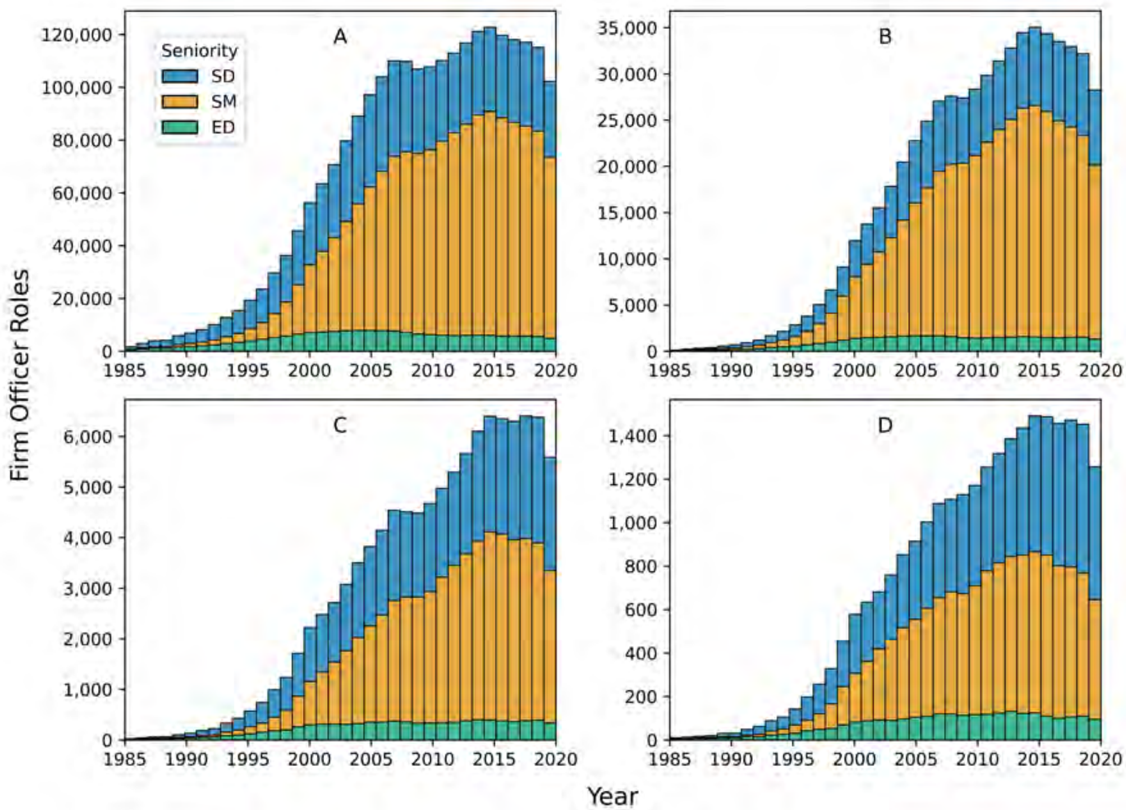

Fig. 4. Distribution of Firm Officer Roles by Seniority
This figure provides an overview of the distribution of the seniority levels of roles occupied by the firm officers heading the firms held by our sample of funds (i.e., funds run by Facebook-identified fund managers). BoardEx assigns different seniority levels to the 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.". Subplot A shows the distribution of seniority levels held by all 261,796 firm officers heading the firms held by the sample of funds. Subplot B shows the distribution of seniority levels held by the 65,756 Facebook-identified firm officers in our sample. Subplot C shows the distribution of seniority levels held by the 8,872 firm officers that are connected to a fund manager on Facebook. Subplot D shows the distribution of seniority levels held by the 1,765 firm officers that are connected to a fund manager on Facebook, and the fund manager is trading the stock during the firm officer's tenure at the firm.

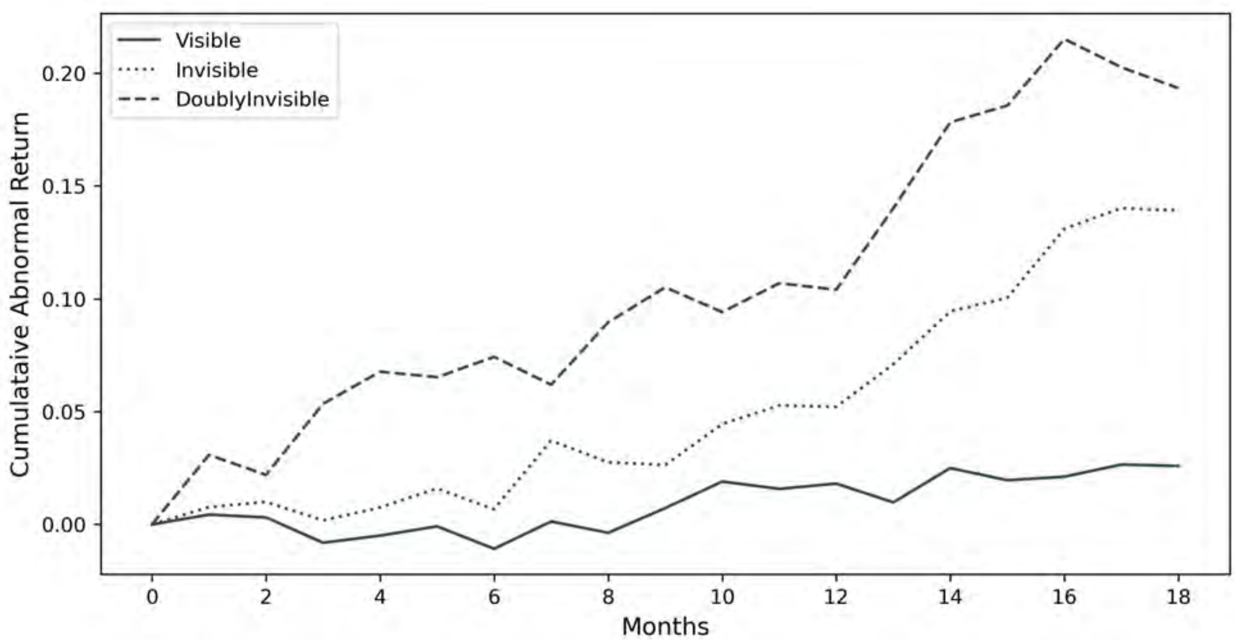

Fig. 5. Cumulative Abnormal Returns on Connected Stocks
This figure presents weighted-average cumulative abnormal returns for the first 18 months following a fund's purchase of a connected stock. We define connected stocks as firms that are managed by one of the fund manager's then-active firm officer 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 of 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.

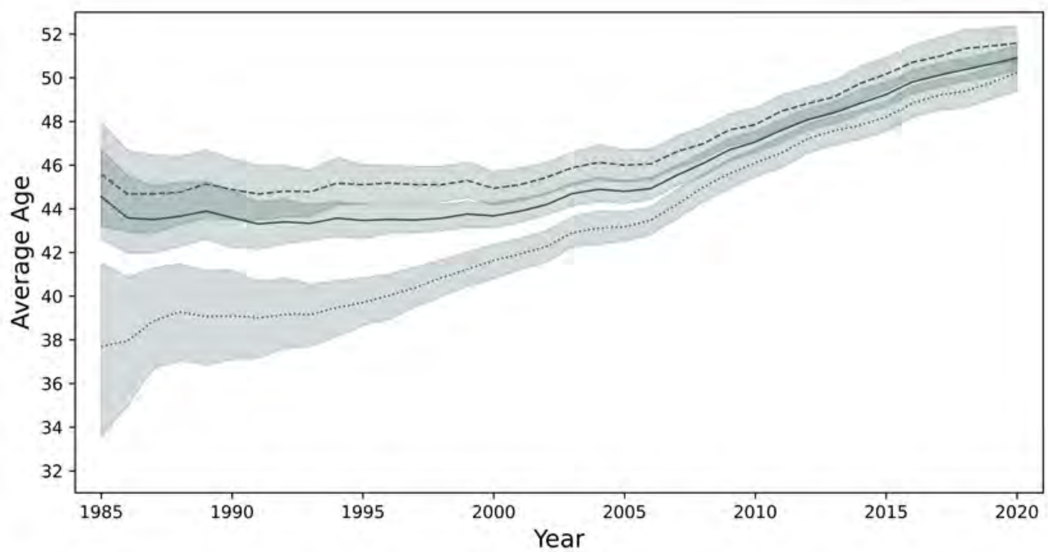

Fig. 6. Age of Facebook-identified and Non-identified Fund Managers
This figure compares the average age of all fund managers (solid line) in the initial sample of domestic actively managed U.S. equity mutual funds covering the period 1984–2020 to both the average age of Facebook-identified fund managers (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 assuming that the undergraduate degree was completed at age 21.

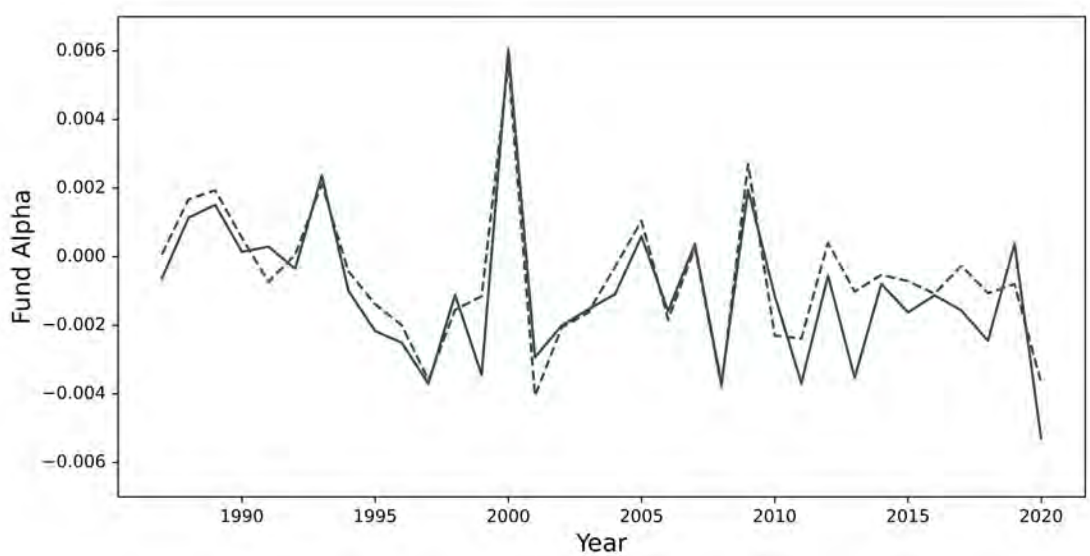

Fig. 7. Performance of Facebook-identified and Non-identified Funds
This figure compares the fund performance of the funds run by Facebook-identified fund managers (dashed line) and the performance of the funds run by non-identified fund managers (solid line) across the sample period. Fund performance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