Hidden Alpha*

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ABSTRACT

This paper documents the central role of hidden connections between fund managers and firm officers in financial markets, drawing on an extensive dataset of over 100 thousand manually identified Facebook profiles and their 35 million Facebook friends. Our findings reveal that the hidden connections between these individuals are associated with the largest and most significant abnormal returns accruing to fund managers, averaging 135 basis points per month (over 16% alpha per year, t-stat = 3.54) across the universe of mutual funds and public firms. In stark contrast, trades involving publicly visible connections generate no significant abnormal returns on average. This premium on hidden connections appears not to be attributable to endogenous selection or familiarity; rather, fund managers exhibit consistent timing ability in knowing when to hold (and when to avoid) stocks of firm officers with whom they share hidden ties. Additionally, the more hidden the connection, the greater the value of the associated trading information. The premium is absent in index funds, where strategic stock selection is not feasible. It is consistent across industries, styles, time periods, and firm types, demonstrating strong and persistent significance to the present day.

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Social networks constitute the structural foundation of groups of individuals, with prior research documenting their importance in disseminating information in financial markets. However, the visibility and management of these connections remain largely unexplored. As the volume and granularity of data continue to expand, our study aims to investigate exactly this: the endogenous choice of key financial agents to disclose or hide their social connections, and the performance implications of these choices. Focusing on the nuances of Facebook friendships, we find strong evidence that the choice to hide connections is strategic rather than random. When fund managers hide their friends on Facebook, and these friends include firm officers whose stocks they trade, they generate significantly higher abnormal returns, especially when the firm officers also hide their friends.

Leveraging data from Facebook (facebook.com), one of the most popular websites in the United States with more than 200 million monthly active users at the time of writing, we compile a dataset of over 100 thousand manually identified Facebook profiles of fund managers and firm officers active from 1984 to 2020, and their 35 million Facebook friends. By analyzing their connections and interactions, we classify their friendship ties as either public or hidden by one or both parties and analyze their impact on investment decisions and subsequent returns.

Facebook connections offer several advantages over previous studies on social networks in financial markets. Notably, the data allow us to observe the visibility of connections and measure their intensity through user interactions, such as likes, comments, and tags. More critically, by uncovering hidden connections between them, we reveal rich and substantive information beyond what is visible on the surface of publicly observable connections. Our measures indicate that the hidden connections are, on average, the most valuable in the network. Ignoring these would result in an incomplete picture of some of the most essential ties in financial markets.

To illustrate our approach, consider an example from our sample involving Ms. Ananke, who has served as CEO and board member of several firms in the technology sector, including her role as the independent chair of TechCorp, a large technology firm. One of her friends, Mr. Bergelmir, is a fund manager of a large actively managed mutual fund, with extensive experience across various buy-side institutions in the financial industry. Bergelmir characterizes his investment style as one that involves deep "fundamental analysis" for portfolio selection. Both individuals are active on Facebook.[1]

[1]Note that the examples provided are derived directly from our sample; however, we have anonymized the name of the individuals, firms, and funds management companies.

Ananke and Bergelmir share what we term a *FullyHidden* connection on Facebook, where both users hide their friends lists, making their connection invisible to conventional social network analysis. They do not share any common network ties, via common schools, workplaces, or geographic locations, nor are there documented meetings suggesting a connection. However, we uncover their friendship by exploiting a unique aspect of the Facebook platform: in spite of users hiding their friends lists, a select few profile items remain visible to non-friends, but can only be engaged with by friends (a detailed description of the process is provided in Section I.C). These engagements can be as ordinary as a single like among many likes on a profile photo, which may itself be removed or replaced a few months later. By analyzing these interactions, we infer connections between users even when both parties hide their friends lists, leveraging the platform's design that evolved from initially prioritizing connectivity to later incorporating increased privacy features, likely resulting in the observed inconsistencies.

Given their *FullyHidden* connection, we analyze Bergelmir's performance on trades related to Ananke's firms and compare it to his performance on other stocks in his portfolio. For instance, Ananke began her role as the independent chairwoman of TechCorp in mid-2015. At that time, Bergelmir's StrategicFund held no shares of TechCorp. Within a quarter, as shown in Figure 1, StrategicFund bought into TechCorp at approximately \$20 a share and continued to build its position over the next four years. During this period, TechCorp experienced several positive events, including acquiring a large rival, expanding into Europe, and forming significant partnerships domestically. Bergelmir eventually exited TechCorp at over \$200 a share, yielding a return of more than 10 times the original investment. After his exit, TechCorp encountered several negative events, including a challenging acquisition integration and large competitors entering the market, leading to a stock price decline of over 60%. This decline occurred while Bergelmir continued to lead StrategicFund but chose not to reinvest in TechCorp. Notably, this pattern was not an isolated incident. Over time and across different funds, Bergelmir traded four different stocks where Ananke held management roles, achieving an average of 264 basis points (t=2.31) per month in abnormal returns.

Zooming out to the broader portfolio level, Bergelmir performed remarkably well across his hidden connections, averaging 208 basis points per month (t=2.41) in abnormal returns over his holding period. In contrast, his non-connected portfolio holdings over the same period had an average monthly abnormal return of only twelve basis points (t=0.69), suggesting that his superior performance was not due to a broader systematic ability in portfolio selection.

This example represents a systematic pattern across the entire universe of Facebook-identified fund managers and firm officers throughout our sample period. Specifically, from 1984 to 2020, we find that the most hidden connections—those that are hidden by both sides of a connected pair—result in abnormal risk-adjusted returns of 135 basis points per month on average (t-stat = 3.54). During the same time, fund managers hiding their network connections are not inherently better performers, as their risk-adjusted returns on non-connected holdings are small and statistically indistinguishable from zero. Furthermore, the outperformance on hidden connections appears uncorrelated with known return determinants, as the monthly risk-adjusted 136 basis points return (t-stat = 3.57) of a value-weighted long-short strategy is nearly identical to the strategy's raw return of 148 basis points (t-stat = 3.88). Consistent with our finding that hidden connections appear to provide significant informational advantages within the network structure, we observe that abnormal returns on connected stocks increase monotonically with their level of hiddenness. Returns on visibly connected stocks yield risk adjusted returns of 1.3% per year, which are statistically insignificant (t-stat = 0.43). Returns on one-sided hidden connections begin to pick up, with those hidden only by firm officers yielding 3.6% per year (t-stat = 1.12) and those hidden only by fund managers associated with risk-adjusted returns of 6.7% per year (t-stat = 1.81). In contrast, returns on connections hidden by both sides generate risk-adjusted returns of over 16% per year (t-stat = 3.54).

The article also explores the individuals' investment behavior vis-a-vis their connections. In particular, we ask whether fund managers overweight connected stocks and find that the most hidden connections are again those associated with the most abnormal weights. More precisely, while we see a 46% weight increase in stocks pertaining to *FullyVisible* connections, the overweight rises to almost 200% for *FullyHidden* connections, and remains statistically large and significant when controlling for time and firm fixed effects—for example, when comparing the weights of two fund managers over the same time period, one of which is visibly connected to the firm's active firm officers, while the other is not.

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

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

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

Our paper connects to the growing body of empirical literature examining the impact of social ties on information transmission among agents in financial markets. Papers in this spirit include Cohen, Frazzini, and Malloy (2008), who find that fund managers tend to execute larger and more profitable trades on firms managed by personnel with whom they share educational backgrounds; Engelberg, Gao, and Parsons (2012), who provide evidence that social connections between firms and banks lead to the issuance of loans with lower interest rates and fewer covenants; Cai and Sevilir (2012), who document that connections between board members of acquirer and target firms are associated with positive announcement returns for the acquirer; Engelberg, Gao, and Parsons (2013), who show that CEOs with social connections to outsiders bring more valuable information into the firm and receive higher compensation; and Pool, Stoffman, and Yonker (2015), who find that fund managers favor investments in companies that are held by other fund managers living in their neighborhood.

Our study is the first empirical investigation to find evidence that money managers who engage in stock trading of firms managed by their friends, when managing their friendships to remain hidden, achieve superior performance in comparison to those who do not hide their friends. This analysis is also unique in its use of large-scale individual-level Facebook data in the field of financial economics, directly observing the extent to which agents in financial markets know and interact with each other rather than relying on indirect proxies. Pool et al. (2015) note that indirect measures of social connections, such as shared school ties or geographic proximity, can be imprecise and prone to misclassifying individuals as connected, which restricts their ability to capture the genuine impact of social connectedness on financial performance.

The remainder of the paper is organized as follows. Section I outlines the data collection procedures, sample construction, and summary statistics. Section II presents the primary outcomes related to the predictability patterns of returns associated with the hidden friendships identified in our data. Section III conducts robustness tests and explores the horizon of the return effect. Section IV concludes.

I. Data and Sample Construction

In this paper, we combine data from multiple sources. To determine the presence and visibility of friendship ties between the individuals in our sample, we use publicly accessible data collected through Facebook by Meta Platforms, Inc. Information on mutual fund holdings, mutual fund returns, and mutual fund managers are obtained from Morningstar Direct

(MS Direct). Details on management personnel of stocks held within the fund portfolios are from BoardEx of Management Diagnostics (BoardEx). Stock returns originate from the Center for Research in Security Prices (CRSP). Stock characteristics come from Compustat. Firm-level news data are from RavenPack Analytics (RavenPack).

A. Facebook Data

The objective of this study is to explore how non-public personal relationships between fund managers and firm officers influence fund holdings and returns, using Facebook friendship characteristics as a laboratory network metric. For this analysis, we create an indicator variable that specifies whether a fund manager and a firm officer are friends on Facebook. This process involves locating their Facebook profiles, which are personal pages featuring the user's name, profile picture, cover photo, friends list, timeline, photos, and an "about" section that includes biographical and descriptive details like work history, educational background, places lived, relationship status, and family members. Facebook profiles serve as organizational tools, enabling users to form connections with other users that typically parallel their real-life relationships, such as friends, family, classmates, co-workers, and romantic partners. Users can establish a connection between their profiles by mutually confirming their friendship on the platform. As a result, they will appear in each other's friends list, may have greater access privileges to each other's content, and may receive updates on information produced by or linked with the other user.

The process of identifying an individual's Facebook profile can be challenging for a variety of reasons. First, due to Facebook's widespread use, many of the attributes that are useful for searching profiles and resolving their creators' identities (e.g., name, workplace, education, and location) are widely shared among Facebook's user base, decreasing their discriminative power. Second, users can restrict the visibility of certain profile attributes to the public by adjusting their privacy settings, which may impede the identification of their profiles and necessitate additional data to support the matching process. Third, users do not necessarily fill in all available data fields, resulting in incomplete profiles with limited identifying information. Lastly, due to the substantial data access restrictions that Facebook has imposed on their platform in recent times,[2] hardly any user-generated Facebook data can be retrieved through APIs, but must instead be manually collected via the web interface.

[2]In response to several controversies (e.g., the Cambridge Analytica incident), Facebook severely restricted Facebook's main API ("Graph API") in April 2018 by deprecating its major endpoints. Further restrictions were imposed in June 2019 when the semantic search engine ("Graph Search") was disabled. These measures have strongly limited the capacity to read Facebook's social graph and access user-generated data.

B. Matching Methodology

As we attempt to identify the Facebook profiles of a large group of individuals, we define a three-step identification procedure to standardize the matching of Facebook profiles. First, for each individual of interest (target) in our sample, we retrieve a plurality of potentially matching Facebook profiles (candidates) that hold attributes similar to the target's known characteristics. Second, we determine each candidate's probability of matching its respective target by calculating a confidence score based on a variety of similarity and proximity measures. Third, we arrange each target's candidates based on their confidence scores and try to manually match the target's true profile from its particular set of candidates. We illustrate these details of the identification procedure using the following description:

In the first step, we populate a list of candidates for each target in our sample by querying the target using Facebook's search engine, which takes a name and an optional set of search parameters as input and returns a list of candidates with matching attributes. Filters available to refine the search include location, work, and education. To overcome limitations arising from the search engine's web interface, we produce the candidates using customized query strings in which we embed the internal identifiers of the search parameters.[3]

In the second step, for each candidate that is associated with a target, we calculate a confidence score indicating the likelihood of the identity behind the candidate being equivalent to the target. The score is calculated based on a range of measures representing similarities between the candidate and the target. With each measure, we focus on capturing a different aspect of potential similarity. Using semantic measures, we analyze a candidate's various profile attributes (e.g., screen name,[4] username, education, workplace, location) and compare their values to those held by the target. Before the comparison of attributes, we selectively augment the target's attributes with their semantically equivalent representations, if applicable. For instance, 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 attributes, we consider flexible matching schemes to capture partial overlaps between the attributes' meaningful units. For various other measures, we use attributes that are not observed but inferred from information associated with the user. For example, for candidates with a Facebook user

[3] 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 to choose from. As this approach is not feasible for executing a large number of search queries, we instead use query strings.

[4] Facebook's real-name policy mandates users to use the name that they are commonly known by in their everyday life. The name must correspond with their identification documents, which they must submit upon request to verify their identity. If a nickname is used, it must be a derivative of the user's authentic name.

ID in the space between zero and $3.5e8$, we infer the educational institution attended by the candidate from the user ID's numeric value, irrespective of whether or not the education attribute can be observed from the candidate's profile.[5] For example, when evaluating the similarity of candidate manu.sekhri.9 to the given target "Manu Kumar Sekhri," a 1996 graduate of University of Waterloo, even though the candidate's alma mater is not disclosed on the profile, we can infer it from the value of the user ID ("122,614,211"), which matches the customized user ID space that used to be assigned to all registrants affiliated with the University of Waterloo (122,600,000–122,699,999). To enable this procedure, we manually identify the user ID clusters of 2,708 schools in the Facebook user ID space ranging from zero to $3.5e8$. In addition to inferring attributes from the user's information, we may also infer attributes from information pertaining to the user's connections. Specifically, for some measures, we retrieve the plurality of the user's friends and determine the most frequently appearing attribute value among those friends. For example, if a significant percentage of the candidate's friends have attended a particular college or are residents of a certain city, the candidate itself may be inferred to have attended that college or be residing in that city. We weight these measures with a confidence factor that indicates the likelihood of the measure being accurate. For example, if the alma mater of a candidate is inferred based on a large number of the user's friends having attended this institution, the confidence factor attached to the inferred attribute is determined to be high; otherwise, it is low. Some measures, depending on the dynamics of the values they generate, are set to be complementary to the match probability, so that they reflect the rarity of a positive match. For example, if we find the alma mater value "Coe College" of a candidate with the common name "James Miller" to match the alma mater of the candidate's target, we denominate the probability of the match by the number of Coe College graduates in our sample by the name of James Miller. Finally, for every target whose portrait we observe during the data collection process (e.g., on the company website or on LinkedIn), we run a face recognition algorithm that compares the particular portrait to the target's candidates' Facebook profile pictures.[6] Following the calculation of the above measures, we aggregate the values produced for each candidate–target pairing into a single confidence score.

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

[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).

In the third step, we identify a target's genuine profile from the pool of potential candidates, where applicable. For optimal matching quality, this process is carried out manually.[7] In order to conserve human resources, any candidate whose confidence score does not exceed a predetermined threshold is eliminated. The remaining candidates for a particular target are ranked based on their respective confidence scores and reviewed in descending order, beginning with the highest-ranked candidate and and progressing to lower ranks. To ensure accuracy, visual confirmation is generally required to establish a match. However, if a candidate's privacy settings are too restrictive to allow for visual confirmation due to missing or hidden profile data, we attempt to establish the match by linking the particular candidate to the profile of someone from the target's environment (e.g., a family member). If we identify the Facebook profile of an immediate family member of the target (i.e., spouse, parent, or child) and determine that the target is not among the subject's friends, we conclude that the target is not the owner of a Facebook account and no further matching is conducted.

C. *Friendship Ties*

After identifying the Facebook profiles of our sampled individuals, we use two distinct approaches to determine their friendship connections. The first approach involves collecting all users listed in the individuals' friends lists. If a particular user's friends list is not publicly available, we may still be able to determine some of their connections through "backlinks" from their friends' friends lists.[8] To enhance the disclosure of backlinks, we exploit Facebook's Mutual–Friends feature, which requires two user IDs A and B as input and returns a list of mutual friends if certain conditions are met. Specifically, if A's friends list is private while B's friends list is public, the feature will return all of B's friends who are connected with A and who publicly disclose the connection on their end. To facilitate this procedure, we design a recursive iteration which pairs each target with users who are likely to have mutual friends with the target (pivot users), and uses all new friends returned for each user at each step as pivot users for further iterations. Once initiated for a particular target, the iteration will continue to call the feature until all pivot users are paired with the target and no additional friends are returned. We query this endpoint four million times before it is deactivated by Facebook in August 2021.

[7] The validation of Facebook profiles was aided by a group of trained research assistants.

[8] Facebook is structured as an undirected graph in which mutual consent is required for a connection to form between two users. Thus, a connection between two users A and B can be disclosed with certainty either by showing that A is connected to B or by showing that B is connected to A.

The second approach that we employ to determine friendship connections relies on analyzing interactions between the users on the platform. To this end, we exploit an inconsistency in Facebook's privacy settings: Despite the option for Facebook users to hide their friends list, doing so does not entirely remove all traces that their friends may leave behind on publicly accessible parts of the profile, which may still make the friendship identifiable. Specifically, Facebook users can interact with each other through likes, comments, and tags, which allow them to respond to content posted by other users. When posting content, users may choose to restrict the audience that can see it, engage with it, or see who has engaged with it to a selected few (e.g., only the user's friends). While such content is no longer available to the general public, a few profile items that Facebook classifies as "public information" cannot be hidden, including the user's current profile picture and current cover photo. These photos always remain visible even to non-friends; however, the audience of users who can interact with them is by default still limited to the user's friends. This unique constellation enables us to disclose connections between users even if both sides hide their friends by analyzing the user reactions to these photos, provided that certain additional criteria are met. For instance, a photo cannot be taken into account for evaluation if other users besides the profile holder are tagged in it, as the audience of this photo (i.e., those who can interact with it) will automatically extend to include the friends of any user that has been tagged. Friendships derived from reactions to restricted content may only be visible for a limited period of time, until the particular photo is replaced. It will then no longer fall into the public information category and thus may no longer be visible to non-friends.

After determining the friendship ties between our sample individuals, we proceed by classifying the degree of visibility of these connections, which produces the key variable for our study (*FriendshipVisibility*). This variable is a vector of four dummy variables capturing the degree of visibility of a Facebook friendship observed between a fund manager and a firm officer depending on whether the friendship is publicly observable through both the fund manager's and the firm officer's friends lists (*FullyVisible*); observable through the fund manager's friends list but not through the firm officer's friends list (*FirmOffcHides*); not observable through the fund manager's friends list but observable through the backlink from the firm officer's friends list (*FundMgrHides*); or neither observable through the fund manager's friends list nor through the firm officer's friends lists (*FullyHidden*).

D. Mutual Fund Sample

In this section, we detail the construction of the sample of funds and fund holdings for our study. The universe of fund-month observations whose fund managers' Facebook profiles we identify will determine the the relevant stock-month observations, which in turn will span the universe of firm officers whose Facebook profiles we are interested in matching.

The original sample of funds contains the universe of actively managed U.S.-domiciled U.S. equity mutual funds covered by MS Direct. While most prior studies in the mutual fund literature rely on the Thomson Reuters Mutual Fund Holdings (TR Holdings) database for holdings data, we chose Morningstar for several reasons. First, we find that fund holdings data from MS Direct are more frequently available than those from TR Holdings. Second, we corroborate prior claims that MS Direct provides a more comprehensive representation of the actual compositions of the funds' portfolios (e.g., Elton, Gruber, and Blake (2011)). Third, MS Direct are recognized for their higher accuracy in reporting the funds' portfolio managers (e.g., Massa, Reuter, and Zitzewitz (2010) and Patel and Sarkissian (2017)).

We construct our sample of funds by including both defunct and active fund share classes to avoid a potential survivorship bias. We obtain the funds' historical Morningstar categories from historical time series data. 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, and funds that focus on bonds, commodities, nontraditional equity, or alternative asset classes). We adhere to standard protocol by eliminating funds with titles that include the terms "index" or "idx." Since funds may be offered in various share classes that differ in their fee structures but provide exposure to the same portfolio of securities, we consolidate observations for funds with multiple share classes into one. For each fund that passes the aforementioned filters, we pull historical management data from MS Direct, which includes the names of the fund managers, start and end dates of their management periods, brief biographies, and educational background information. We exclude fund-month observations for which this data is unavailable. For the stocks held by the funds, we obtain one-month-ahead return data from the CRSP Monthly Stock Files, merging this return data with the funds' holdings using historical CUSIP numbers. Following this procedure, our sample comprises 415,676 fund-month observations spanning January 1984 through December 2020. The sample includes 5,053 unique funds, with an average of 1,386 funds per calendar quarter. We use this sample, hereafter referred to as the benchmark universe of funds, when constructing weights for our benchmark portfolios.

E. Fund Manager Sample

The 5,053 mutual funds that pass the initial filtering process are managed by a total of 10,036 fund managers.[9] To prepare for matching their Facebook profiles according to the methodology outlined in Section I.B, we collect additional biographical data on the fund managers. We begin by determining their most complete names (including middle names, nicknames, birth names, surnames adopted upon marriage, and suffixes) using the Financial Industry Regulatory Authority's BrokerCheck database, the Securities and Exchange Commission's (SEC's) Investment Adviser Public Disclosure database, and the Chartered Financial Analyst's (CFA's) Institute's member directory. Next, we gather information on vital dates, portraits, places of residence, family members, academic degrees, graduation years, and occupational backgrounds through a cross-database search of various sources such as LinkedIn profiles, Bloomberg executive profiles, The Wall Street Transcript profiles, 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 with matching the fund managers' profiles on Facebook and successfully identify 4,198 (41.8%) out of the 10,036 fund managers present in the benchmark universe of funds. This ratio aligns well with general figures on Facebook usage in the United States, which suggest that approximately six in ten adults use or have used Facebook at some point in their lives. The left subfigure of Figure 2 illustrates the percentage of Facebook-identified fund managers with respect to the total number of fund managers meeting the pre-established criteria in the benchmark universe throughout the sample period. We then restrict the sample of funds to only those managed by fund managers whose Facebook profiles we are able to identify. Team-managed funds are included if we identify the Facebook profile of at least one team member. These steps result in a sample reduction to 265,320 of 415,676 fund-month observations and 4,100 of 5,053 funds.

[9]Our fund manager sample is subject to two adjustments. First, we address instances where multiple individual records pertain to the same entity by consolidating them (309 individuals were consolidated into 153). These duplications often arise due to name changes (e.g., Katherine Lieberman née Buck being referred to as either "Katherine Buck" or "Katherine Lieberman") or pseudonyms (e.g., Langton C. "Tony" Garvin being referred to as either "Langton C. Garvin" or "Tony Garvin"). Second, we exclude any fund managers who died before the launch of Facebook in February 2004 (39 individuals). Individuals who passed away after the threshold date are included in the sample, as their potential Facebook profiles may still be active.

F. Firm Officer Sample

We obtain employment data and biographical information on the firm officers leading the firms whose stocks are held by our sample of Facebook-identified funds from BoardEx, a data purveyor that 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 multiple sources, such as the SEC, press releases, primary websites, and U.S. stock exchanges, and have been used in various economic studies to analyze the impact of social networks (Cohen et al. (2008), Cohen, Frazzini, and Malloy (2010), Engelberg et al. (2012), and Chen, Cohen, Gurun, Lou, and Malloy (2020)). BoardEx offers comprehensive overviews of the composition of boards and senior management, with data collecting beginning in 1999, although most individual company records extend back further in time. BoardEx provides information on the current and past roles of firm officers at active and inactive firms, including start/end dates for these roles, educational backgrounds, and affiliations with charitable or volunteer organizations.

BoardEx data are categorized into four geographical regions to which firms are allocated based on the most recent location of their headquarters.[10] To assemble the sample of firm officers for this study, we start by combining the management personnel of both currently and formerly U.S.-headquartered public companies from the four files into one file. We proceed by merging the data with the funds' portfolio holdings using historical linking tables furnished by Wharton Research Data Services (WRDS), which provide a link between the respective firm identifiers of BoardEx (companyid) and CRSP (permco). We discard employment records for which BoardEx does not provide the start date of an individual's role at a company. If BoardEx does not specify an end date for a role, we adhere to the provider's instructions and assume that the position is still held by the individual. Additionally, we exclude individuals for whom BoardEx's records indicate that they passed away prior to Facebook's launch in February 2004. After applying the aforementioned filters, we are left with 281,829 distinct firm officers involved in the management of 8,646 distinct firms held by the Facebook-identified funds. Next, for the purpose of matching the firm officers' profiles on Facebook, we collect their biographical information from various BoardEx files including comprehensive names, educational backgrounds and work histories.

[10]BoardEx assigns each firm to one of four geographically-themed files (North America, United Kingdom, Europe, Rest of World) based on the current location of its headquarter. For instance, if a firm's headquarter is relocated from the U.S. to Europe, BoardEx will transfer all observations associated with that firm into the Europe file, including those pertaining to years when it was headquartered in the U.S.

With this data available, we successfully identify the Facebook profiles of 101,866 (36.1%) of the 281,829 firm officers in the full sample. These individuals are managing 8,444 of the 8,646 firms in the full sample. The right subfigure of Figure 2 illustrates the percentage of Facebook-identified firm officers with respect to the total number of firm officers meeting the pre-established criteria in the benchmark universe throughout the sample period.

G. Descriptive Statistics

This study uniquely leverages large-scale individual-level Facebook data, warranting a more detailed description. The sample includes data collected from the Facebook profiles of 4,198 fund managers and 101,866 firm officers. We gather various information from each of these profiles, including, if available, the user's screen name, username (unique alphanumeric identifier), user ID (unique string of numbers), gender, date of birth, contact information, relationship status, number of friends, the screen names and usernames of friends, family members, and relationships, details on workplaces, high schools, and colleges attended, information on current city, hometown, and places lived, details on life events, and all uploaded photos, including profile pictures, cover photos, photos in miscellaneous albums, and photos in the timeline (i.e., timeline posts with photographic elements). We individually examine each photo for its upload date, user-generated description, alternative text,[11] and the screen names and usernames of any users who are tagged in it, expressed liking towards it, or provided comments on it, as well as the contents of said comments.

In Table I, we present a summary of profile-level data collected from the Facebook profiles of fund managers and firm officers. For each data category, we report the percentage share and the total number of profiles from which we obtain information specific to that category. The profiles of fund managers and firm officers do not show substantial differences in terms of the information that we are able to collect from them. Screen names, usernames, and user IDs are fully available across the sample, as these attributes cannot be concealed from the public. Friends lists are accessible for slightly over 50% of both fund managers' and firm officers' profiles. Profile pictures and cover photos are visible in about 90% of profiles, respectively, while additional photos, such as those uploaded to miscellaneous albums, are displayed in about 70% of profiles. The data types typically provided by users to assist their real-life friends in finding and connecting with them on the platform, such as work, college, current city, and hometown, are prevalent in the mid-thirties to lower fifties range. The

[11] Facebook employs an algorithm for object recognition to automatically create descriptions of photos for the visually impaired, listing the objects, individuals, and scenery that are discernible within an image (e.g., "May be an image of 1 person, child, standing, smiling, outerwear, twilight, sky, beach, ocean, and car.").

availability of more sensitive data types, such as relationship status and family members, is less frequent, with percentages ranging in the lower twenties. It is noteworthy that the quality of the disclosed information may vary widely, depending on various factors such as the method by which the user submitted the data.[12]

In Table II, we present descriptive statistics on item-level data collected on the sample individuals' Facebook friends, photos, and reactions. For each variable, we report the mean, median, standard deviation, total number of data items collected, and the number of profiles for which we collect items in that category. The statistics are computed based on observations with non-missing values. Our data collection efforts result in a total of 35.2 million Facebook friends disclosed for the sample individuals, with 1.1 million for 4,066 of the 4,198 fund managers and 34.1 million for 100,193 of the 101,866 firm officers. The median number of friends per fund manager and firm officer is 167 and 188, respectively. Note that we collect these friends not only from the individuals' profiles but also from others sources, such as backlinks of other users' friends lists and reactions given to photos uploaded by other users on their profiles (refer to Section I.C for our approaches on collecting friends). We report figures on friends segmented by the different approaches used to collect them, including friends collected from publicly disclosed friends lists (*Friends–Published*), friends collected through backlinks from other users' friends lists (*Friends–Backlinks*),[13] and friends collected through examining reactions received on or given to restricted photos (*Friends–Reactions*). Additionally, we report statistics on photos collected from the Facebook profiles, which include a total of ten million photos uploaded by the sample individuals. Of these, 187 thousand photos are collected from 3,374 of the 4,198 fund manager profiles, and 9.8 million photos are collected from 89,294 of the 101,866 firm officer profiles. These photos include profile pictures, cover photos, and those in miscellaneous albums. Lastly, the table presents statistics on the reactions (i.e., likes, comments, and tags) that were received by the uploaded photos, excluding reactions that the individuals gave themselves to their uploads. Overall,

[12]By way of example, the user may have entered certain information manually ("Went to Bayreuth"), or declared it through a menu interface designed to assist users in aligning an entry with a concept that is known to Facebook. In the latter case, a standardized entry is established, which includes a hyperlink directing to the Facebook page devoted to the corresponding concept ("Studied at Uni Bayreuth").

[13]The reason for the low number of disclosed friends for firm officers through backlinks is the discontinuation of the the Mutual–Friends feature on Facebook in August 2021 (see Section I.C). It is important to note, however, that we had already collected data from this feature for all fund managers in our sample prior to its termination. Therefore, the count of connections between fund managers and firm officers used in this study remains unaffected by this development.

we collect at total of 61.6 million reactions for our sample individuals, with 3,226 of the 4,198 fund managers receiving 2.1 million reactions, and 85,512 of the 101,866 firm officers receiving 59.4 million reactions. Of the reactions observed on the profiles, 85% are likes, 14% are comments, and 1% are tags.

In Table III, we provide summary statistics reflecting the annual composition of the Facebook-identified sample of funds, including details on fund managers, the funds' common stock holdings, and management personnel of the firms whose stock is held by the funds. The sample comprises 265,320 fund-month observations managed by 4,198 Facebook-identified fund managers in the period 1984–2020. The Morningstar benchmark universe used to calculate percentage coverages for the funds is the sample consisting of 415,676 fund-month observations whose construction we detail in Section I.D. The BoardEx benchmark universe used to calculate percentage coverages for firm officers is the sample constructed in Section I.F. The statistics reported for each variable include the mean, median, minimum, maximum, and standard deviation. In median terms, the sample includes 1,508 funds per year, accounting for an annual coverage of 59% of the 5,053 funds in the benchmark universe over the study period or 53% of the benchmark universe's total net assets under management. The sample of Facebook-identified fund managers includes 1,166 individuals per year, corresponding to an annual coverage of 38% of the 10,036 fund managers active in the benchmark universe during the study period. The Facebook-identified funds invest in 4,267 firms per year, representing an annual coverage of 57% of the stocks covered by the CRSP universe and covering 96% of the CRSP universe's market capitalization. These firms are managed by 64,050 firm officers per year, or an annual coverage of 99% of the 281,829 firm officers present in the BoardEx benchmark universe. The sample of Facebook-identified firm officers includes 18,405 individuals per year, accounting for an annual coverage of 29% of the aforementioned firm officers whose firms' stock is held by the Facebook-identified funds.

In Table IV, we present data on the Facebook friendships that we observe between the fund managers and firm officers in our sample, broken down by the friendships' visibility levels as defined in Section I.C. We report on three types of fund manager–firm officer friendships: total observed friendships (*Friendships–All*), tradable friendships (*Friendships–Tradable*), and traded friendships (*Friendships–Traded*). A friendship is deemed "tradable" if the fund manager's tenure at the fund coincides with the firm officer's tenure at the firm and if the firm's stock, during the given month, is held by at least one fund in the same Morningstar category as the relevant fund. Similarly, a friendship is deemed "traded" if the fund manager's fund holds the firm's stock during the firm officer's tenure at the firm. We provide information on tradable friendships (in addition to total and traded friendships) as supplementary information to enhance the context of the results. Tradable friendships exclude those that could not have been traded due to the connected fund manager and firm officer not simultaneously managing the fund and the firm, as well as friendships that are unlikely to be traded as per the fund's objectives (approximated through holdings of peers in the same Morningstar category), such as the friendship between a fund manager of a large-cap value fund and a firm officer of a small growth firm. The table reports figures on the number of connected pairs, the number of distinct fund managers and firm officers involved in these pairs, the number of stocks associated with the pairs, and the number of underlying fund-month-stock observations. In total, our analysis reveals 18,478 Facebook friendships between 2,803 fund managers and 10,748 firm officers. With regard to tradable friendships, we observe 9,012 friendships between 2,107 fund managers and 6,050 firm officers. Of these friendships, 2,908 (32%) are traded, involving 1,052 fund managers and 2,143 firm officers. When categorizing the traded friendships based on their visibility levels, 930 (32%) are assigned to the *FullyVisible* category, 959 (33%) are classified as *FundMgrHides*, 758 (26%) are classified as *FirmOffcHides*, and 261 (9%) are classified as *FullyHidden*. Notably, a comparison between the tradable and traded friendships indicates that the desire to hide Facebook friends lists coincides with a higher likelihood of these friendships being activated. Specifically, while only about 28% of the *FullyVisible* friendships are traded, this percentage increases to 31% for *FirmOffcHides* friendships and to 37% and 44% for *FundMgrHides* and *FullyHidden* friendships, respectively.

Table IV also suggests that the sample of connected pairs does not stem from a few super-connectors, but involves a large number of individuals from both groups—fund managers and firm officers. These individuals are dispersed across various funds and firms. To illustrate this dispersion, Figure 3 presents a network graph depicting Facebook-identified connections between fund managers (blue nodes) and firm officers (red nodes) classified as tradable. The darker shades indicate traded connections within the subset of tradable connections. Each node represents an individual, and edges signify Facebook friendships between fund managers and firm officers. Individuals are clustered by their current or most recent employer, as labeled. In cases of multiple affiliations, individuals are assigned to the firm where they hold their most senior role. This graph visually demonstrates the extensive and intricate network of connections, highlighting the dispersion and richness of these relationships across different funds and firms. This visual representation provides a clear overview of the widespread nature and potential impact of these hidden connections on fund managers' investment decisions.

II. Main Results

A. Portfolio Weights

In this section, we examine whether fund managers' hidden friendships have an effect on the funds' holdings. If fund managers with non-public connections to company executives are better informed, they may allocate a larger proportion of their funds to securities managed by those individuals. To assess this possibility, we calculate the portfolio weights in Facebook-connected stocks for each fund-month observation as the dollar investment in these stocks divided by the fund's total dollar holdings during that period. We then estimate various forms of the regression equation

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

where $w_{i,k,t}$ is the weight of fund i in stock k at time t; $FriendshipVisibility_{i,k,t}$ is a vector of dummy variables reflecting the visibility of the Facebook friendship between a fund manager of fund i and a firm officer of firm k, as defined in Section I.C; and $\Gamma' Controls_{i,k,t}$ 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 non-public firm officer friends, we would expect to find that β is positive and statistically significant.

In Table V, we present coefficient estimates and standard errors clustered at the fund level from Panel OLS estimations of various specifications of Equation 1. All regressions include period fixed effects, and the unit of observation is stock-fund-month. The main results are shown in columns 1–4, which include an expression of $FriendshipVisibility_{i,k,t}$ and a constant in the regression. Columns 1–4 reveal over-allocations to securities of friends that vary significantly depending on whether or not the friendship between a fund manager and a firm officer is publicly visible through their friends lists. Specifically, fund managers invest an additional 35.2 basis points in securities of firms managed by firm officers friends in the *FullyVisible* category, compared to the average weight of 74.6 basis points. They allocate 63.9 additional basis points to securities of friends in the *FirmOffcHides* category, 95.8 additional basis points to securities of friends in the *FundMgrHides* category, and 136.5 additional basis points to securities of friends in the *FullyHidden* category. In columns 5 and 6, the regressions from columns 1 and 4 are estimated with fund fixed effects, focusing solely on variation at the stock level (i.e., firm officer changes). While fund fixed effects explain the variation in fund managers' portfolio allocations toward *FullyVisible* friends, the coefficient on *FullyHidden* friends remains statistically significant at 50.9 basis points. Finally, columns 7 and 8 estimate both specifications with firm fixed effects to control for the average weight funds have in each stock. This approach relies on the variation at the fund level over time (i.e., fund manager changes) to explain portfolio weights. After controlling for firm fixed effects, the results indicate that fund managers allocate significantly more capital to securities of both *FullyVisible* and *FullyHidden* friends, with the latter effect being 2.5 times larger. These findings are economically important. In conclusion, the different specifications indicate a consistent pattern: Fund managers invest more heavily in their friends' securities, and these allocations appear to be highly dependent on the visibility of their friendships.[14]

B. *Performance*

Our findings thus far indicate that fund managers allocate significantly more capital to firms managed by non-visibly connected firm officer Facebook friends. We now explore whether this trend is associated with superior performance; that is, if the funds' holdings in the fund managers' non-visibly connected stocks outperform their holdings in visibly connected and non-connected stocks. If fund managers benefit from managing the visibility of their friendships, we would expect to observe positive returns in stocks associated with such connections. In contrast, if fund managers allocate money to these stocks for other reasons, such as familiarity, we would anticipate nonpositive results. To investigate this question, we use a conventional calendar time portfolio approach similar to Coval and Moskowitz's (2001) to create replicating portfolios based on the funds' holdings. In this process, we sort the funds' connected stocks into portfolios depending on their *FriendshipVisibility* levels. For the sake of brevity in the following descriptions, we subsume the various expressions of this variable under the term "connected." For each fund-month observation, we assign the stocks in a fund's portfolio into subportfolios based on whether any of the fund's managers maintain a Facebook friendship with any of the firm's same-month officers. We calculate monthly portfolio returns for each fund under the assumption that the funds did not change their holdings between two reporting dates as

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

and

[14] In specifications not reported, we control for industry fixed effects (based on the 48-industry classification used in Fama and French (1997)) and fund fixed effects (using the fund's Morningstar categories), both leading to more pronounced results than the specification in column 8.

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

where $\mathcal{N}$ is the set of stocks of a firm with an officer connected to at least one of fund i's fund managers, and $\mathcal{O}$ is the set of non-connected stocks in fund i's portfolio. Following stock assignments into "Connected" and "Non-Connected" subportfolios, we keep stocks in the subportfolios until the next reporting date, when the portfolios are rebalanced to reflect changes in holdings. We weight stocks by their dollar values in the fund's respective subportfolio. We then compute value-weighted averages of the returns in Equations 2 and 3 across funds at time t, weighting each fund portfolio return by the fund's total net asset value in the subportfolio. This approach assigns greater weight to funds that have larger dollar values of investments, and effectively corresponds to a simple investment strategy of investing in the entirety of connected and non-connected stocks in proportion to the amounts held by our sample of funds.[15] The sample averages 169 Facebook-connected funds per month, with each fund each month on average holding two connected stocks and 146 non-connected stocks.

To assess the performance of the calendar time portfolios, we employ three distinct measures: simple raw returns, risk-adjusted returns, and characteristics-adjusted returns. Risk-adjusted returns are computed based on the four-factor model of Carhart (1997), using the intercept from 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's (1997) momentum factor; the data are obtained from Ken French's data library. To address potential biases highlighted in prior research (e.g., Cremers, Petajisto, and Zitzewitz (2013)), we also calculate characteristics-adjusted returns following the methodology of Daniel et al. (1997), referred to hereafter as DGTW-adjusted returns. Specifically, we determine a stock's monthly DGTW-adjusted return by subtracting 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 from the stock's raw return.

Table VI presents our primary results, emphasizing the role of *Friendship Visibility* in determining the performance differences between connected and non-connected stock portfolios. Across all three performance metrics—raw returns, risk-adjusted returns, and DGTW-adjusted returns—the degree of *Friendship Visibility* significantly amplifies the outperformance of connected stocks over their non-connected counterparts.

[15]When applying equal-weighting schemes instead of value-weighting schemes, the tests presented in the remainder of this section generally produce slightly more pronounced results.

Notably, stocks classified in the *FullyHidden* category demonstrate the most substantial abnormal returns, achieving a monthly four-factor alpha of 135 basis points (t-stat = 3.54). Furthermore, a long-short strategy that involves purchasing *FullyHidden* stocks and selling short the fund managers' non-connected stocks generates an average monthly four-factor alpha of 136 basis points that is highly statistically significant (t-stat = 3.57), underscoring the considerable performance advantage associated with hidden connections. Stocks in the *FundMgrHides* category also exhibit positive abnormal returns, though to a lesser extent, with a monthly four-factor alpha of 56 basis points (t-stat = 1.81). Similarly, a long-short strategy involving *FundMgrHides* stocks yields an alpha of comparable magnitude. In contrast, trading *FirmOffcHides* and *FullyVisible* stocks results positive but statistically insignificant four-factor alphas of 30 and eleven basis points, respectively. The findings are consistent across different performance metrics, including DGTW-adjusted returns. In summary, our results indicate that fund managers' investment ideas in connected stocks experience very different fates: those associated with *FullyHidden* connections generate consistent, large, and significant risk-adjusted returns that outperform trades in visibly connected and non-connected stocks, underscoring the critical role of hidden connections in driving superior investment performance.

In addition to assessing the performance of non-visibly connected stocks based on the funds' holdings, we also analyze the fund managers' informational advantage using their trades, which provides additional insight into both buy side and sell side behavior. To extract trades from holdings, we adopt a method similar to the one described in Pool et al. (2015), which zeroes out periods of non-trading in a stock from the return series. Specifically, for each fund-month observation, we assign connected and non-connected stocks into "Buy" and "Sell" portfolios depending on whether a stock was bought or sold compared to the previous fund-month observation. The funds' initial stock transactions are excluded from this process. Within a given subportfolio, stocks are assigned the new dollars allocated relative to the previous month, and stock returns are weighted using the fund's total new dollar holdings in the subportfolio. We then compute value-weighted returns by aggregating across funds, using their total new subportfolio dollars as weights. We further expand our analysis by decomposing "Buy" and "Sell" transactions into extensive and intensive margin trades, depending on whether—relative to the previous month—a fund's position in a stock is newly established ("extensive margin buy"), entirely sold off ("extensive margin sell"), expanded ("intensive margin buy"), or reduced ("intensive margin sell").

We present the results of our trade-based evaluation of portfolio returns in Table VII. For brevity, we focus on the four-factor alphas, noting that the DGTW-adjusted returns are very similar. Aligning with our earlier findings, the *FullyHidden* portfolio remains the most notable in terms of four-factor alpha, yielding a monthly return of 127 basis points (t-stat = 2.75) on the buy side (column 1) and -68 basis points (t-stat = -1.34) on the sell side (column 2). Implementing a long-short strategy, combining buying the buy side and short-selling the sell side, results in a monthly four-factor alpha of 189 basis points (t-stat = 2.83), as detailed in column 3. The observed performance discrepancy between the buy and sell sides is plausibly explained by mutual funds' short-selling constraints. Further, segmenting the trades into intensive and extensive categories reveals that intensive buys yield 112 basis points, and extensive buys 225 basis points per month. Conversely, intensive sells result in -53 basis points, and extensive sells -190 basis points per month. Notably, the performance ratio of extensive to intensive trades on the sell side is much higher (approximately 3.5 to one) compared to the buy side (roughly two to one). The stark variation in these ratios may signal underlying differences in how fund managers can respond to buy and sell ideas. When considering a stock favorably, a fund manager may establish a new position if the stock is not yet held or increase the position's size if it is. Conversely, when viewing a stock unfavorably, closing a position may reflect a stronger conviction compared to merely reducing the size of the position, as the latter suggests a deliberate choice not to divest completely.

Next, we examine whether the managerial information that we seem to capture has implications for the stocks' fundamental values by exploring the evolution of the portfolios' connected legs using event-time returns. Specifically, we compute value-weighted cumulative abnormal returns sorted by *FriendshipVisibility* for the first 18 months following a fund's purchase of a connected stock. Consistent with our main results in Table VI, we find abnormal returns to increase with the level of *FriendshipVisibility*—we report these findings in Figure 4. Over the course of 18 months, the portfolio of stocks formed based on *FullyHidden* connections does not fall below the portfolio formed based on invisible connections, which in turn does not fall below the portfolio of visibly connected stocks. The figure further indicates that the returns accrue gradually over the course of the subsequent months. In addition, it appears that the information that we seem to capture eventually gets incorporated into the stock prices and then never reverses.

C. Connected Not-Held Portfolios

Motivated by the results presented in the previous section, we further analyze the relation between the fund managers' non-visibly connected securities and performance. Given that mutual funds are limited in their ability to engage in short selling, the funds' active portfolio allocations may not accurately reflect the fund managers' full informational advantage. If positive information is reflected in the connected stocks held by the funds, we would expect negative information to be evident in the performance of the fund managers' connected stocks when they are not held by the funds. To gain further insights into this hypothesis, employing a similar portfolio construction approach to the one used in Section II.B, we investigate returns on connected stocks that fund managers choose not to hold. In particular, for each fund-month observation, we sort the stocks in each fund portfolio into "Connected Held"[16] and "Connected Not-Held" portfolios. We place stocks in the Connected Not-Held portfolio if they are headed by a fund manager's then-active firm officer Facebook friend and are not held by the particular fund while being held by at least one other fund in the same Morningstar category in the given month. Assuming that funds do not modify their holdings between two reporting dates, we construct monthly portfolios by retaining the not-held stocks in the portfolio until the next reporting date, when the portfolios are rebalanced to reflect changes in holdings. Within a given portfolio, we weight a stock's returns by the stock's respective market capitalization. We then compute value-weighted returns by aggregating across funds, weighting each fund portfolio return by the fund's total net asset value in the subportfolio. The resulting sample comprises 2,613 distinct funds and 177,156 fund-month observations covering the period from January 1984 through December 2020. On average, a fund's Connected Not-Held portfolio per month includes 2.96 stocks managed by an average of 2.25 of the fund managers' then-active firm officer friends.

Table VIII presents the results of the analysis, indicating that the fund managers' hiddenly-connected stocks do not exhibit significant outperformance during the periods when they are not held by the funds. This observations holds true whether the assessment is based on four-factor alpha, shown in column 5, or DGTW-adjusted returns, shown in column 6. Additionally, we report the returns from a long-short strategy that involves selling short the Connected Not-Held portfolio while buying the Connected Held portfolio. For the *FullyHidden* portfolio, the set of connected stocks held by the funds outperforms the set of connected stocks not held by 119 basis points per month (t-stat $= 2.59$) in four-factor alpha, as shown in column 8, with DGTW-adjusted returns of a similar magnitude, as shown in column 9.

[16] We have previously referred to this type of portfolio as the "Connected" portfolio. However, in Sections II.C and II.D, to better distinguish it from additional portfolio types introduced in these sections, we will refer to it as the "Connected Held" portfolio.

Stepping back, the Connected Not-Held results offer a more granular exploration of the same fund manager's decision to hold versus not hold hiddenly-connected stocks. This analysis provides evidence against a stock-specific selection narrative, as it involves a long-short strategy on the same set of hiddenly-connected stocks—focusing solely on the manager's active decision to hold or not hold these stocks.

D. Returns Around Corporate News

Building on our previous analyses of returns earned on stocks with varying levels of *FriendshipVisibility*, we now aim to better understand the mechanisms behind the superior performance associated with stocks in the *FullyHidden* category. If fund managers trading these stocks are better informed, we would expect the returns on these stocks to be more concentrated around corporate news announcements—when information that possibly prompted the fund manager to purchase the connected stock is eventually incorporated into the stock price. Accordingly, we would expect returns to be less pronounced around news announcements for both non-connected stocks and the set of connected stocks that fund managers choose to avoid.

To investigate this further, we extend the portfolio construction methodology introduced in Sections II.B and II.C. Specifically, we construct the Connected Held/Non-Connected Held and Connected Not-Held portfolios by assigning to each stock in each fund portfolio its daily return earned in the following month. For each fund-day observation, we sort the stocks in each fund portfolio into "News" and "No News" portfolios, based on whether the given stock was the subject of a news announcement on that particular day. We weight stocks in the Connected Held/Non-Connected Held portfolios by their dollar values and stocks in the Connected Not-Held portfolios by their respective market capitalization. We then compute value-weighted returns by aggregating across funds, weighting each fund portfolio return by the fund's total net asset value in the subportfolio.

To compile information on firm-specific news events, we use data available via RavenPack. The service provides collection and analysis of entity-related news using natural language processing and machine learning techniques. The RavenPack data are 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 we use for our test convey material information about the firms rather than information about market movements, we follow Weller (2018) in excluding news reports on trading or prices (technical analysis signals, stock price movements, order imbalance reports) and on investor relations themes (typically announcements of future information revelation dates). We further filter the data down to include only news in which RavenPack considers the related firm to be playing a key role (i.e., news items with an "event relevance" score of 100). To remove duplicate news reports, we isolate the first news item in chains of items that relate to the same subject (using RavenPack's "event similarity days" analytic). Following these preliminary data cleaning steps, we use the CUSIP bridge provided by RavenPack's entity mapping file to merge RavenPack's firm identifier (rp entity id) with CRSP's firm identifier (permco) and map the firms' news items to their respective 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.[17] Because the RavenPack data begin in 2000, the following analysis runs from January 2000 to December 2020.

Table IX compares the average daily performance of the Connected Held, Non-Connected Held, and Connected Not-Held portfolios across all levels of *FriendshipVisibility* on days with and without news announcements. Initially, we observe that the Connected Held portfolio earns significantly positive returns around news announcements for all levels of *FriendshipVisibility*, with the most pronounced results in the *FullyHidden* specification, showing a daily four-factor alpha of six basis points (significant at the 1% level). In contrast, returns for the Connected Held portfolio on non-news days are small and statistically indistinguishable from zero, suggesting that the observed return premium is primarily generated on days with news headlines. This pattern is also evident for stocks in the Non-Connected Held portfolio. Notably, a long-short strategy that buys connected stocks in the *FullyVisible* specification on news days and sells short non-connected stocks yields an insignificant daily four-factor alpha of 1.2 basis points, which more than triples to four basis points in point estimate (significant at the 1% level) in the *FullyHidden* specification. A similar trend is observed in the Connected Not-Held portfolio, with positive returns concentrated around news announcements. However, a long-short portfolio strategy that buys the Connected Held portfolio in the *FullyHidden* specification and sells short Connected Not-Held portfolio reveals that the Connected Held portfolio experiences significantly greater news returns on average than the Connected Not-Held portfolio, corroborating the evidence presented in Section II.C.

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

III. Robustness

A. Alternative Stock-Level Performance Test

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

Table X presents the regression coefficient estimates for the average risk premia. Corroborating our findings in Table VI, we observe that the outperformance on Facebook-connected stocks increases with the level of *FriendshipVisibility*. For connected stocks in the *FullyVisible* category, the coefficient estimate of $\mathit{DiffWeight}_{k,t}$ is insignificant. However, we find significant coefficients of 152 and 171 basis points for stocks in the *FundMgrHides* and *FirmOffcHides* categories, respectively. For stocks in the *FullyHidden* category, the coefficient estimate is significant at 0.0228, indicating that a one standard deviation increase in the weight difference predicts an increase in monthly excess returns by 228 basis points. Overall, the results from our multivariate Fama-MacBeth regression analyses support the significance of hidden connections compared to publicly visible connections.

B. Friendship Intensity

If the systematic outperformance patterns we have documented are influenced by the varying levels of social ties that we collect and measure, including those that have been hidden, we would anticipate that more intense interactions among financial agents would lead to stronger results. To explore this, we leverage a unique aspect of Facebook data, which offers advantages over the traditional network membership measures: the ability to measure not only the existence of connections but also the interactions within the network. Specifically, we collect detailed interaction data on likes, comments, and tags for our sample of individuals on the Facebook platform.

Among the 57.4 million interactions collected from our sample individuals' Facebook profiles, including interactions with ten million uploaded photos (refer to Table II for details on the item-level Facebook data collected for this paper), we identify 73 thousand interactions exchanged directly between fund managers and firm officers. Of these, eleven thousand interactions occurred between pairs that we term "traded." Leveraging this data, we compute portfolio returns on funds' connected stocks, sorted by an interaction dummy indicating whether the fund manager and firm officer associated with each connected stock have interacted with each other's Facebook content (through likes, comments, or tags) within the one-year period preceding the fund's investment in the stock, or whether no such interaction was recorded. This analysis analysis spans from February 2005 to December 2020, following Facebook's launch in February 2004.

Table XI presents our results from the above test, shown across the various levels of *FriendshipVisibility*. For *FullyVisible* friendships, we observe modest monthly four-factor alphas of 15 basis points (t-stat $= 0.41$) with interactions and 13 basis points (t-stat $= 0.39$) without interactions, both of which are statistically insignificant. For *FirmOffcHides* friendships, the four-factor alphas increase to 38 basis points in point estimate (t-stat $= 1.30$) with interactions and 33 basis points (t-stat $= 1.19$) without interactions, but again, these results are statistically indistinguishable from zero. For *FundMgrHides* friendships, we see four-factor alphas of 136 basis points (t-stat $= 3.08$) with interactions compared to 56 basis points (t-stat $= 1.70$) without. However, for stocks in the *FullyHidden* category, we again observe the strongest and most telling results: four-factor alphas of 235 basis points (t-stat $= 3.80$) with interactions and 129 basis points (t-stat $= 2.56$) without interactions. These findings suggest that while the intensity of relationships, indicated by interactions, influences performance across all categories, it is the most hidden connections that drive the largest and most statistically significant outperformance.

C. Comparison of Fund Manager Characteristics

Throughout this paper, we delve into the portfolio decisions of fund managers, focusing on the varying degrees of visibility of their friendships with firm officers, particularly where friends lists are hidden by both parties. Despite observing consistent and substantial patterns in the investment behavior and information value associated with these hidden connections, concerns arise regarding potential systematic differences between fund managers identified through Facebook and those who remain unidentified. By the end of our sample period, we successfully identify the Facebook profiles of 41.8% of the then-active fund managers in the benchmark universe of funds (as shown in Figure 2). Nevertheless, a sizable portion of fund managers remains unidentified. To explore this further, we conduct a comprehensive comparison between Facebook-identified and non-identified fund managers, presented in Table XII.

From Panel A of Table XII, we find that Facebook-identified (FB-identified) fund managers are very similar to non-identified fund managers across a range of demographic and portfolio characteristics. The only significant differences are that FB-identified managers tend to be slightly younger on average (and so with shorter tenure and experience) and have a higher representation of females (seven percentage points higher). Besides these differences, they are similar across portfolio sizes (TNA), percentage with an MBA, CFA, Ivy League degree, and percentage of growth, value, small-cap, and large-cap funds. To further explore the performance of these two groups, we compare the actual performance of funds run by FB-identified fund managers to those run by non-identified fund managers in Figure 5. As shown, FB-identified fund managers perform almost identically as non-identified fund managers, with a performance correlation of 97%. However, a distinct subset of stocks, specifically those in the *FullyHidden* category, exhibit significant outperformance when they are held by FB-identified fund managers, highlighting an area of notable divergence.

Although Section II.C demonstrates that even within fund manager–firm officer hidden connections, fund managers seem to know when to hold or not hold a connected stock, there may still be questions about differences in their characteristics. In Panel B of Table XII, we examine the characteristics of fund managers with hidden friends versus those with public friends. We find that fund managers with hidden friends are nearly identical to those with public friends across all demographic and portfolio characteristics. The marginally significant difference is in fund manager age—a difference of 1.45 years (t-stat = 1.71)—which does not translate into significant differences in experience or tenure. In all other portfolio choice dimensions, they are statistically indistinguishable from each other.

D. *Replication with Index Funds*

Our findings suggests that the beneficial effects of hidden connections between fund managers and firm officers should apply exclusively to actively managed funds, implying that our measure of *FriendshipVisibility* should not reveal any performance differences in holdings of index funds, where strategic stock selection is not practiced. To test this assumption, we conduct a placebo exercise by replicating the primary performance analysis reported in Table VI, but using a sample of passively-managed funds. We follow the same procedures described in Sections I.B through I.F to select U.S.-domiciled U.S.-equity index mutual funds available in MS Direct and to gather the data on fund managers, firm officers, and the friendship ties between them. We identify index funds by using the index fund flag in MS Direct and by searching fund names for the terms "index" or "idx." This process results in a sample of 434 index funds between 1984 and 2020, with an average of 115 funds per calendar quarter and a total of 34,003 fund-month observations. These index funds are managed by 677 distinct fund managers. Among these fund managers, we identify 284 individuals (41.9%) on Facebook, resulting in a final sample of 385 funds and 24,587 fund-month observations. Using this information, we construct portfolios of connected and non-connected stocks, sorting these on levels of *FriendshipVisibility*.

The results of this falsification test are presented in Table XIII. Unlike our findings for actively managed funds, we observe no performance differences across *FriendshipVisibility* levels for index funds, with insignificant four-factor alphas across all expressions of this variable. These results support our hypothesis that the beneficial effects of hidden connections are specific to actively managed funds.

IV. Conclusion

This paper examines the influence of hidden social connections on financial market performance, using data collected from over 100 thousand Facebook profiles and their 35 million Facebook friends. Leveraging unique aspects of Facebook's functionality, we measure the extent to which friendships among asset managers and firm officers are public versus hidden. Our analyses indicate that the most valuable information is traded across hidden connections, while the premium is notably absent for visible connections. These findings suggest that not just the existence of connections, but the active management of their visibility, plays a crucial role in investment decisions and outcomes. The premium on hidden connections remains strong and significant through the present day and does not appear to be driven by familiarity or selection biases. Instead, fund managers appear to be correctly timing when to hold and when to avoid stocks of the firms to which they are hiddenly tied. This effect is consistent across industries, firm types, time periods, and investment styles.

These findings shed new light on the dynamics of information flow in financial markets and the role of social networks in shaping investment strategies. Stepping back, this research underscores the need for a deeper consideration of personal relationships and their active, strategic management in terms of visibility—public versus hidden—in investment decision-making. Future studies could further investigate the mechanisms through which this strategic management of connections relates to market behavior, along with potential regulatory implications.

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Table I. Profile-Level Facebook Data

This table provides a summary of profile-level Facebook data collected from the profiles of the 4,198 fund managers and 101,866 firm officers included in our sample of 4,100 mutual funds and their stock holdings from the period 1984–2020. For each data category, we report the percentage share (% Share) and the total number of Facebook profiles (N Profiles) from which we obtain information specific to that category.

	Fund Managers (N Profiles = 4,198)		Firm Officers (N Profiles = 101,866)	
	% Share	N Profiles	% Share	N Profiles
Screen Name	1	4,198	1	101,866
Username	1	4,198	1	101,866
User ID	1	4,198	1	101,866
Gender	.79	3,320	.71	72,127
Date of Birth	.01	37	.02	1,884
Friends List	.56	2,353	.53	54,423
Relationship Status	.21	885	.21	21,542
Family Members	.24	988	.23	23,554
Profile Picture	.90	3,793	.94	96,153
Cover Photo	.88	3,707	.89	90,864
Other Photos	.67	2,815	.77	78,023
Work	.33	1,379	.36	36,774
College	.46	1,939	.52	52,776
High School	.37	1,548	.44	45,070
Current City	.53	2,245	.48	49,172
Hometown	.43	1,815	.43	43,428
Other Places Lived	.22	919	.17	17,818
Life Events	.25	1,054	.33	33,209

Table II. Detailed Item-Level Facebook Data

The table reports descriptive statistics on item-level Facebook data collected on friends, photos, and reactions for the 4,198 fund managers and 101,866 firm officers in the Facebook-identified sample of 4,100 mutual funds and their stock holdings in the period 1984–2020. The statistics reported for each variable include the mean, median, standard deviation (SD), total number of data items collected (N Items), and number of profiles for which we collected items specific to that category (N Profiles). Statistics are computed based on observations with nonmissing values. Figures reported on friends are subsegmented by the different approaches used to collect them (refer to Section I.C for our approaches on collecting friends), including friends collected from publicly disclosed friends lists (Friends–Published), friends collected through backlinks from other users' friends lists (Friends–Backlinks), and friends collected through examining reactions received on or given to restricted photos (Friends–Reactions). Photos include profile pictures, cover photos, and those in miscellaneous albums. Reactions are those received by the photos uploaded to the profiles, excluding reactions that the individuals gave themselves to their uploads.

	Fund Managers (N Profiles = 4,198)					Firm Officers (N Profiles = 101,866)				
	Mean	Median	SD	N Items	N Profiles	Mean	Median	SD	N Items	N Profiles
Friends	269	167	394	1,095,018	4,066	341	188	635	34,148,303	100,193
Friends–Published	310	213	425	728,897	2,353	443	275	561	24,102,607	54,423
Friends–Backlinks	110	66	144	180,951	1,648	10	5	19	402,652	41,613
Friends–Reactions	126	69	199	180,058	1,425	196	111	664	7,932,927	40,540
Photos	56	6	321	187,328	3,374	110	12	420	9,831,174	89,294
Reactions	663	118	2,601	2,138,914	3,226	695	215	2,039	59,448,651	85,512
Likes	525	91	2,094	1,666,017	3,173	598	184	1,752	50,593,776	84,627
Comments	148	33	537	435,814	2,954	105	35	322	8,283,007	78,817
Tags	37	5	144	37,083	1,014	17	5	67	571,868	33,803

Table III. Summary Statistics for Facebook-Identified Sample of Funds

The table provides summary statistics reflecting the annual composition of the Facebook-identified sample of mutual funds (FB Funds), fund managers, the funds' common stock holdings, and management personnel of the firms whose stock is held by the funds. The sample comprises the 265,320 fund-month observations managed by the 4,198 Facebook-identified fund managers in the period 1984–2020. The statistics reported for each variable include the mean, median, minimum, maximum, and standard deviation (SD). The Morningstar benchmark universe (MS Universe) used to calculate percentage coverages for the funds is the sample whose construction we detail in Section I.D. The BoardEx benchmark universe used to calculate percentage coverages for firm officers is the sample constructed in Section I.F.

	Mean	Median	Min.	Max.	SD
Facebook-identified Funds (FB Funds)	1,126	1,508	23	1,985	755
% of Funds in MS Universe	.53	.59	.15	.75	.19
% of TNA in MS Universe	.50	.53	.09	.79	.22
Facebook-identified Fund Managers	934	1,166	22	1,584	614
% of Fund Managers in MS Universe	.35	.38	.13	.47	.11
Stocks held by FB funds	3,768	4,267	310	5,314	1,443
% of Stocks in CRSP Universe	.50	.57	.05	.70	.19
% of Market Cap. in CRSP Universe	.85	.96	.32	1	.18
Firm Officers held by FB Funds	59,949	64,050	1,122	115,811	45,273
% of Firm Officers in BoardEx Universe	.95	.99	.56	1	.10
Facebook-identified Firm Officers	22,116	18,405	169	55,596	19,903
% of Firm Officers held by FB Funds	.29	.29	.15	.52	.11

Table IV. Statistics on Facebook Friendships by Visibility

This table presents data on the Facebook friendships that we observe between the fund managers and firm officers in our sample, broken down by the friendships' visibility levels. We report on three types of fund manager–firm officer friendships: total observed friendships (*Friendships–All*), tradable friendships (*Friendships–Tradable*), and traded friendships (*Friendships–Traded*). The table reports figures on the number of connected pairs (*N Pairs*), the number of distinct fund managers (*N Fund Mgrs.*) and firm officers (*N Firm Offcs.*) involved in these pairs, the number of stocks associated with the pairs (*N Stocks*), and the number of underlying fund-month-stock observations (*N Obs.*). A friendship is deemed "tradable" if the fund manager's tenure at the fund coincides with the firm officer's tenure at the firm and if the firm's stock, during the given month, is held by at least one fund in the same Morningstar category as the relevant fund. A friendship is deemed "traded" if the fund manager's fund holds the firm's stock during 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 both the fund manager's and the firm officer's friends lists (*FullyVisible*); observable through the fund manager's friends list but not through the firm officer's friends list (*FirmOffcHides*); not observable through the fund manager's friends list but observable through the backlink from the firm officer's friends list (*FundMgrHides*); or neither observable through the fund manager's friends list nor through the firm officer's friends lists (*FullyHidden*).

	N Pairs	N Fund Mgrs.	N Firm Offcs.	N Stocks	N Obs.
Friendships–All	18,478	2,803	10,748	–	–
FullyVisible	6,748	1,583	4,590	–	–
FirmOffcHides	6,211	1,438	3,968	–	–
FundMgrHides	4,235	927	3,008	–	–
FullyHidden	1,284	426	993	–	–
Friendships–Tradable	9,012	2,107	6,050	3,371	–
FullyVisible	3,298	1,105	2,516	2,043	–
FirmOffcHides	3,084	1,007	2,253	1,730	–
FundMgrHides	2,038	658	1,600	1,354	–
FullyHidden	592	273	486	461	–
Friendships–Traded	2,908	1,052	2,143	1,510	171,755
FullyVisible	930	459	768	755	45,542
FirmOffcHides	959	441	779	680	45,020
FundMgrHides	758	343	618	576	51,350
FullyHidden	261	136	214	245	29,495

Table V. Portfolio Weights in Connected Stocks by Visibility

This table reports the coefficient estimates and standard errors from Panel OLS regressions of funds' portfolio weights. The dependent variable w represents the fund's dollar investment in a stock as a percentage of the fund's total net assets. The independent variables measure the level of *FriendshipVisibility*, defined by a vector of four dummy variables capturing the degree of visibility of a Facebook friendship between a fund manager and a firm officer depending on whether the friendship is publicly observable through both the fund manager's and the firm officer's friends lists (*FullyVisible*); observable through the fund manager's friends list but not through the firm officer's friends list (*FirmOffcHides*); not observable through the fund manager's friends list but observable through the backlink from the firm officer's friends list (*FundMgrHides*); or neither observable through the fund manager's friends list nor through the firm officer's friends lists (*FullyHidden*). Where included, control variables are *Style*, defined as the percentage of the fund's total net assets allocated to the style of the stock under consideration (style is calculated as in Daniel et al. (1997)), and *pME*, *pBM*, and *R12*, which are percentiles of market value of equity, book to market, and past 12-month return, respectively. Each regression includes period fixed effects. Fund and firm fixed effects are included where indicated. The sample period covers 1984–2020. Unit of observation is stock-fund-period. Standard errors are adjusted for clustering at the period level and are reported in brackets. Significance levels are denoted by *, **, and ***, corresponding to the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	74.59***	74.59***	74.59***	74.59***	1.42*	1.43*	-24.80***	-24.83***
	[0.01]	[0.01]	[0.01]	[0.01]	[0.79]	[0.79]	[1.03]	[1.02]
FullyVisible	35.18				1.05		8.68***	
	[1.20]				[0.75]		[0.96]	
FirmOffcHides		63.88						
		[1.51]						
FundMgrHides			95.80***					
			[1.55]					
FullyHidden				136.47***		50.94***		21.64***
				[2.68]		[2.06]		[2.91]
Controls	No	No	No	No	Yes	Yes	Yes	Yes
Fixed effect	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	0.36	0.36	0.40	0.40

Table VI. Returns on Connected Stocks by Visibility

This table reports monthly calendar time portfolio returns sorted by levels of *FriendshipVisibility*, which is a vector of four dummy variables capturing the degree of visibility of a Facebook friendship observed between a fund manager and a firm officer depending on whether the friendship is publicly observable through both the fund manager's and the firm officer's friends lists (*FullyVisible*); observable through the fund manager's friends list but not through the firm officer's friends list (*FirmOffcHides*); not observable through the fund manager's friends list but observable through the backlink from the firm officer's friends list (*FundMgrHides*); or neither observable through the fund manager's friends list nor through the firm officer's friends lists (*FullyHidden*). For each fund-month observation, we sort the stocks in each fund portfolio into "Connected" and "Non-Connected" portfolios. "Connected" stocks are defined as firms headed by one of the fund manager's then-active firm officer friends. Assuming that funds do not modify their holdings between two reporting dates, we construct monthly portfolios by retaining the stocks in the portfolios until the next reporting date, when they are rebalanced to reflect changes in holdings. Within a given portfolio, stock returns are weighted by the fund's dollar holdings. We then compute value-weighted returns by aggregating across funds, weighting each fund portfolio return by the fund's total net asset value in the subportfolio. Long-Short (LS) is the monthly return of a zero-cost strategy that buys the Connected portfolio and sells short the Non-Connected portfolio. 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's (1997) momentum factor. DGTW-adjusted returns are defined as raw return minus the return 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 in brackets below the coefficient estimates. Significance levels are denoted by *, **, and ***, corresponding to the 10%, 5%, and 1% levels, respectively.

	Raw Return			Four-Factor Alpha			DGTW-Adjusted		
	Connected	Non-Conn.	LS	Connected	Non-Conn.	LS	Connected	Non-Conn.	LS
FullyVisible	1.05***	0.98***	0.07	0.11	-0.00	0.11	0.15	0.03	0.12
	(3.07)	(3.92)	(0.28)	(0.43)	(-0.14)	(0.44)	(0.70)	(0.63)	(0.57)
FirmOffcHides	1.18***	0.98***	0.20	0.30	-0.01	0.32	0.34	0.02	0.32
	(3.42)	(3.72)	(0.74)	(1.12)	(-0.43)	(1.16)	(1.62)	(0.41)	(1.53)
FundMgrHides	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)
FullyHidden	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 VII. Trade-Based Returns on Connected Stocks by Visibility

This table reports monthly trade-based portfolio returns sorted by levels of *FriendshipVisibility*, which include the expressions *FullyVisible*, *FirmOffcHides*, *FundMgrHides*, and *FullyHidden*. To construct the portfolios, we assign connected and non-connected stocks into "Buy" and "Sell" portfolios depending on whether a stock was bought or sold compared to the previous fund-month observation. Within a given subportfolio, stocks are assigned the new dollars allocated relative to the previous month, and stock returns are weighted using the fund's total new dollar holdings in the subportfolio. We then compute value-weighted returns by aggregating across funds, using their total new subportfolio dollars as weights. Additionally, we differentiate Buy and Sell transactions into extensive (new or fully divested positions) and intensive (increased or decreased holdings) margin trades. Long-Short (LS) is the monthly return of a zero-cost strategy that buys the Buy portfolio and sells short the Sell portfolio. We report monthly four-factor alphas 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's (1997) momentum factor. *t*-statistics are shown in brackets below the coefficient estimates. Significance levels are denoted by *, **, and ***, corresponding to the 10%, 5%, and 1% levels, respectively.

	Connected			Non-Connected			
	(1)	(2)	(3)	(4)	(5)	(6)	(3)-(6)
	Buy	Sell	LS	Buy	Sell	LS	Spread
FullyVisible							
All Trades	0.32	-0.18	0.46	0.05	0.16	-0.11	0.57
	(0.54)	(-0.31)	(0.55)	(0.37)	(1.26)	(-0.77)	(0.67)
Extensive Trades	0.30	-0.27	0.60	0.15	0.17	-0.04	0.64
	(0.35)	(-0.30)	(0.57)	(0.97)	(1.00)	(-0.20)	(0.60)
Intensive Trades	0.35	-0.11	0.46	0.08	0.16	-0.09	0.55
	(0.61)	(-0.25)	(0.66)	(0.52)	(1.18)	(-0.56)	(0.75)
FirmOffcHides							
All Trades	0.48	-0.23	0.67	0.02	0.11	-0.11	0.78
	(0.94)	(-0.45)	(1.02)	(0.12)	(0.92)	(-0.75)	(1.17)
Extensive Trades	0.40	-0.56	0.80	0.18	0.25	0.05	0.75
	(0.51)	(-0.70)	(0.81)	(0.96)	(1.62)	(0.23)	(0.79)
Intensive Trades	0.51	-0.19	0.69	0.02	0.00	-0.02	0.71
	(0.96)	(-0.39)	(1.10)	(0.12)	(0.03)	(-0.12)	(1.07)
FundMgrHides							
All Trades	0.77**	-0.61*	1.36***	-0.09	-0.10	-0.01	1.36***
	(2.14)	(-1.94)	(3.15)	(-1.09)	(-0.91)	(-0.04)	(3.01)
Extensive Trades	1.45**	-1.04*	2.29***	-0.06	-0.05	0.12	2.17***
	(2.00)	(-1.85)	(3.06)	(-0.43)	(-0.38)	(0.66)	(2.86)
Intensive Trades	0.69*	-0.28	0.95**	-0.05	-0.09	0.03	0.92**
	(1.81)	(-0.89)	(2.10)	(-0.55)	(-0.98)	(0.30)	(2.02)
FullyHidden							
All Trades	1.27***	-0.68	1.89***	-0.04	0.01	-0.04	1.93***
	(2.75)	(-1.34)	(2.83)	(-0.34)	(0.06)	(-0.31)	(2.89)
Extensive Trades	2.25**	-1.90*	2.76***	-0.11	-0.21	0.02	2.74***
	(2.21)	(-1.84)	(2.79)	(-0.71)	(-1.27)	(0.14)	(2.78)
Intensive Trades	1.12**	-0.53	1.56**	0.02	0.15	-0.13	1.68***
	(2.42)	(-1.20)	(2.58)	(0.18)	(1.51)	(-0.96)	(2.75)

Table VIII. Returns on Connected Not-Held Stocks by Visibility

This table reports monthly calendar time portfolio returns for the funds' Connected Held and Connected Not-Held portfolios. Portfolios are sorted by levels of *FriendshipVisibility*, which include the expressions *FullyVisible*, *FirmOffcHides*, *FundMgrHides*, and *FullyHidden*. For each fund-month observation, we sort the stocks in each fund portfolio into Connected Held (CH) and Connected Not-Held (CNH) portfolios. We place stocks in the Connected Not-Held portfolio if they are headed by a fund manager's then-active firm officer Facebook friend and are not held by the particular fund while being held by at least one other fund in the same Morningstar category in the given month. Assuming that funds do not modify their holdings between two reporting dates, we construct monthly portfolios by retaining the not-held stocks in the portfolio until the next reporting date, when the portfolios are rebalanced to reflect changes in holdings. Within a given portfolio, we weight a stock's returns by the stock's respective market capitalization. We then compute value-weighted returns by aggregating across funds, weighting each fund portfolio return by the fund's total net asset value in the subportfolio. Long CH/Short CNH is the monthly return of a zero cost portfolio that buys the CH portfolio and sells short the CNH portfolio. We report raw returns (Raw), four-factor alphas (Alpha), and DGTW-adjusted returns (DGTW) in 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's (1997) momentum factor. DGTW-adjusted returns are defined as raw return minus the return 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 in brackets below the coefficient estimates. Significance levels are denoted by *, **, and ***, corresponding to the 10%, 5%, and 1% levels, respectively.

	Connected Held (CH)			Connected Non-Held (CNH)			Long CH/Short CNH		
	Raw	Alpha	DGTW	Raw	Alpha	DGTW	Raw	Alpha	DGTW
FullyVisible	1.05***	0.11	0.15	1.12***	0.06	0.05	0.05	0.11	0.17
	(3.07)	(0.43)	(0.70)	(3.09)	(0.30)	(0.28)	(0.15)	(0.35)	(0.63)
FirmOffcHides	1.18***	0.30	0.34	1.18***	0.09	0.16	-0.09	0.10	0.08
	(3.42)	(1.12)	(1.62)	(3.44)	(0.56)	(0.97)	(-0.26)	(0.31)	(0.30)
FundMgrHides	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)	(1.59)	(1.66)	(2.57)
FullyHidden	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)	(0.50)	(0.67)	(2.75)	(2.59)	(2.73)

Table IX. Returns on Connected Stocks by News and Visibility

This table reports daily calendar time portfolio returns on corporate news for the funds' Connected Held (CH), Non-Connected Held (NCH), and Connected Not-Held (CNH) portfolios. Portfolios are sorted by levels of *FriendshipVisibility*, which include the expressions *FullyVisible*, *FirmOffcHides*, *FundMgrHides*, and *FullyHidden*. To construct the CH, NCH, and CNH portfolios for this analysis, we modify the portfolio construction approaches used in Tables VI and VIII by assigning to each stock in each fund portfolio its daily return earned in the following month. For each fund-day observation, we sort the stocks in each fund portfolio into "News" and "No News" portfolios, based on whether the given stock was the subject of a news announcement on that particular day. We weight stocks in the Connected Held/Non-Connected Held portfolios by their dollar values and stocks in the Connected Not-Held portfolios by their respective market capitalization. We then compute value-weighted returns by aggregating across funds, weighting each fund portfolio return by the fund's total net asset value in the subportfolio. Long/Short represents the daily return of a zero-cost portfolio that buys the Connected Held portfolio and either sells short the Non-Connected Held portfolio or sells short the Connected Not-Held portfolio. 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's (1997) momentum factor. t-statistics are shown in brackets below the coefficient estimates. Significance levels are denoted by *, **, and ***, corresponding to the 10%, 5%, and 1% levels, respectively.

	Connected Held (CH)		Non-Connected 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
FullyVisible	0.031*	0.006	0.019***	0.004	0.019**	-0.006	0.012	0.002	0.012	0.011
	(1.68)	(0.76)	(3.94)	(1.08)	(2.21)	(-0.75)	(1.02)	(0.24)	(1.04)	(1.21)
FirmOffcHides	0.035*	0.006	0.019***	0.004	0.019**	-0.005	0.016	0.002	0.016	0.011
	(1.80)	(0.77)	(3.96)	(1.08)	(2.20)	(-0.72)	(1.32)	(0.25)	(1.44)	(1.17)
FundMgrHides	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)
FullyHidden	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)

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Table X. Cross-Sectional Fama-Macbeth Regressions by Visibility

This table reports risk premium estimates from monthly cross-sectional Fama and MacBeth (1973) regressions for the period 1984–2020. The main independent variable of interest is $DiffWeight_{k,t}$, which represents the difference between the average weight that Facebook-connected funds allocate to a given stock and the average weight that all other funds allocate to 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 is next month's stock excess returns (*ExcessRet*), calculated as raw return minus the risk free rate. All dependent and independent variables are winsorized at the 1st and 99th percentile each month. Regressions are run separately for levels of *FriendshipVisibility*, which include the categories *FullyVisible*, *FirmOffcHides*, *FundMgrHides*, and *FullyHidden*. Standard errors are adjusted for clustering at the period level and are reported in brackets. Significance levels are denoted by *, **, and ***, corresponding to the 10%, 5%, and 1% levels, respectively.

	FullyVisible	FirmOffcHides	FundMgrHides	FullyHidden
Constant	0.0104***	0.0108***	0.0124***	0.0111***
	[0.0038]	[0.0038]	[0.0038]	[0.0039]
DiffWeight	0.0142	0.0152*	0.0171**	0.0228***
	[0.0088]	[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	0.0002	0.0003	0.0002	0.0002
	[0.0023]	[0.0023]	[0.0023]	[0.0024]
STR	-0.0238***	-0.0240***	-0.0230***	-0.0238***
	[0.0057]	[0.0057]	[0.0057]	[0.0058]
IMOM	0.0846***	0.0830***	0.0826***	0.0839***
	[0.0187]	[0.0186]	[0.0190]	[0.0190]
SUE	-0.0009	-0.0010	-0.0006	-0.0011
	[0.0012]	[0.0013]	[0.0012]	[0.0013]
Adj. R squared	0.0680	0.0702	0.0783	0.0814
N	1,234,981	1,234,612	1,235,862	1,233,925
N Months	290	290	289	288

Table XI. Returns on Connected Stocks by Interactions by Visibility

This table reports monthly calendar time portfolio returns on funds' connected stocks, sorted by an interaction dummy indicating whether the fund manager and firm officer associated with each connected stock have interacted with each other's Facebook content (through likes, comments, or tags) within the one-year period preceding the fund's investment in the stock ("Interacted"), or whether no such interaction was recorded ("Non-Interacted"). Additionally, portfolios are sorted by levels of *FriendshipVisibility*, which include the expressions *FullyVisible*, *FirmOffcHides*, *FundMgrHides*, and *FullyHidden*. To construct the connected portfolios for this analysis, we use the portfolio construction approach detailed in Table VI. Long-Short (LS) is the monthly return of a zero-cost strategy that buys the Interacted portfolio and sells short the Non-Interacted portfolio. We report raw returns, four-factor alphas, and DGTW-adjusted returns in the period 2005–2020. 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's (1997) momentum factor. DGTW-adjusted returns are defined as raw return minus the return 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 in brackets below the coefficient estimates. Significance levels are denoted by *, **, and ***, corresponding to the 10%, 5%, and 1% levels, respectively.

	Raw Return			Four-Factor Alpha			DGTW-Adjusted		
	Interacted	Non-Inter.	LS	Interacted	Non-Inter.	LS	Interacted	Non-Inter.	LS
FullyVisible	1.12***	1.07***	0.05	0.15	0.13	0.02	0.13	0.18	-0.05
	(2.86)	(3.05)	(0.25)	(0.41)	(0.39)	(0.28)	(0.29)	(0.34)	(-0.19)
FirmOffcHides	1.29***	1.18***	0.12	0.38	0.33	0.05	0.39	0.37	0.02
	(2.99)	(3.41)	(0.33)	(1.30)	(1.19)	(0.51)	(1.18)	(1.12)	(0.06)
FundMgrHides	2.36***	1.47***	0.89*	1.36***	0.56*	0.81*	1.21***	0.68*	0.53*
	(4.03)	(3.61)	(1.87)	(3.08)	(1.70)	(1.82)	(2.67)	(1.85)	(1.69)
FullyHidden	3.42***	2.32***	1.11**	2.35***	1.29**	1.06**	2.46***	1.38***	1.09***
	(4.41)	(4.89)	(2.16)	(3.80)	(2.56)	(2.43)	(3.94)	(2.68)	(2.59)

Table XII. Characteristics of Facebook-Identified and Non-Identified Fund Managers

This table compares the demographic and portfolio characteristics of fund managers based on their identification status and the visibility of their connections. Panel A contrasts Facebook-identified (FB-Identified) fund managers with non-identified fund managers. Panel B compares fund managers with hidden friends lists to those with public friends lists. The characteristics examined include age, experience, tenure, gender, professional qualifications (CFA, MBA, Ivy League education), total net assets (TNA) managed, and fund type (growth, value, small-cap, large-cap). The statistics include mean and standard deviation (SD) for each characteristic, along with the difference (Diff.) between groups. The results of t-tests for differences in means are indicated with stars. Significance levels are denoted by *, **, and ***, corresponding to the 10%, 5%, and 1% levels, respectively.

	Panel A					Panel B				
	FB-Identified		Non-Identified			Hidden Friends		Public Friends		
	Mean	SD	Mean	SD	Diff.	Mean	SD	Mean	SD	Diff.
Fund Mgr. Age	44.43	3.53	47.67	2.29	-3.25***	43.52	3.91	44.98	3.41	-1.45*
Fund Mgr. Exp.	7.30	2.35	8.42	2.37	-1.11**	7.09	2.33	7.47	2.41	-0.39
Fund Mgr. Tenure	4.59	1.24	5.37	1.11	-0.78***	4.32	1.27	4.77	1.25	-0.46
Fund Mgr. Male	0.86	0.02	0.93	0.02	-0.06***	0.86	0.05	0.87	0.02	-0.01
Fund Mgr. CFA	0.56	0.06	0.54	0.07	0.02	0.58	0.08	0.56	0.07	0.02
Fund Mgr. MBA	0.61	0.05	0.59	0.04	0.02*	0.60	0.06	0.61	0.04	-0.01
Fund Mgr. IvyLg.	0.33	0.09	0.30	0.09	0.02	0.33	0.11	0.32	0.09	0.01
Fund TNA (bn.)	1.29	1.01	0.98	0.60	0.31	1.45	1.13	1.18	0.93	0.27
Growth Fund	0.41	0.07	0.38	0.08	0.03	0.39	0.06	0.41	0.08	-0.02
Value Fund	0.20	0.03	0.22	0.07	-0.02	0.21	0.05	0.20	0.05	0.01
Small-Cap Fund	0.21	0.04	0.19	0.07	0.02	0.22	0.14	0.20	0.04	0.02
Large-Cap Fund	0.50	0.03	0.52	0.08	-0.02	0.51	0.08	0.49	0.04	0.01

Table XIII. Returns on Connected Stocks of Index Funds by Visibility

This table reports monthly calendar time portfolio returns for connected and non-connected holdings of index funds. Portfolios are sorted by levels of *FriendshipVisibility*, which include the expressions *FullyVisible*, *FirmOffcHides*, *FundMgrHides*, and *FullyHidden*. We construct the portfolios using the portfolio construction approach detailed in Table VI. Long-Short (LS) is the monthly return of a zero-cost strategy that buys the Connected portfolio and sells short the Non-Connected portfolio. We report raw returns and four-factor alphas 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's (1997) momentum factor. t-statistics are shown in brackets below the coefficient estimates. Significance levels are denoted by *, **, and ***, corresponding to the 10%, 5%, and 1% levels, respectively.

	Raw Return			Four-Factor Alpha		
	Connected	Non-Conn.	LS	Connected	Non-Conn.	LS
FullyVisible	0.87**	0.88***	-0.01	-0.03	0.03	-0.06
	(2.38)	(3.33)	(-0.09)	(-0.25)	(0.85)	(-0.12)
FirmOffcHides	0.84**	0.82***	0.02	0.03	-0.00	0.03
	(2.34)	(2.97)	(0.12)	(0.31)	(-0.06)	(0.28)
FundMgrHides	0.84**	0.84***	0.00	0.01	0.02	-0.01
	(2.36)	(2.91)	(0.08)	(0.20)	(0.66)	(-0.09)
FullyHidden	0.88**	0.86***	0.02	-0.02	0.02	0.00
	(2.41)	(2.79)	(0.13)	(-0.19)	(0.52)	(0.11)

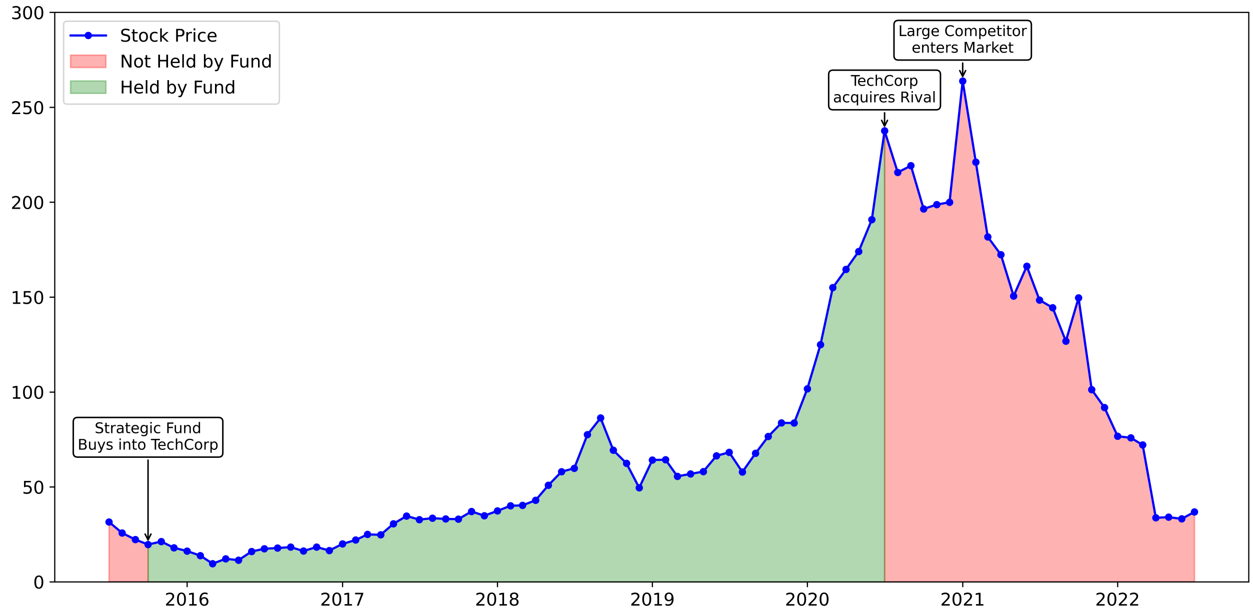

Figure 1. Holding Status of Ananke's Firm's Stock by Bergelmir's Fund
This figure shows the evolution of the stock price of the firm chaired by Ananke and the holding status of Bergelmir's fund in this stock between mid-2015 and mid-2022. The blue line with circular markers represents the monthly closing prices of the stock. The green shaded areas indicate periods during which the stock was held by the fund, while the red shaded areas represent periods when the stock was not held by the fund. The y-axis denotes the stock price in USD, and the x-axis represents the time period in months.

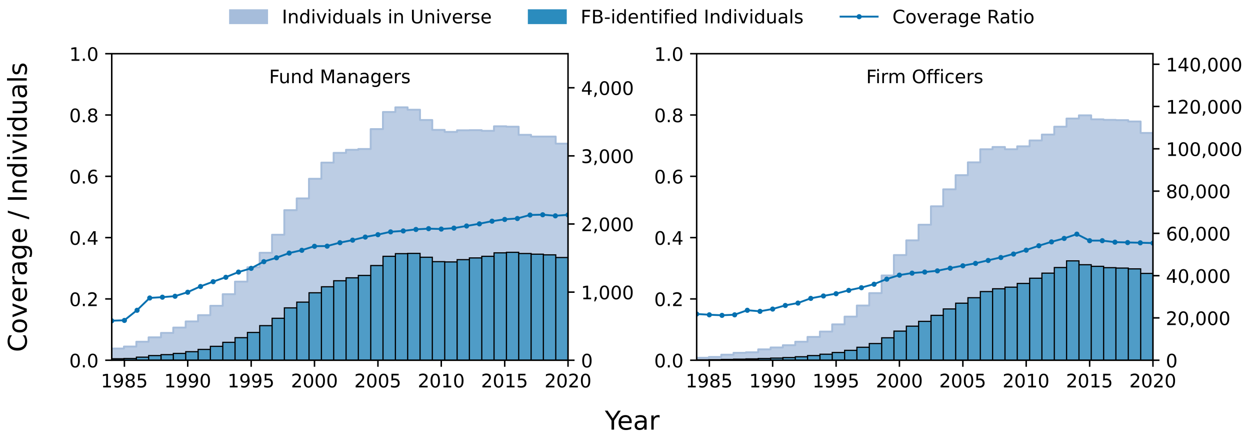

Figure 2. Ratio of Facebook-Identified Fund Managers and Firm Officers
This figure provides an overview of the identification rates of fund managers and firm officers on Facebook within their respective benchmark universes. The left subfigure shows the percentage of Facebook-identified fund managers out of the total number of fund managers in the benchmark universe of funds throughout the sample period, with 4,198 of 10,036 fund managers identified. The right subfigure shows the percentage of Facebook-identified firm officers out of the total number of firm officers in the benchmark universe of firms throughout the sample period, with 101,866 of 281,829 firm officers identified.

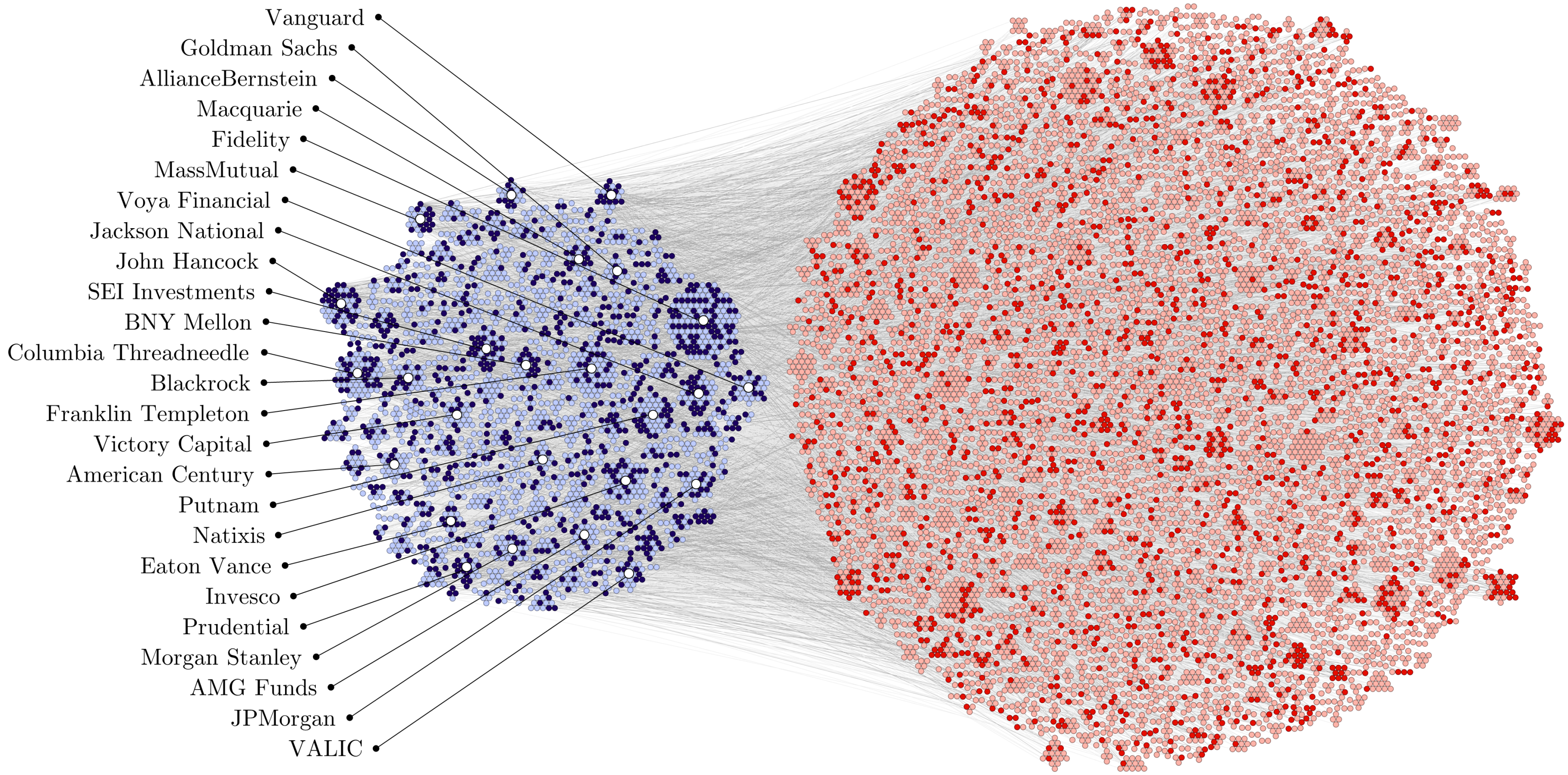

Figure 3. Network Graph of Connections Between Fund Managers and Firm Officers
This figure illustrates the network of Facebook-identified connections between fund managers (blue nodes) and firm officers (red nodes), emphasizing the connections classified as tradable. The darker shades represent fund managers and firm officers with traded connections within the subset of tradable connections. Each node denotes an individual, and edges represent Facebook friendships between fund managers and firm officers. Individuals are clustered by their current or most recent employer, as labeled. In cases of multiple affiliations, individuals are assigned to the firm where they hold their most senior role. Distances between nodes have no economic interpretation. The graph is created using a circle packing algorithm.

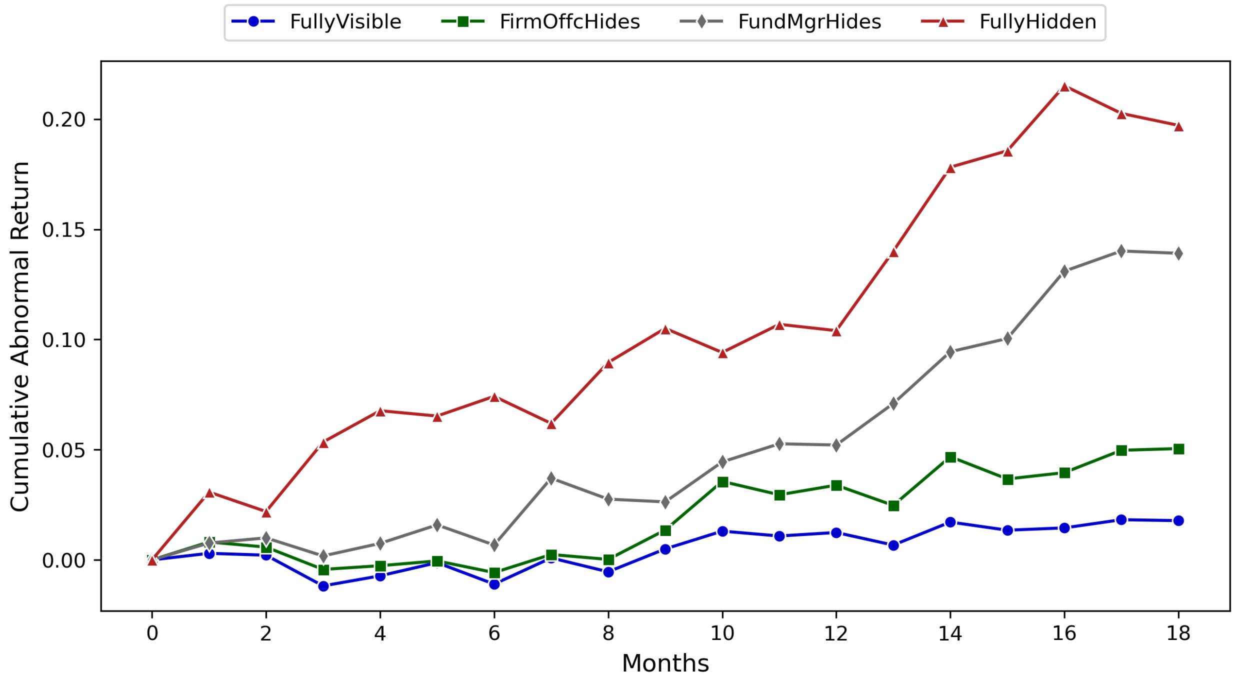

Figure 4. Cumulative Abnormal Returns on Connected Stocks
This figure presents weighted-average cumulative abnormal returns for the first 18 months following a fund's purchase of a connected stock, sorted by levels of *FriendshipVisibility*, which include the expressions *FullyVisible*, *FirmOffcHides*, *FundMgrHides*, and *FullyHidden*. If the stock position is sold and later repurchased, this repurchase is counted as a new event. Abnormal returns are adjusted for market returns, and the market values of stock positions are adjusted for inflation.

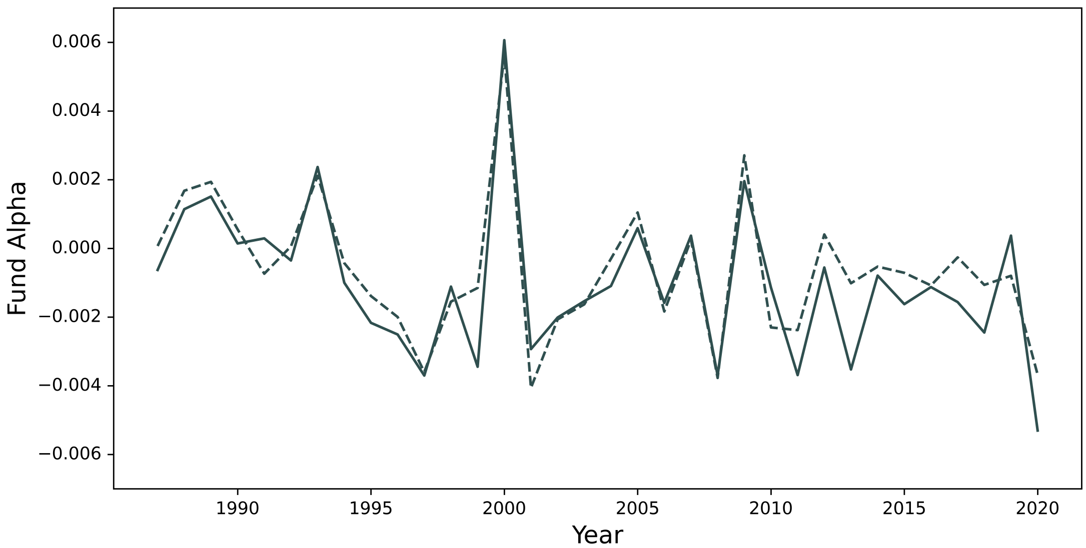

Figure 5. Performance of Facebook-Identified Funds vs. Non-identified Funds
This figure compares the performance of funds run by Facebook-identified fund managers (dashed line) and the performance of the funds run by non-identified fund managers (solid line) across the sample period 1984–2020. Fund performance is calculated as annualized four-factor alpha using funds' monthly net returns over the past 36 months, and a minimum window of 24 observations. Fund return data are obtained from MS Direct.